MODIFICATION, ELABORATION AND EMPIRICAL EVALUATION OF THE BURGER LEARNING POTENTIAL STRUCTURAL MODEL

by

JESSICA PRINSLOO

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SUPERVISORS: PROF C.C. THERON AND DR G. GöRGENS

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DECLARATION

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OPSOMMING

Suid-Afrika se verlede wat gelei was deur die Apartheidsisteem, het die meeste Suid-Afrikaners die geleentheid om toegang tot ontwikkelingsgeleenthede ontneem. Dit het gelei tot die onderontwikkeling van meeste Suid-Afrikaners se bevoegdheidspotensiaal wat hulle moet help om die eise wat tans in die wêreld van werk aan hul gestel word suksesvol te hanteer. Dié politieke sisteem het veroorsaak dat Suid-Afrika ‘n reeks probleme ervaar, insluitende; ‘n tekort aan kritieke vaardighede in die mark, baie hoë werkloosheid en armoede, ongelykheid in terme van inkomste-verdeling en ongelyke rasverteenwoordiging in die werksplek, asook oormatige misdaad, afskuwelike leefsomstandighede vir meeste Suid-Afrikaners, en ‘n toenemende afhanklikheid van maatskaplike toelaes (Van Heerden, 2013). Hierdie uitdagings verhoed dat Suid-Afrika sy globale mededingendheidspotentiaal realiseer.

Organisasies word direk deur hierdie uitdagings beïnvloed, en hulle deurlopende worsteling met hierdie nalatenskap van Apartheid is veral duidelik wanneer hulle probeer voldoen aan twee vereistes wat personeelkeuring stel. Hierdie sluit in (1) om die mees bevoegde werknemers aan te stel wat produkte/dienste van hoë kwaliteit en hoë ekonomiese nut verseker, en (2) om die werksplek onder morele, ekonomiese, politieke en wetlike druk te diversifiseer (Theron, 2009). As gevolg van Suid-Afrika se Apartheidsisteem, het die meeste indiwidue onderontwikkelde werksbevoegdheidspotensiaal wat hulle verhoed om suksesvol te wees in hulle aanstellings. Die gevolg daarvan is dat, sodra organisasies poog om aan die eerste verantwoordelikheid van personeelkeuring te voldoen dan lei die keuring tot nadelige impak. As organisasies aan die ander kant poog om aan die tweede verantwoordelikheid te voldoen deur die implimentering van tradisionele regstellende aksie, dan laat hulle onbevoegde indiwidue toe om in ‘n pos in te tree. Hierdie onbevoegdheid is nie die gevolg van ‘n fundamentele verskil in bevoegdheidspotensiaal tussen rassegroepe nie. Dit is die gevolg van die feit dat Suid-Afrika se intellektuele potentiaal nie eweredig tussen rasse ontwikkel is nie (Burger, 2012). Die huidige situasie waarin organisasies hul bevind moet op gelos word om drie belangrike redes.

‘n Oplossing kan eerstens die globale mededigendheid van die land verbeter. ‘n Oplossing kan tweedens die druk van die geïdentifiseerde sosiale uitdagings verlig, en laastens, ‘n oplossing is nodig nie net omdat ons huidige situasie moontlik haglik kan word nie, maar eenvoudig omdat dit die regte ding is om te doen.

Daar word glad nie geïmpliseer dat regstellende aksie tot niet gemaak moet word nie. Hierdie studie stel slegs voor dat die interpretasie van regstellende aksie asook die fokus daarvan ‘n meer ontwikkelings-benadering moet aaneem. Dit behels dat ‘n groter klem daarop geplaas moet word om lede van voorheen benadeelde groepe die geleenthede te gee om die nodige bevoegdheidspotensiaal te ontwikkel om suksesvol in the werksplek te wees. Hulpbronne vir hierdie ontwikkelingsgeleenthede is egter beperk. Die behoefte bestaan dus om daardie indiwidue te identifieer wat die grootste voordeel hieruit sal trek. Daarom is dit nodig om eerstens indiwidue wat die hoogste vlak van leerpotensiaal het te identifiseer, en tweedens om die omstandighede/kondisies te skep wat hierdie leerpotensiaal sal laat aktualiseer. Om uiteindelik sulke indiwidue te identifiseer asook om die persoon- en omgewingstoestande te skep wat as voorvereistes vir suksesvolle leer geld, moet die leerpotensiaalkonstruk verstaan word. Leerpotensiaalnavorsings-studies deur De Goede (2007), Burger (2012), en Van Heerden (2013) is reeds voltooi, maar om die kompleksiteit van hierdie konstruk ten volle te verstaan moet opeenvolgende studies onderneem word. Hierdie studie het gevolglik gefokus op die uitbreiding van hierdie bestaande modelle om sodoende ‘n meer volledige begrip van leerprestasie te ontwikkel.

Die doel van hierdie studie was daarom om die bestaande Burger (2012) leerpotensiaal strukturele model te wysig en uit te brei deur die toevoeging van addisionele nie-kognitiewe veranderlikes. Die strukturele model was empiries geëvalueer en die metingsmodel het ‘n goeie passing getoon. Die strukturele model het aanvanklik slegs ‘n redelike passing bereik, maar na die oorweging van die volle spektrum pasgehaltemaatstawwe, gestandaardiseerde residue, modifikasie-indekse and parameterskattings is ‘n aantal wysigings aan die model aangebring. Die finaal-gewysigde strukturele model het goed gepas. Al die bane in die finale model is empiries bevestig. Die beperkinge van die navorsingsmetodiek, die praktiese implikasies van die studie en aanbevelinge vir toekomstige navorsing was ook bespreek.

ABSTRACT

South Africa's social political past that was led by the Apartheid system has deprived the majority of South Africans of the opportunity to develop and accumulate human capital. As a result, this political system has left this country with a range of challenges including; a shortage of critical skills in the marketplace, high unemployment and poverty rates, inequality in terms of income distribution, unequal racial representation in the workplace, together with other social challenges such as high crime rates, extensive poverty, horrendous living conditions and a consequent increasing dependence on social grants (Van Heerden, 2013). These challenges prohibit this country from realising its global competitive potential.

Organisations are primarily affected by these struggles faced by the country, and their continuous fight with these legacies of Apartheid is especially evident when they try to comply with the two responsibilities that form part of the personnel selection function. These include their responsibility to (1) employ the 'best' employee for the job to result in the production of products and services of high economic utility, and (2) to act under moral, economic, political and legal pressure to diversify their workforce (Theron, 2009). Due to South Africa's past political system, the majority previously disadvantaged individuals have underdeveloped job competency potential which currently prohibits them from succeeding in the world of work. Consequently, if organisations try to comply with their first responsibility, the process of selecting the 'best' employee results in adverse impact. If organisations comply with their second responsibility through traditional affirmative action measures, they allow incompetent employees to be appointed. The incompetence is not due to one race having fundamentally less competency potential then another. It is because South Africa's intellectual capital is not, and has not been uniformly developed and distributed across races (Burger, 2012). This current situation faced by organisations should be dealt with for three important reasons. Firstly, a solution could improve the global competitiveness of this country. Secondly, a solution could contribute to solving the social challenges faced by this country, and lastly, not only because the situation could possible become precarious, but simple because it is the right thing to do.

It is not implied that affirmative action should be abolished. This study rather suggests that the interpretation of affirmative action should change and the focus of this corrective policy should shift to a more developmental approach. This entails that more emphasis should be placed on providing the previously disadvantaged with the necessary training and development to foster the needed competency potential to succeed in the world of work. However, resources for these developmental opportunities are scarce, and as a result, a need exist to identify a method that could identify individuals who will gain maximum benefit from these suggested affirmative development opportunities. Consequently, a need exist to identify individuals who display the highest potential to learn and to create the conditions conducive for learners with high learning potential to actualise that potential. In order to successfully identify the individuals who display a high level of learning potential and to create the person- and environmental characteristics that have to be present to facilitate successful learning, the learning potential construct must be understood. De Goede (2007), Burger (2012), and Van Heerden (2013) have completed research studies on this specific construct, and to assist in the understanding of the complexity of this construct, it made more empirical sense to build on existing structural models. This should result in the production of a more complete understanding of learning and the determinants of *learning performance*.

The objective of this study was therefore to modify and elaborate the Burger (2012) learning potential structural model by expanding the model with the inclusion of additional non-cognitive variables. The proposed hypothesised learning potential structural model was empirically evaluated. The measurement model achieved good close fit. However, the first analysis of the structural model only obtained reasonable model fit. After the consideration of the full range of fit indices, standardised residuals, modification indices and parameter estimates, a few modifications were made to the model. The final revised structural model achieved good fit. All of the paths in the final model were empirically corroborated.

The limitations of the research methodology, the practical implications of this study, and recommendations for future research are also discussed.

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CHAPTER 1

INTRODUCTORY ARGUMENT

1.1 INTRODUCTION

The introductory argument contends the necessity of this study by firstly elaborating on the context of this study, and secondly, by presenting the research objectives of the research conducted. It focused on providing a thorough explanation as to why the research objectives are considered relevant and important for the discipline and practice of Human Resource Management and Industrial/Organisational Psychology.

Economic growth at a high and consistent level is a requirement which would allow a country to compete in the global market. Through constant economic growth a country is able to gain a competitive advantage, and also be able to prevent economic stagnation, poverty and unemployment. This high and consistent level of economic growth will only be reached if a country produces goods and delivers services in a productive, effective and efficient way (De Goede, 2007).

Organisations are formed primarily to produce goods and deliver services by maintaining a high level of productivity. This is done to ensure the development of economic value for all their stakeholders and also to comply with their responsibility towards society; to efficiently and effectively combine and convert scarce resources into desired products and services with economic utility (Burger, 2012). Organisations consist of different inter-related functions with different expertise, all working together to reach these goals of the organisation. These organisational functions focus on achieving the goals of the organisation, and also to enable the organisation to maintain a sustainable competitive advantage. One of these functions within the organisation is the human resource (HR) function, which utilises human capital[1] as a key success factor for sustained organisational performance (Luthans, Luthans & Luthans, 2004).

[1] The term is used to collectively refer to the knowledge, experience, skills and expertise of employees.

Nel, Gerber, Van Dyk, Haasbroek, Schultz, Sono and Werner (2001) explains that this function focuses on the attainment and maintenance of a motivated workforce, as well as the effective and proficient utilisation of such a workforce through the execution of a human resource strategy. A strategy derived from, and aligned with, an appropriate business strategy in a manner that contributes to a competitive advantage (De Goede & Theron, 2010). More specifically, this function focuses on the collective attitudes, skills and abilities of people to contribute to organisational performance and productivity. They focus on the attainment, maintenance and utilisation of labour in order to achieve the organisational goals and maintain sustainable levels of growth and performance. Labour is the life-giving production factor through which the other factors are mobilised and thus represents the factor which determines the effectiveness and efficiency with which the other factors of production are utilised (Gibson, Ivancevich & Donnelly, 1997). The human resource function provides an organisation with an asset that is valuable, rare and difficult to replicate-and therefore a source of sustainable competitive advantage (Luthans, et al., 2004). This function justifies its inclusion in the range of organisational functions not just based on the argument up to this point but also when considering the fact that this function shows a persistent commitment to contribute towards the organisations goals through interventions that affect employee performance in such a manner that the monetary value of the improved performance exceeds the investment required to affect the improvement in performance. Thus, based on these reasons, it is evident that the human resource function of the organisation is of critical importance to achieve organisational effectiveness, efficiency and productivity.

The human resource function contributes to the production of market-satisfying goods and/or services by affecting the performance of employees through an integrated and co-ordinated network of human resource interventions. These interventions are either aimed at employee flow or employee stock (De Goede & Theron, 2010). For the purpose of this study, the focus will be on employee flow interventions, which attempts to alter the composition of the workforce by adding removing or reassigning employees, with the prospect of influencing overall work performance. Personnel selection serves as one of the primary interventions utilised to control employee flow. Through selection the human resource function can control and regulate the movement of employees into, through and out of the organisation (Theron, 2007).

With regards to personnel selection, organisations in South Africa have two very important responsibilities; firstly, they are accountable towards stakeholders and society to efficiently combine and convert scarce resources into products and/or services, with high economic utility (i.e., products and/or services that are valued by the market). To accomplish this they require capable, knowledgeable and high-performing employees, which will function in an efficient, effective and productive manner. Secondly, organisations also carry the responsibility to act under the moral, economic, political and legal pressure, to diversify their workforce (Theron, 2009).

When selecting employees organisations should satisfy both these obligations, but this is something South African companies are struggling to comply with. This is due to of the fundamental challenges which arise from South Africa's socio-political past. South Africa has a history of racial discrimination that was led by the Apartheid system. This system was characterised by legal racial segregation enforced by the National Party of South Africa during the 1949 to 1993 time frame, where the rights of the majority 'non-White' citizens of South Africa were limited and minority rule by White South Africans was maintained (Van Heerden, 2013). The government designed this system for the purpose of benefiting Whites and discriminating against the Blacks. This was achieved by segregating amenities and public services and providing Black South Africans with services inferior to those of White South Africans. It should be recognised that the term Blacks, is a generic term which refers to Black Africans, Coloured individuals, Indians and Chinese, who have been South African citizens prior to 1994, now called the *previously disadvantaged group* (Burger, 2012).

The segregation deprived this group of many things, including; proper education, adequate healthcare, access to enriching activities, proper sanitation, and acceptable living arrangements. Despite these, the worst wrongdoing ever done to these individuals were the deprivation of the opportunities to accumulate human capital (Burger, 2012). This became especially evident when considering the education received by Blacks in South Africans during this time. The government segregated education by means of the 1953 Bantu Education Act, where a separate education system was crafted for Black South Africans, which denied them access to the education and other developmental opportunities that White students were afforded.

The racial segregation experienced in South Africa were emphasised by Thabo Mbeki's "two nations" speech delivered in parliament in 1998 (Seekings & Nattrass, 2005, p. 342):

> *One of these nations is White, relatively prosperous, regardless of gender or geographical dispersal. It has ready access to a developed economic, physical, educational, communication and other infrastructure. This enables it to argue that, except for the persistence of gender discrimination against woman; all members of this nation have the possibility of exercising their right to equal opportunity, and the development opportunities to which the constitution of 1993 committed our country. The second and larger nation of South Africa is Black and poor, with the worst affected being woman in the rural areas, the Black rural population in general and the disabled. The nation lives under conditions of grossly underdeveloped economic, physical, educational, communication and other infrastructure. It has virtually no possibility of exercising what in reality amounts to a theoretical right to equal opportunity, that right being equal within this Black nation only to the extent that it is equally incapable of realisation.*

This segment of the speech presented by Thabo Mbeki in 1998 emphasised the unequal and divided society crafted by the Apartheid regime (Cameron, 2003; Gibson, 2004). However, despite these unmistakable negative consequences of the Apartheid system, South Africa was also left with having one of the lowest economic growth rates in the world, an increased occurrence of violent civil unrest among previously disadvantaged South Africans, and international boycotts including trade rest and being banned from international sporting events (Gibson, 2004). It was these occurrences that led to the Apartheid regime being demolished in a series of negotiations from 1990 to 1993, which resulted in the first democratic elections in 1994 (Van Heerden, 2013). This ensued in the election of the new government and the dismantling of the Apartheid regime in 1994 (Cameron, 2003; Gibson, 2004). The newly elected government embarked on a much needed process of redistribution of economic, social, cultural and political power and resources, to assist in rectifying the inequalities left by the Apartheid system (Van Heerden, 2013).

Significant progress has been made towards transforming the unequal society evident in this country and considerable achievements have been managed in many respects. However, despite these notable achievements, this country is still confronted by a range of challenges. The most critical of these include; a shortage of critical skills in the marketplace, high unemployment and poverty rates, inequality in terms of income distribution and unequal racial representation in the workplace and other social challenges such as high crime rate and increasing dependence on social grants (Van Heerden, 2013).

The severity of these challenges increased when organisations attempt to comply with the first responsibility of efficiently combining and converting scarce resources into products and/or services of high economic utility, as presented at the beginning of this section. In their attempt to comply with this responsibility they have no choice but to employ highly productive, capable, and skilful employees. However, as already explained the previously disadvantaged individuals were deprived of the opportunity to accumulate human capital. Consequently, they did not have the chance to obtain a proper education, develop the necessary abilities and skills to succeed in the world of work, as was afforded to White individuals. Thus, the process of selecting the 'best' employee invariably results in adverse impact. Adverse impact refers to the situation where a specific selection strategy affords members of a specific group a lower likelihood of selection in comparison to another group (Theron, 2009). Adverse impact is not in the final analysis the result of an unfair selection procedure, but rather because of the past leaving Black South Africans with underdeveloped job competency potential (Burger, 2012). The 'playing field'[2] within South Africa is unequal, and when an organisation is pressured with the responsibility to select the 'best' employee, the *previously advantaged* group will be more advantaged by being selected and gaining more developmental opportunities, while the *previously disadvantaged* will be further deprived. The reality lies in the fact that South Africa has a vast untapped reservoir of human potential that need to be unlocked.

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[2] A central underlying assumption in this thesis is that no <u>fundamental</u> difference exists between the groups within South Africa. Inequalities exist in the level of skills, abilities and knowledge, because of the unequal distribution of opportunities, but no difference exist in the levels of potential and talent of the different groups. Thus, development is a fruitful option, because of the fact that no fundamental differences between the different groups exist.

The major concern lies in the fact that the talent of innumerable individuals will never be discovered or developed (De Goede & Theron, 2010). Stephen J. Gould (1981, p. 57) highlights this concern, by emphasising the consequence of complying with the first responsibility:

> *I am somehow less interested in the weight and convolutions of Einstein's brain than in the near uncertainty that people of equal talent have lived and died in cotton fields and sweatshops.*

The second responsibility of organisations forces them to act under the moral, economic, political and legal pressure, to diversify their workforce. The past history of racial segregation and discrimination on the basis of race influenced millions of South Africans. The country was confronted with divisions and inequalities in society and the disparities between the racial groups were blatantly obvious (Rabe, 2001). Thus, it was expected that attempts to reverse the legacy of discrimination would be a priority of the newly, democratically elected, government (Burger & Jafta, 2010). This was the main reason for the legal framework developed to redress the economic imbalances of the past (Seekings & Nattrass, 2005).

The Employment Equity Act 55 of 1998 (Republic of South Africa, 1998) was developed and implemented to correct the embedded inequalities in employment, by "eliminating unfair discrimination" and through the implementation of "Affirmative Action measures to redress the disadvantages in employment experienced by designated groups". The Act was primarily developed to redress past and present[3] social imbalances by advancing those who have been discriminated against (Twyman, 2001, p. 324).

This Affirmative Action policy was a source of great hope for many Black South Africans, but at the same time it triggered an equally intense resentment by those Whites who perceive themselves as the new victims of reverse discrimination (Adam, 1997). Despite the rejection of this policy, the legitimacy of the rationale for the implementation of Affirmative Action measures cannot be denied.

[3] Since the election of the new government in 1994, numerous attempts have been made to rectify the imbalances within the South African society. However, even today, there still exists an obvious division. Therefore, the Employment Equity Act was developed not only to address past inequality, but also to address inequality visible in the society in 2013.

Firstly, the *remedial* rationale remains the most prevalent. This rationale is a moral justification aimed at righting the past wrongs and emphasising compensatory, corrective action to rectify unfair treatment (Moses, 2010). Secondly, as explained by Moses (2010), an economic argument that centres on a solid instrumental rationale for this policy exists. In South Africa where majority of the population were affected by the past wrongdoings, a societal need exist for these previously disadvantaged individuals to be educated and developed to be able to join the workforce and contribute to the economy. It simply makes economic and socio-political sense to provide greater opportunities for such a large portion of the population.

Despite these rationales for the policy, the attitudes towards the implementation of Affirmative Action measures are more strongly resented now, then when it was initiated. Kanya Adam made a statement in 1997, explaining that this policy has the potential to do well, but at the same time it has the potential to undermine reconciliation and divide South Africa further (Adam, 1997). This is precisely the consequence of this policy, because even though a need for it exists, it is implemented and utilised in completely the wrong manner. A heightened rejection of the policy has as a consequence developed over time. Joubert and Calldo (2008, p. 4), explain the biggest mistake made with the implementation of this policy:

> *The current way of empowering people through Affirmative Action does not actually empower. It is merely the powerful government actor using its power to place disempowered people in jobs.*

Shen, Chanda, D'Netto and Monga (2009) reiterate the sentiment expressed in the above statement by commenting that, the Affirmative Action programs quite often demand the appointment of a Black person above a better qualified White candidate. According to Alexander (2006) people are put into jobs where they are simply not up to the task. Thus, economists believe that the appointment of the previously disadvantaged individuals that are clearly inexperienced and undertrained has led to the disaster in both the public and private sectors (Alexander, 2006). Skilled workers are replaced by unskilled labour, just to satisfy the need for transformation. The rationale for Affirmative Action undeniably does exist, and the need for transformation and rectifying the past is crucial to South Africa, but the government seems to be willing to sacrifice economic growth on the altar of racial preferencing at all costs (Joubert & Calldo, 2008).

South Africa needs its skilled human capital to fight the challenges faced by this country. Skilled human capital forms the foundation of high economic growth by assisting in the alleviation of the devastating poverty and unemployment figures and by eliminating inequality in income distribution and unequal racial representation in the workplace (Van Heerden, 2013). The question that the government should ask itself is: transformation at all cost, or alleviation of these challenges through economic growth (Joubert & Calldo, 2008)? It should be South Africa's goal to achieve both these objectives, because both these conditions are necessary to strengthen South Africa's global competitiveness.

To adjust this policy for the better, a fundamental mind shift is essential. The focus should not fall on employing the individual with the right skin colour, but rather to provide those previously disadvantaged individuals with the opportunity to receive a proper education, and develop the necessary abilities and skills to succeed in the world of work. If people are educated and trained in skills, they themselves become empowered and do not need to rely on outside interference by the government. Affirmative Action should not focus (solely) on the rather emotive aspect of output (i.e., the proportional representation of various race groups in the labour market), but rather on inputs in the form of training and development (Theron, personal communication, 12 June 2012). Training and development will lead to growth, which is the best method of correction (Joubert & Calldo, 2008).

Focussing on training and development will not only increase the fruitfulness and acceptability of the Affirmative Action policy, it will also allow, over the longer term, a decrease in the occurrence of adverse impact. If these individuals have the opportunity to train and develop the needed skills and abilities to succeed in the world of work, the likelihood of a selection strategy not affording them with an equal chance of being selected for a particular job will decrease. For organisations to successfully minimize adverse impact in the selection process, and also diversify their workforce with capable employees, the emphasis, according to this study, should fall on affirmative development programs. Affirmative development programs are the only way in which previously disadvantaged individuals can acquire the necessary skills to compete on an equal footing with the previously advantaged (Jinabhai, 2004).

These programs will empower individuals with the necessary knowledge, skills, abilities, and coping strategies to successfully participate in the economy (Burger, 2012). These proposed programs will therefore firstly assist organisations in complying with the two responsibilities[4] expected of them. However, this will not be the only advantage of these programs; it will secondly aid South Africa in fighting the challenges resulting from the Apartheid regime.

Van Heerden (2013) explained that when previously disadvantaged individuals are empowered with the needed skills, abilities and knowledge sought after in the marketplace, they will be able to find employment, earn a decent living wage and thereby uplift themselves from conditions of excessive poverty. This will fight the challenge of high unemployment rates, extreme poverty figures and excessive social grant dependence[5]. In addition to these advantages a developmental approach will also address the challenge of inequality in income distribution in this country, as well as unequal racial representation in the workplace. The Gini coefficient[6] will only be minimized if those currently excluded from the economy are empowered through skills development and training opportunities to productively participate in the economy (Van Heerden, 2013). Skills, knowledge and abilities will assist these previously disadvantaged individuals to competently fill a position, thereby restoring equality in racial representation in the workforce.

Lastly, a final argument exists that further emphasised the necessity of Affirmative Development programs. This case was introduced by Van Heerden (2013), and goes beyond business considerations or alleviation of economic and social challenges.

[4] These two challenges include: (1) the production of products and/or services of high economic utility where competent, productive, efficient and effective employees are needed, and (2) the moral, political and legal pressure to diversify the workforce, and thus employing previously disadvantaged individuals.

[5] The skill development programs will assist in individuals finding employment, which would decrease unemployment figures. When individuals are employed they will earn a decent wage that will result in alleviation of poverty among previously disadvantaged. When these individuals earn an income, the reliance on social grants from the government will decrease, as individuals will become more self-reliant and no longer need social assistance. Thus, allowing the availability of funding for other national developmental programs.

[6] The Gini coefficient measures the equality of the income distribution among South Africans. Currently, the South African society is extremely unequal in terms of income distribution. White individuals and a handful of Black individuals are at the high-middle end of the income hierarchy, while majority of the South African population, consisting of mostly Black previously disadvantaged, is at the lower end of the income distribution. South Africa has the dubious honor of having one of the highest Gini coefficients in the world. Skill development will result in individuals finding employment, and earning a decent wage, that should result in a declining Gini coefficient.

This argument takes the moral standpoint that contributing towards the Millennium Developmental Goals (MDGs)[7] such as the eradication of hunger and poverty, achieving universal primary education, promoting gender equality and woman empowerment, reducing child mortality, improving maternal health, combating diseases such as HIV/AIDS and malaria, ensuring environmental sustainability, and developing global partnerships of development, are worthy of support simply because it is the right thing to do. Economic growth and development is the most powerful tool available to realise the eight MDGs.

The Accelerated and Shared Growth initiative in South Africa (ASGISA) (2008) as well as the Joint Initiative on Priority Skills Acquisition (JIPSA) (2007) suggested that the removal of skill shortages with respect to engineers and scientists, the development of managerial staff, and the development of a skilled and educated labour force are prerequisites for economic growth and development and subsequent meeting of the MGDs. Consequently, it is proposed that affirmative development programs will serve as one of the most effective mechanisms to firstly assist organisations to comply with the two responsibilities expected of them, secondly, to fight the challenges faced by South Africa that is prohibiting their global competitiveness, and lastly to take a moral standpoint and contribute to the Millennium Development Goals and help redress the severe challenges faced by this country.

Affirmative development programs depend on a number of different resources and as a result they are very expensive. So, despite the fact that millions of previously disadvantaged individuals require access to such a program, South Africa has limited resources, which means that only a relatively limited number of individuals will have the opportunity to take part in these programs. Therefore, it is crucial that all attempts should be made to ensure that those that are given the opportunity to participate in such a program will succeed in both the program and their job thereafter (Burger, 2012). To identify the individuals that would be successful, it is vital to remember that these programs are there to empower individuals with the necessary job competency potential and job competencies required to deliver the outputs for which the job exist (De Goede & Theron, 2010).

[7] The eight Millennium Development Goals (MDGs) were initiated by the United Nations (UN) in collaboration with all the world's countries including the world's leading development institutions. These parties agreed to mobilize all unprecedented efforts to meet the eight goals by the target date of 2015.

Thus, individuals which has the *potential to learn*, who show the greatest probability to acquire the deficient attainments and dispositions, and who would subsequently gain maximum benefit from such opportunities, should be identified (De Goede & Theron, 2010). The method used to identify these individuals with the greatest *potential to learn*, should not only focus on the level of learning performance that the individual can reach at present, but also one that reveals hidden, reserved capacities and potential of future levels of learning performance (De Goede, 2007). This is necessary for two very different reasons.

Firstly, a distinction should be made between *classroom learning performance* and *learning performance during evaluation*. *Classroom learning performance* refers to the learning behaviours that take place during the training and development opportunity, while *learning performance during evaluation* refers to the learning that occurs when an individual has to apply their classroom learned knowledge to a novel or partially novel problem subsequent to the classroom learning opportunity. In a well-constructed post-development test that attempts to evaluate the extent to which learners have truly grasped and internalised the learning material covered in the development program, the learner will be confronted with novel problems not as yet previously encountered but that could realistically be encountered in the world of work. Finding a valid solution to the problem will require the learner to adapt and transfer the newly developed insights onto the novel problem. The methods used to identify individuals who has the greatest potential to learn, should not solely focus on the individual's ability to learn in the 'classroom', but also their ability to use their newly learned knowledge and apply it to subsequent novel problems in World 3[8] (Babbie & Mouton, 2001). The ability to transfer learned knowledge to a novel problem is crucial skill that will assist the individual to function successfully in a job (De Goede, 2007). It is precisely the inability to successfully solve job-related problems in World 3, due to the inability to transfer existing but inadequate crystallised abilities/job competency potential, that make previously disadvantaged individuals fail under the traditional interpretation of affirmative action.

[8] Babbie and Mouton (2001) established a basic framework that was designed to assist individuals in organizing the way they think about science and the practice of scientific research. The framework reflected three different worlds. *World 1* referred to the world of metascience (the critical interest), *World 2* referred to the world of science (the epistemic interest), and World 3 referred to everyday life (the pragmatic interest). The different worlds highlighted the different interests or motives that underlie knowledge production. Therefore, by emphasizing World 3 in this section, highlighted the focus and reflection on social/practical problems (Babbie & Mouton, 2001).

Consequently, the method should focus on identifying an individual's present potential to learn, but also those hidden reserved capacities that give an indication of the individual's ability to apply the learned knowledge to a novel problem and reveal their future potential to learn.

Secondly, South Africa's intellectual capital is not and has not been uniformly developed and distributed across race. Consequently, instead of evaluating the individual's past skill acquisition, a need exist to use a method aimed at assessing the individual's capacity to learn in the future (Burger, 2012). Thus, it is necessary to differentiate between individuals who possess potential and who are classified as disadvantaged, from those that are also disadvantaged but do not possess the same levels of learning potential (Murphy & Maree, 2006). More specifically, the question is; which individual considered for affirmative development will achieve the highest level of *classroom learning performance* and eventually *learning performance during evaluation*. So, it is proposed that the previously disadvantaged individuals with the potential to benefit from a cognitively challenging affirmative development opportunity should be identified and subsequently developed[9]. Attempts to ensure that those disadvantaged South Africans that are allowed the opportunity to attend an affirmative development program should, however, not be restricted to selection based on learning potential. Once those disadvantaged individuals with sufficient learning potential have been selected on to the affirmative development program further steps should be taken to ensure that the learning conditions, internal and external to the learner, are optimal.

It is important to take note of the fact that this study agrees with Van Heerden (2013, p. 16) that "it is by no means implied that skill development has gone unacknowledged by the government thus far". In reality the government has attached great importance to this initiative. Their commitment to skill development is firstly demonstrated when considering the vital legislation that was promulgated.

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[9] According to Burger (2012), this argument implies that past social injustices had a direct impact on attributes required to perform successfully and not (so much) on psychological processes and structures that play a role in the development of the attributes required to succeed on the job. If past social injustices had the latter, more far reaching impact, rehabilitation of the psychological processes and structures through which critical attributes and competencies develop, would also be required. Moreover the argument implies that the competency potential latent variables relevant to job performance that were negatively affected by the lack of opportunity are sufficiently malleable to respond to development interventions.

These include the South African Qualifications Authority Act No 58, 1995; the Skills Development Act No 97, 1998; and the Skills Development Levies Act No 9, 1999. Van Heerden (2013) further explains that twenty five Sector Education and Training Authorities (SETAs) were introduced, which oversee the training and skill development in specific national sectors. The South African Qualification Authority (SAQA) and the Education and Training Qualification Assurance (ETQA) that act as 'quality authority' of all education and training in South Africa, were also introduced. The National Qualifications Framework (NQF) was formulated to provide a unified system for all education and training qualifications in South Africa (Meyer, Mabaso, Lancaster, & Nenungwi, 2004). The government has also invested the largest portion of the budget into the improvement and development of education and training in South Africa. In 2011, R189.5 billion of the budget was allocated towards education and training (Van Heerden, 2013). However, to ensure an increased urgency for the implementation of these affirmative development initiatives, a close collaboration between government and the private sector should exist. Organisations in the private sector cannot passively sit and wait for government to remedy the damages done by Apartheid (Dinokeng scenarios, undated). Rather, the third scenario[10] envisaged by the Dinokeng scenario team needs to be actively promoted in which organised business (along with ordinary citizens) actively engage with government in pursuit of a shared vision of a peaceful and prosperous South Africa in which all its citizens benefit from the new democracy (Dinokeng scenarios, undated).

Most organisations would however argue that education, poverty, housing, and welfare are all part of the core functions of the government, and that businesses should not assist government in executing their functions. Nevertheless, businesses are suffering due to the lack of education that is directly evident in the present skills shortage. Furthermore, businesses are also negatively affected by social issues such as poverty and unemployment through increased crime rates and decreased spending on economic development (Van Heerden, 2013). Consequently, active participation and commitment is required from the private sector, in addition to that already showed by the government.

[10] The three Dinokeng scenarios do not serve as predictions; they are possible pathways into a specific future. Each of the scenarios reflects a possibility of a different future for South Africa. The first scenario reflects a 'Walk apart' possibility, while the second scenario emphasise a 'Walk Behind' possibility, and the third scenario highlights a 'Walk Together' possibility (Dinokeng scenarios, undated).

The active and committed role of professionals in the private sector are also emphasised by the Broad Based Black Economic Empowerment (BBBEE) Codes that consist of important provisions on employment equity as well as human resource development. Also, the Commission for Employment Equity (CEE) (2008) reported that disparities in training interventions in terms of race and gender, as well as in terms of various occupational levels are evident. Consequently, the CEE would like to encourage a greater focus of resources on the upgrading of skills.

Despite the efforts of the government, every human resource department has a crucial role to play in skill development and the implementation of affirmative development programs (Burger, 2012). This results in asking the question of where and how this form of training should be offered. There exists two answers to this question; the first possibility would be to commit to the appointment of specific individuals before they have actually realised their potential. This will result in identifying individuals with potential, selecting them into a job and developing them on-the-job. This constitutes an interpretation of affirmative development that is in accordance with the approach that the Employment Equity Act (Republic of South Africa, 1998, p. 22) had in mind when stating the following:

> *For the purpose of this Act, a person may be suitable qualified for a job as a result of any one of, or combination of that person's-*
>
> *(a) formal qualification;*
> *(b) prior learning;*
> *(c) relevant experience; or*
> ***(d) Capacity to acquire, within reasonable time; the ability to do the job.***

The second possibility would be to not commit to the appointment of an individual before they have actually realised their potential. This suggests a two-stage selection process; where previously disadvantaged individuals who would gain maximum benefit from a developmental opportunity are selected during phase one[11]. They are then provided with an affirmative developmental program and developed off-the-job.

[11] As resources are very scarce, it is sensible to suggest that only previously disadvantaged individuals who would derive maximum benefit from such developmental opportunities should be identified and invested in. This will again be emphasised later on in this discussion.

During the second-stage of the selection process the individuals with the highest expected job performance can be selected. This decision, as proposed by Burger (2012), can be based on a battery of predictors that could include an evaluation of performance on the affirmative development program. However, due to the low predictive validity of any selection procedure, the second possibility seems more cautious than selecting an individual directly into a shadowing position. The direct selection into a shadowing position increases the possibility of prediction errors (Burger, 2012) in that it compounds the errors made in the prediction of learning performance and those made in the prediction of job performance, while the two-stage process allows for the prediction errors of the first stage to be formally acknowledged in the second-stage of prediction. Although the second possibility is probably not what the Employment Equity Act originally had in mind when the Act was promulgated, it can nonetheless use the following clause in the Act (Republic of South Africa, 1998, p.24) to argue its legitimacy along with the previous argument presented:

> *(6) An employment equity plan may contain other measures that are consistent with the* ***intentions*** *of this Act.*

Based on the argument presented up to this point, it is evident that all attempts should be made to ensure that the individual who is chosen for this opportunity succeed in the program and the job thereafter. This is possible because the level of *classroom learning performance* an individual achieves when provided with a developmental opportunity as well as the level of *learning performance during evaluation* is not a random event. It is systematically, though complexly determined, by a nomological network of latent variables characterising the individual and the context/situation in which the learning takes place (Burger, 2012). The nomological network of influence underlying an individual's level of learning performance is complex because of three reasons, firstly; a large number of latent variables characterising the learning environment and the learner, combine to determine the level of *classroom learning performance* as well as the level of *learning performance during evaluation*. Secondly, these latent variables are richly interconnected, so that almost every variable is directly or indirectly affected by every other latent variable, and lastly, feedback loops exist that link outcome variables with latent variables positioned earlier in the causal chain to form a dynamic system (Smuts, 2011).

These three characteristics in combination means that a valid understanding of learning performance does not lie in any individual latent variable or individual relationship but rather in the richly interconnected nomological net as a whole (Cilliers, 1998). Dissecting the network or describing only a limited portion of the network of structural relations existing between the latent variables therefore unavoidably results in a loss of meaning or understanding (Cilliers, 1998).

According to De Goede (2007), an individual will only achieve a specific level of *classroom learning performance* and *learning performance during evaluation* if they satisfy the preconditions set by the nomological network. These preconditions set by the nomological network consist of both malleable and non-malleable latent variables characterising the learning context and latent variables characterising the learner (e.g. learner competency potential latent variables). In order to successfully ensure that selected individual will make a success of the affirmative developmental opportunity, it is crucial to identify as many of these latent variables as possible and also to develop a thorough understanding of the manner in which they combine to affect *classroom learning performance* and eventually *learning performance during evaluation*. Smuts (2011) supports this notion by affirming that attempts to influence the learning performance of an individual will succeed to the extent that this complexity is accurately understood. Consequently, the constructs of *classroom learning performance* and *learning performance during evaluation* along with the intricate nomological network that shape their levels must be thoroughly understood in order to ensure that the individual admitted to an affirmative developmental program will make a success of such an opportunity and the job thereafter.

It is therefore suggested that a performance@learning competency model should be developed in the form of a structural model that identifies the critical learning competency potential latent variables, the learning competencies and the learning outcomes as well as the manner in which they combine to affect learning performance (Saville & Holdsworth, 2000, 2001). This suggested learning performance structural model should captures as many of the determinants of learning performance and as much of the richness of the structural relations that exist between these determinants as possible.

Such a learning performance structural model can then successfully inform human resource management attempts to influence the level of *classroom learning performance* that affirmative development candidates achieve as well as the eventual level of *learning performance during evaluation* that these candidates accomplish.

The level of *classroom learning performance* that affirmative development candidates attain as well as the ultimate level of *learning performance during evaluation* that they achieve, can be influenced by regulating the flow of candidates into the affirmative learning opportunity. They can be regulated with the help of the non-malleable determinants of learning performance (i.e., the learning competency potential variables). The level of *classroom learning performance* that affirmative development candidates admitted onto the program achieve, as well as the eventual level of *learning performance during evaluation* that they achieve can in addition be influenced by manipulation of the malleable (person-centered and situation-centered) determinants of learning performance to levels conducive to optimal learning.

Human resource interventions aimed at enhancing learning performance by regulating the flow of learners into the affirmative learning opportunities based on the (malleable) characteristics of learners and the characteristics of their learning environment, will only be fruitful if they are based on a valid understanding of what constitutes learning. This understanding should evolve around grasping the complexity of the nomological network of latent variables that determine the level of learning performance that is achieved in the classroom, during evaluation and subsequently in the world of work. The more restricted our understanding of the nomological complexity, the greater the loss of understanding, and the more limited our ability to influence learning performance.

A single explanatory research study is unlikely to result in an accurate understanding of the comprehensive nomological network of latent variables that determine learning performance (Burger, 2012). It must be understood that, because of the complexity of this phenomenon, the models established through the research of any single research study only succeeds in explaining a portion of this intricate network. Meaning lies spread over the whole of the nomological network. If subsequent research studies would therefore chose to focus on a new aspect of learning potential in isolation the full meaning will never be attained (Theron, personal communication, 1 March 2012).

Although man most likely never will achieve omniscience (Versfeld, 2009), reasonably close approximations of a comprehensive nomological network of latent variables that determine learning performance can only be achieved through an extensive series of cumulative research studies where later researchers modify and elaborate on the learning performance structural models developed by earlier researchers. Therefore, despite the fact that the construct of learning performance has been researched by several researchers, specifically De Goede (2007), Burger (2012) and Van Heerden (2013) in more recent times; meaningful progress will only be achieved if explicit attempts are made at successive research studies, which takes effort in expanding and elaborating the latest version of the explanatory learning potential structural model (Smuts, 2011). This will assist with the gradual uncovering[12] of the nomological network of latent variables underlying learning performance and in the process, over time, reveal as much of the complexity underpinning this construct, as is humanly possible.

Based on the systematic argument presented, this study strives to elaborate Burger's (2012) answer to the research initiating question; why do variance in learning performance of previously disadvantaged individuals partaking in an affirmative developmental opportunity occur? More specifically the research initiating question is, therefore, what other cognitive and/or non-cognitive person-centered latent variables as well as situation-centered latent variables, over and above those already considered in the Burger (2012) model, cause variance in the learning performance of a previously disadvantaged individual?

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[12] It needs to be acknowledged that the term "uncover" is somewhat problematic in as far as it suggests a potentially discoverable "truth" as to what determines learning performance. Complete certainty as to the nature of the psychological process underlying learning performance is, however, an unattainable ideal (Babbie & Mouton, 2001). At best one can aspire to obtain a valid (i.e., permissible) explanation of learning performance that can be considered permissible in as far as it is able to satisfactorily account for empirical observations made.

1.2 RESEARCH OBJECTIVES

The primary objective of this study is to modify and elaborate on the learning potential structural model presented by Burger (2012), by:

- Formulating additional learning competency potential latent variables, other than *Conscientiousness*, *Academic Self-efficacy* and *Learning motivation*, as presented by Burger (2012), that also influence the level of proficiency on the classroom learning competencies.
- Developing an elaborated learning potential structural model based on a reasoned funnel-like argument, that explicates the nature of the causal relationships that exist between the learning competency potential variables, between the learning competencies, and between the learning competency potential latent variables and the learning competencies.
- Empirically evaluating the fit of the proposed theoretically derived, learning potential structural model by first testing the separate measurement model and thereafter the structural model. If acceptable model fit is achieved, the significance of the path coefficient estimates will be evaluated.
- Modifying the structural model if necessary, based on the modification indices provided by the statistical analysis, and to compare the fit of the revised learning potential structural model to that of the original model.

CHAPTER 2

LITERATURE STUDY

2.1 INTRODUCTION

In this section of the thesis, the De Goede - Burger learning potential structural model will be briefly explained and thereafter the proposed expanded model will be presented. Firstly, the argument presented in the De Goede (2007) thesis in terms of which the De Goede learning potential structural model was derived will be discussed, followed by the structural model as well as a summary of the results found. Secondly, the argument presented by Burger (2012) in terms of which she derived the De Goede - Burger learning potential structural model will be discussed, after which the structural model will be presented, which will be followed by a discussion of the results found. Thirdly, this section will also include the proposed Burger - Prinsloo learning potential structural model. Each added construct will be individually defined and discussed in order to systematically uncover the logic underlying the structure of the proposed expanded learning potential structural model. More specifically, the reasoning behind each added construct, as well as how each construct fits into the nomological network, will be explained.

2.2 THE DE GOEDE (2007) LEARNING POTENTIAL STRUCTURAL MODEL

The De Goede (2007) study investigated the internal structure of the learning potential construct as measured by the Apil-B developed by Taylor (1992; 1994). De Goede argued that the measurement of learning potential in South Africa is critical because of the fact that it is a core fundamental ability, as opposed to abilities heavily influenced by exposure to previous opportunities. The importance of the assessment of learning potential can be explained partly in terms of the necessity of equalling the proverbial ‘playing field’ and ensuring the previously disadvantaged individuals are not becoming more disadvantaged by being further denied of opportunities, and partly in terms of attempts to compensate and correct for a system that clearly oppressed the development of important job related skills, knowledge and abilities in certain groups (De Goede, 2007).

The De Goede learning potential structural model is based on five latent variables; two learning competency latent variables and two learning competency potential latent variables. These latent variables will be briefly discussed, because the De Goede (2007) learning potential structural model forms the conceptual basis of the Burger (2012) model and also the further expansions suggested in this study.

2.2.1 Learning Competencies

Taylor (1992; 1994) argued that *transfer of knowledge* and *automisation of information*; to be the two fundamental dimensions of *classroom learning performance* or the learning competencies that constitute successful *classroom learning performance* and subsequent *learning performance during evaluation* (De Goede & Theron, 2010).

2.2.1.1 Transfer of Knowledge

The first learning competency variable refers to *transfer of knowledge*. This latent variable constitutes the core of academic learning as it involves the transfer of existing knowledge on to novel learning material in an attempt to create meaningful structure in the learning material. Transfer involves the adaptation of knowledge and skill to address problems somewhat different from those already encountered. Taylor (1992) considered transfer as the most basic learning competency. De Goede (2007, p. 37) summarised the importance of this learning competency by writing:

> *An individual should be able to transfer if he/she is to function successfully in a job (in the sense of solving a novel problem via transfer from newly learned competency potential) and in an educational or training and development environment.*

Consequently, transfer of knowledge was included in the presented learning potential structural model as a learning competency constituting *classroom learning performance*. *Transfer of knowledge* is, however, not restricted to the classroom. Learning also occurs when the extent to which classroom learning took place is evaluated by means of a post-development test, where the learners would be confronted with novel problems that they have not encountered during the development program, but whose solution requires the adaptation of the knowledge that they gained on the program.

Adequate *classroom learning performance* is therefore a prerequisite to achieve adequate *learning performance during evaluation*. The problem-solving that takes place on the job again essentially is transfer of knowledge gained through earlier learning experiences. No sharp division exists between learning in the classroom and subsequent learning during evaluation and action learning on the job. De Goede (2007) viewed this construct as a critical learning competency.

2.2.1.2 Automisation

The second learning competency refer to *automisation*, which in contrast to *transfer of knowledge*, does not have to do with tasks that are different but rather tasks that do not change over time (Burger, 2012). This variable involves the process in which the individual is becoming more efficient and effective at what he/she is doing, because the individual is automating many of the operations involved in performing the tasks. Thus, *automisation* refer to the individual pre-consciously making what he/she has learned a part of him or herself (De Goede & Theron, 2010). *Automisation* comprises writing the insight gained through *transfer of knowledge* to knowledge stations in memory in a manner that allows it to again be easily retrieved when needed for subsequent transfer/problem solving (De Goede, 2007).

If an individual does not successfully automate many of the operations involved in performing a task, they will not become efficient and effective at the execution of a task. This is due to the fact that the stimulus will remain a novel problem to be solved every time it is encountered. This will greatly reduce the adaptive value of learning, as subsequent transfer would be inhibited since newly derived insights would not accumulate in knowledge stations to form the basis from which future novel problems are solved (De Goede & Theron, 2010). As a result, this construct is also included in the structural model on learning potential.

2.2.2 Learning Competency Potentials

The extent to which learners successfully transfer and automate is not due to chance, as the level of competence learners achieve on these two learning competencies depends on a complex nomological network of person-centered characteristics (learning competency potential) as well as situational characteristics (De Goede & Theron, 2010).

As a result, Taylor (1992) hypothesised that the capacity to form abstract concepts and the capacity to process information efficiently is determined by the intelligence of the learner (De Goede, 2007). Taylor (1992; 1994) in addition made a distinction between two dimensions of intelligence, namely *abstract thinking capacity* and *information processing capacity*. These two dimensions of intelligence constitute the nucleus of the cognitive learning competency potential that drives the two learning competencies that constitutes learning (De Goede & Theron, 2010).

2.2.2.1 Abstract Thinking Capacity

According to Burger (2012), *abstract thinking capacity* develops as fluid intelligence and consists of a set of general cognitive tools and strategies for application to novel problems. *Abstract thinking capacity* plays an essential part in work activities requiring additional effort above simple routines. De Goede (2007) stated that an individual's *abstract reasoning capacity* plays an important role in dealing with novel kinds of problems and learning. Consequently, this capacity to think in an abstract manner will contribute to an individual's capacity to make sense of a learning task. *Abstract thinking capacity*, however, does not in itself, in isolation, solve novel learning problems. It is the learner's *abstract thinking capacity* that allows the adaptation of existing crystallised intelligence and the transfer of the insight thereby gained onto the novel problem[13]. This learning competency potential variable is considered as an innate or unlearned variable, thus less susceptible to effects of environmental deprivation (Taylor, 1994).

2.2.2.2 Information Processing Capacity

Sternberg (1984) explains *information processing capacity* in the following manner: in a learning context the individual is faced with novel, intellectual challenging tasks. Such tasks cause the individual to experience uncertainty, which the individual naturally tries to reduce. In order to reduce the uncertainty, the individual needs to firstly use executive processes, which will help to process bits of information provided in the tasks and select a strategy to follow. Secondly, the individual has to use non-executive processes to actually carry out the strategy.

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[13] It is, however, important to note that the De Goede (2007) model did not formally reflect this fact.

The ability to process bits of information through cognitive processes which are activated in an uncertain situation in order to reduce uncertainty could be termed *information processing capacity*. An individual with a high level of information processing capacity can more accurately, more quickly, and more flexibly process information, and is able to acquire more information, learn faster and perform better in tasks requiring the retrieval and storage of various forms of information.

2.2.3 Learning Performance

Operationally *learning performance during evaluation* refers to the extent to which an individual will achieve academic success within the context of school learning performance measures (i.e. test and exam results). More specific to this study, *learning performance during evaluation*, as explained by De Goede (2007), can be interpreted as the extent to which an individual has acquired a specific skill, knowledge or ability (job competency potential) and can use that specific skill, ability or knowledge in solving novel problems through transfer of that knowledge or ability in situations corresponding to the job for which the affirmative development is initiated. This is summarised in the argument presented by De Goede and Theron (2010, p. 38):

> *Learning performance refers to the creative use of newly acquired knowledge rather than the level to which job relevant knowledge and abilities have been developed. Development programs are designed to empower employees with both the job competency potential and job competencies required to deliver the outputs for which the job in question exists. This should refer to more than simply the retrieving of previously transferred and automated (i.e. learned) responses to now familiar stimuli (the application of newly acquired skills should not be dismissed altogether). The expectation rather would be that the affirmee would be able to apply the newly derived knowledge to novel stimuli not explicitly covered in the affirmative action development program.*

This again illustrates the point made earlier that *learning performance during evaluation* and action learning on the job is fundamentally no different from *classroom learning performance*. All three essentially involve fluid intelligence creating meaningful structure in initially meaningless stimuli.

This is achieved through the transfer and the adaptation of knowledge gained through prior learning and *information processing capacity*, editing existing memory structures to record the elaborated knowledge. Learning is a never-ending spiral of making sense of new learning problems through transfer of existing knowledge and automating the elaborated knowledge to serve as cognitive platform for future transfer.

2.2.4 Proposed Structural Model and Results

De Goede (2007) in accordance with the argument presented by Taylor (1992; 1994), hypothesised that the level of competence learners achieve on the *transfer of knowledge* learning competency is primarily determined by the *abstract thinking capacity* of the learner. In addition De Goede (2007) hypothesised that the level of competence learners achieve on the automisation learning competency is primarily determined by the *information processing capacity* of the learner. These two learning competency potential latent variables (*abstract thinking capacity* and *information processing capacity*) were also hypothesised to affect *learning performance during evaluation* directly based on the argument that *classroom learning performance* and *learning performance during evaluation* essentially is the same behavioural phenomenon. The level of competence learners achieve on the *transfer of knowledge* learning and the automisation competencies in classroom learning was hypothesised to affect *learning performance during evaluation*. Lastly, De Goede (2007) hypothesised that the level of competence achieved in the transfer of knowledge in the classroom depended on the competence at automisation. The faster insights gained through transfer can be written to memory the more intellectual capacity is freed to again devote to subsequent transfer (Taylor, 1992; 1994).

The De Goede (2007) learning potential structural model is shown in Figure 2.1. The model obtained *reasonable model fit* as judged by the overall goodness-of-fit statistics. The close fit null hypothesis was not rejected ($p>.05$). The results of the statistical analysis of the De Goede (2007) learning potential structural model showed the relationship between *information processing capacity* and *automisation* to be significant ($p<.05$). The direct paths that were hypothesised between *information processing capacity* and *learning performance* and between automisation and *transfer of knowledge* were also supported ($p<.05$).

Support was found for the indirect effect of *information processing capacity* on *learning performance* mediated by *automisation* ($p<.05$). The remaining paths that were hypothesised in Figure 2.1 were statistically insignificant ($p>.05$). No support was therefore found for the hypotheses that *abstract thinking capacity* influences *transfer of knowledge*, that *transfer of knowledge* affects *learning performance* and that *abstract thinking capacity* directly affects *learning performance*.

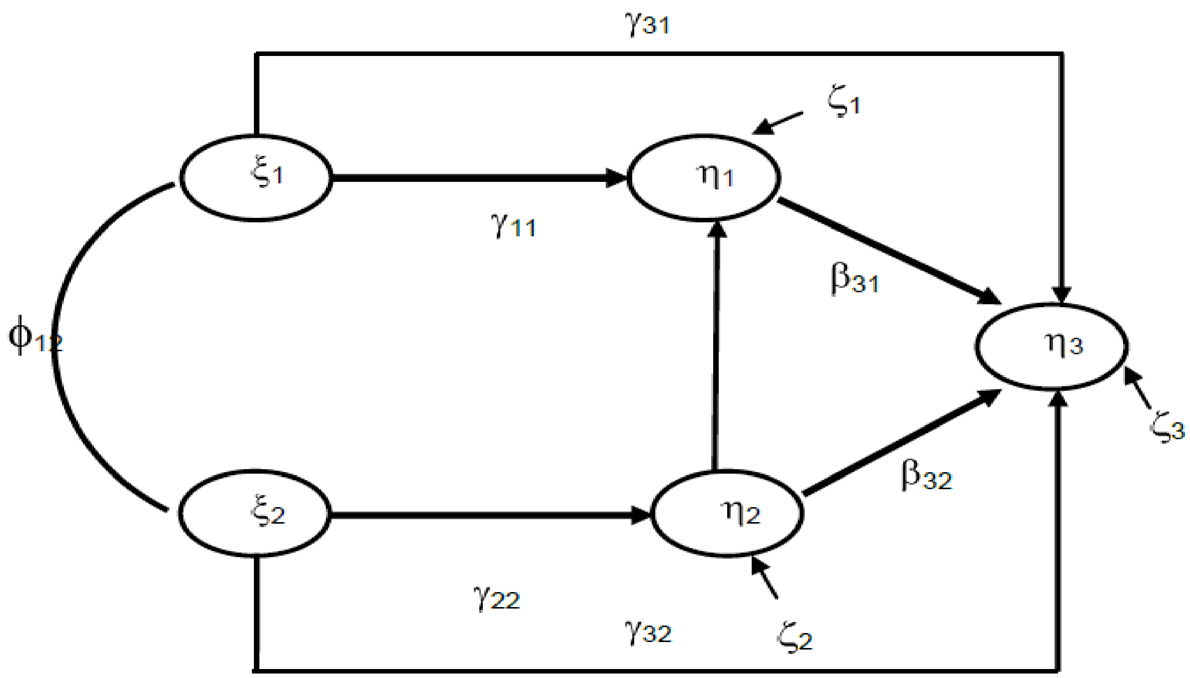

***Figure 2.1*: De Goede (2007, p. 59) Learning Potential Structural model**

Where:

ξ_1 = *Abstract thinking capacity*

ξ_2 = *Information processing capacity*

η_1 = *Transfer of knowledge*

η_2 = *Automisation*

η_3 = *Job Competency Potential*

2.3 THE EXPANDED DE GOEDE – BURGER LEARNING POTENTIAL STRUCTURAL MODEL

Burger (2012) agreed with the argument presented in the De Goede (2007) thesis; but expanded that argument by concluding that a more comprehensive understanding of the learning competencies and learning outcomes that constitute successful learning performance is required. Individuals are assigned to affirmative development treatments with the aim of achieving specific learning objectives through specific learning outcomes. Burger (2012) argued that these learning objectives are to exceed the minimum critical job competency potential required to display the job competencies on a quality level sufficient to achieve the outcomes for which the job exist. Specific learning competencies are instrumental in attaining these specific, desired learning outcomes (Burger, 2012). These learning behaviours depend on and are expressions of a complex nomological network of person-centred characteristics (learning competency potential), some of which are malleable (attainments) and some of which are less easily changeable (dispositions) (Burger, 2012). Thus, Burger (2012) wanted to explore the structural relationship between the characteristics of the learner required to exhibit the learning behaviours needed to develop the qualities necessary to prepare the individual for the world of work.

Burger (2012) also agreed with De Goede (2007) that cognitive ability is a determinant of performance on the two learning competencies *transfer of knowledge* and *automisation.* However, Burger (2012) further argued that it seems extremely unlikely that cognitive ability would be the sole determinant of learning performance. Individuals must invest in numerous cognitive and non-cognitive resources to succeed in a learning situation (Burger, 2012). To accommodate additional non-cognitive learning competency potential latent variables, required the identification of additional learning competencies (Theron, personal communication, 1 March 2012). Burger (2012) argued that it was extremely unlikely that non-cognitive learning competency potential latent variables will directly affect the learning competencies *transfer of knowledge* and *automisation*. It seemed more likely that additional learning competencies mediate the effect of non-cognitive competency potential latent variables on *transfer of knowledge* and *automisation*. Consequently, this expanded model included non-cognitive factors, i.e. additional learning competency potential latent variables, as well as additional learning competencies.

Burger (2012) therefore started to develop *classroom learning performance* into a multidimensional behavioural construct characterised by a specific internal dynamic. Specific structural relations were hypothesised to exist between the learning competencies comprising learning performance.

The original casual paths hypothesised by De Goede (2007) were retained in the expanded De Goede – Burger learning potential structural model. The model is depicted in Figure 2.2.

Burger (2012) argued that when a learner engages with learning material, their *information processing capacity* directly positively influences their *automisation* and indirectly through their *automisation* affects their *transfer of knowledge*. Additionally, as was already hypothesised in the De Goede model (Figure 2.1); the Burger model further proposed that *abstract reasoning ability* positively influenced *transfer of knowledge*. The new variables included in the expanded De Goede - Burger learning potential structural model, are discussed next. This will assist in the formation of a general understanding of Burger's (2012) reasoning, and also in the extensions proposed.

2.3.1 Learning Competencies

a.) Time Cognitive Engagement

Cognitive engagement is defined as the extent to which students are attending to, and expending mental effort in the learning task at hand. According to Burger (2012), higher levels of learner's engagement are generally associated with higher levels of learning. It is a deceptively simple premise, perhaps self-evident, according to Burger (2012), as the more students study or practice, the more they tend to learn. This specific variable is specifically important to learners from the previously disadvantaged group, due to their lower levels of crystallised abilities. Burger (2012) argued that as a result of the lack of opportunity and the ensuing lower levels of crystallised abilities, it could be hypothesised that such learners would have to exert more effort and spend more *time cognitively engaged* in their studies to achieve successful transfer (Burger, 2012). The reasoning presented by Burger was supported by a study completed by Carini, Kuh and Klein (2004), where they found that low-ability students benefit more from engagement than their high-ability counterparts.

The results of the study showed that low ability students had a .17 correlation between total time spent preparing/studying for class and their RAND[14] score, while high ability students obtained a correlation of .01[15] (Carini et al., 2004).

Through the addition of this learning competency latent variable, Burger (2012) assumed that learning tasks are resource sensitive, and therefore resource dependant (especially at the start of academic skill acquisition). Consequently, if level of effort exerted by an individual is conceptualised as the amount of attention resources devoted to the task, then an increase in effort would be likely to cause an increase in performance (Burger, 2012). Consequently, Burger (2012) suggested that *time cognitively engaged* would significantly influence *transfer of knowledge* and will constitute *learning performance*.

b.)Academic Self- Leadership

Self-leadership is the process through which people influence themselves to achieve the self-direction and motivation necessary to perform (Burger, 2012). This process allows individuals to control their own behaviour, influence and lead themselves through the use of a specific set of behavioural and cognitive strategies. Burger (2012) defined self-leadership more narrowly as *academic self-leadership*. The self-leadership construct included in the expanded model is therefore confined to the influencing, self-direction and motivation geared towards the academic domain and subsequent learning.

Burger (2012) separated *academic self-leadership* into three primary dimensions, namely: behaviour focussed-, natural reward-, and constructive-thought pattern strategies. Behaviour focussed strategies are aimed at increasing self-awareness leading to the management of behaviours involving necessary but perhaps unpleasant tasks. These strategies include: self-observation, self-goal setting, self-reward, self-corrective feedback, cueing and practice. Burger (2012) hypothesised that *academic self-leadership*; will positively influence *learning motivation,* based on the sub-strategy of *self-goal setting*. This is based on the argument that the act of setting goals that are challenging and specific should have a positive effect on learners' motivation to learn.

[14] The RAND tests consider an individual's general intellectual ability to a large degree. It consists of six 90-minute critical thinking and performance problems (Carini, et al, 2004).
[15] This suggests a time cognitively engaged x ability interaction effect on learning performance.

Burger (2012) hypothesised that this relationship also should operate in the opposite direction, since *learning motivation* serves as a mobiliser and driver of *academic self-leadership*. Based on the sub-strategies of self-set reward and self-set goals, Burger (2012) furthermore hypothesised that *academic self-leade*rship positively influences *time cognitively engaged*. This relationship was based on the idea that self-rewards provide sufficient leverage for action (Burger, 2012).

Secondly, natural reward strategies are designed to leverage intrinsic motivation to enhance performance. Self-leadership extends beyond external rewards, and also includes natural rewards that result from the performance of the task or activity itself. Thus, natural reward strategies create situations where individuals are motivated or rewarded by the inherently enjoyable aspects of the given task or activity. As a result, individuals who are motivated internally to learn will be motivated to learn (Burger, 2012). This argument supports the hypothesised relationship between *academic self-leadership* and *learning motivation*.

Lastly, the constructive-thought pattern strategies involve the creation and maintenance of functional constructive patterns of habitual thinking that can positively impact performance. Constructive thought-pattern strategies have been refined and more fully developed under the label of *thought self-leadership* (TSL). Specific *thought self-leadership strategies* include: self-management of beliefs and assumptions, mental imagery, and self-talk. These mental practices enable self-guided verbal persuasion, which are an important source that assist in improving self-efficacy (Ruvolo & Markus, 1992).

Based on this, Burger (2012) hypothesised that *academic self-leadership* positively influences *academic self-efficacy*. This relationship was also hypothesised to be reciprocal, based on the idea that effective leaders require higher levels of confidence, which amplifies the fact that self-efficacy is important for achieving success and effectiveness as a leader (Hannah, Avolio, Luthans & Harms, 2008).

2.3.2 Learning Competency Potential Latent Variables

a.) Conscientiousness

Personality refers to the rather stable characteristics of individuals that influence both their cognitions and behaviour.

An increased body of evidence suggests the importance of measures of personality traits in the prediction of academic and work-related achievement (Burger, 2012). Unlike cognitive ability measures, personality measures tend not to show significant differences between racial groups (Burger, 2012). Consequently, Black individuals generally obtain the same scores as Whites, while woman generally tend to get similar scores as men. Burger (2012) provides support for this statement by highlighting that most personality traits reveal small to non-existent mean score differences between ethnic and racial groups. However, this evidence should not be interpreted in a way that suggests that the use of personality measures will ameliorate the adverse impact created by the fair use of valid cognitive predictors (De Goede & Theron, 2010).

Conscientiousness has been added to the expanded structural model, because this variable appear to be highly relevant to learning potential and has been shown to positively affect performance across occupational groups (Burger, 2012). *Conscientiousness* assesses the degree of organisation, persistence, control, and motivation in goal-directed behaviour. If an individual scores high on conscientiousness they tend to be organised, reliable, hardworking, self-directed, punctual, scrupulous, ambitious and persevering (Burger, 2012). This is a valuable resource, because it allows individuals to more effectively regulate other resources and enable them to cope effectively with many demands they may face. *Conscientiousness* has been consistently found to positively correlate with academic performance (Chamorro-Premuzic & Furnham, 2003), as well as training proficiency (Barrick & Mount, 1991). Chamorro-Premuzic and Furnham (2003) and Barrick and Mount (1991) argued that individuals with a high degree of *conscientiousness* would make an effort to learn and spend more time on their study material. Consequently, Burger (2012) hypothesised that *conscientiousness* will positively influence *time cognitively engaged*. Also, individuals high in *conscientiousness* are likely to be better self-regulators. Burger (2012) mentioned that a number of studies have demonstrated a relationship between self-regulation and *conscientiousness* (e.g. Koestner, Bernieri & Zuckerman, 1992) that supports this notion. In section 2.3.1(b), it is emphasised that *self-leadership* is a more developed form of self-regulation. Based on this thought pattern, Burger (2012) suggested that *conscientiousness* positively influences *academic self-leadership.* Research conducted by Houghton et al. (2004) and Stewart et al. (1996) were highlighted to support this hypothesis.

Houghton et al. (2004) found that the *conscientiousness* factor was significantly positively related with the behaviour focused skills factor (r = .57), the natural reward skills factor (r = .33) and the constructive thought-pattern processes skills factor (r = .29); known dimensions of the *academic self-leadership* construct. Also, Stewart et al. (1996) directly examined the relationship between self-leadership and *conscientiousness* and found a positive relationship between *conscientiousness* and employee self-directed behaviours. Given this evidence, Burger (2012) hypothesised that *conscientiousness* should, in a learning context, positively influence *academic self-leadership*.

b.) Learning Motivation

Cognitive ability was, and is, widely considered to be the single best predictor of learning and job performance, especially when the individual is faced with difficult and complex tasks (Ree & Earles, 1991). However, according to Burger (2012), more recent research indicates that ability in the absence of motivation, or motivation in the absence of ability is insufficient to yield performance[16]. *Learning motivation* can be defined as the desire on the part of the trainees to learn the training material. Motivated individuals are more ready to learn, as they take a more active role in their learning, and therefore get more out of the learning experience than those individuals who are not motivated (Burger, 2012). From this line of reason it seems safe to argue that motivation and learning performance are related. As a result, Burger (2012) argued that *learning motivation* would positively influence *time cognitively engaged*, as there appears to be a positive relationship between motivation to learn and learning outcomes. Burger (2012) further argued that the primary means through which an individual's personality affects their work behaviour, is most likely through motivation. This argument was supported by evidence presented by Colquitt, LePine and Noe (as cited in Burger, 2012), that personality variables have a moderate to strong relationship with motivation to learn and learning outcomes. Burger (2012) specifically considered *conscientiousness* as a determinant of *learning motivation*, as it made sense that someone high on *conscientiousness* will set a high standard for themselves, and will be more willing to work hard. Consequently, Burger (2012) hypothesised that *conscientiousness* will positively influence *learning motivation.*

[16] This suggests a *learning motivation* x ability interaction effect on learning performance which Burger (2012) chose not to include in her structural model presumably due to anticipated methodological problems in evaluation the fit of a model containing latent interaction effects.

c.) Academic Self-efficacy

According to Burger (2012), self-efficacy refers to an individual's opinion of their own intrinsic ability to organise their behaviour to do things in such a way as to be satisfied with the outcome. Basically, it concerns the answer to the question, 'can I do this task in this situation?' Self-efficacy therefore is not a measure of the skills a person possesses but rather concerns the person's *beliefs* that they can do what they have to do under different sets of conditions, with whatever skills they possess. The construct that Burger (2012) included in the learning potential structural model, was labelled *academic self-efficacy*, and refers to an individual's perceived capability to manage learning behaviour, master academic subjects, and fulfil academic expectations. Consequently, *academic self-efficacy* refers to the belief about one's capability to learn or perform an academic task effectively (Burger, 2012).

According to Burger (2012), even though studies have related *academic self-efficacy* directly to achievement, recent research investigated the impact of the mediating effect of motivational behaviours more thoroughly. It therefore means that an individual, who has confidence in his/her ability to learn, may actually be more motivated to learn. Bandura, Barbaranelli, Caprara and Pastorelli (2001) as cited in Burger (2012), explained that an individual's core belief in their own power to produce results through their own actions', influences their strength of commitment to these actions, as well as their level of motivation and perseverance. This statement strengthens the argument presented by Burger (2012) that self-efficacy beliefs determine how individuals think, feel, motivate themselves and behave. This latent variable therefore either boosts or impedes motivation. Consequently, Burger (2012) hypothesised that *academic self-efficacy* positively influences *learning motivation*.

2.3.3 Feedback Loops

Burger (2012) presented two feedback loops in her proposed structural model, which constitutes a formal acknowledgement that *classroom learning performance* and *performance during evaluation* are complexly determined. The first feedback loop proposes that *learning performance during evaluation* positively influences *academic self-efficacy* (Burger, 2012). The level of performance that is achieved is known to be a persuasive source of self-efficacy information (Burger, 2012).

Burger (2012) argued that feedback that contains information about an individual's skills or progress can raise self-efficacy and subsequent performance. This argument is based on Bandura's (1997) explanation, as cited in Burger (2012); that self-efficacy is developed via several mechanisms (performance accomplishments, vicarious experiences, verbal persuasion and physiological states), the most influential being self-referenced information such as performance accomplishments. This statement strengthens the argument presented by Burger (2012) that high *learning performance during evaluation* will positively impact on an individual's level of *academic self-efficacy* and through that on the learning competencies comprising *classroom learning performance*. Enhanced *classroom learning performance* in turn will positively impact on future *learning performance during evaluation*.

The second feedback loop proposed by Burger (2012), suggests that *time cognitively engaged* positively influences *academic self-efficacy*. The argument for this proposed path, as justified by Bandura (1997), and cited in Burger (2012), explains that the most influential sources of self-efficacy information are the nature of the student's engagement during their learning. Therefore, tasks that afford an individual with opportunity to generate internal feedback about their learning and achievement, affects their self-efficacy (Burger, 2012).

2.3.4 The Structural Model Proposed by Burger (2012)

In her review of the literature Burger (2012) concluded that learning potential was a function of both cognitive variables, as well as non-cognitive learning competency potential latent variables. As a result of this conviction, the De Goede (2007) structural model was expanded with the inclusion of the variables discussed in the previous sections. Figure 2.2 represents the expanded De Goede - Burger learning potential structural model.

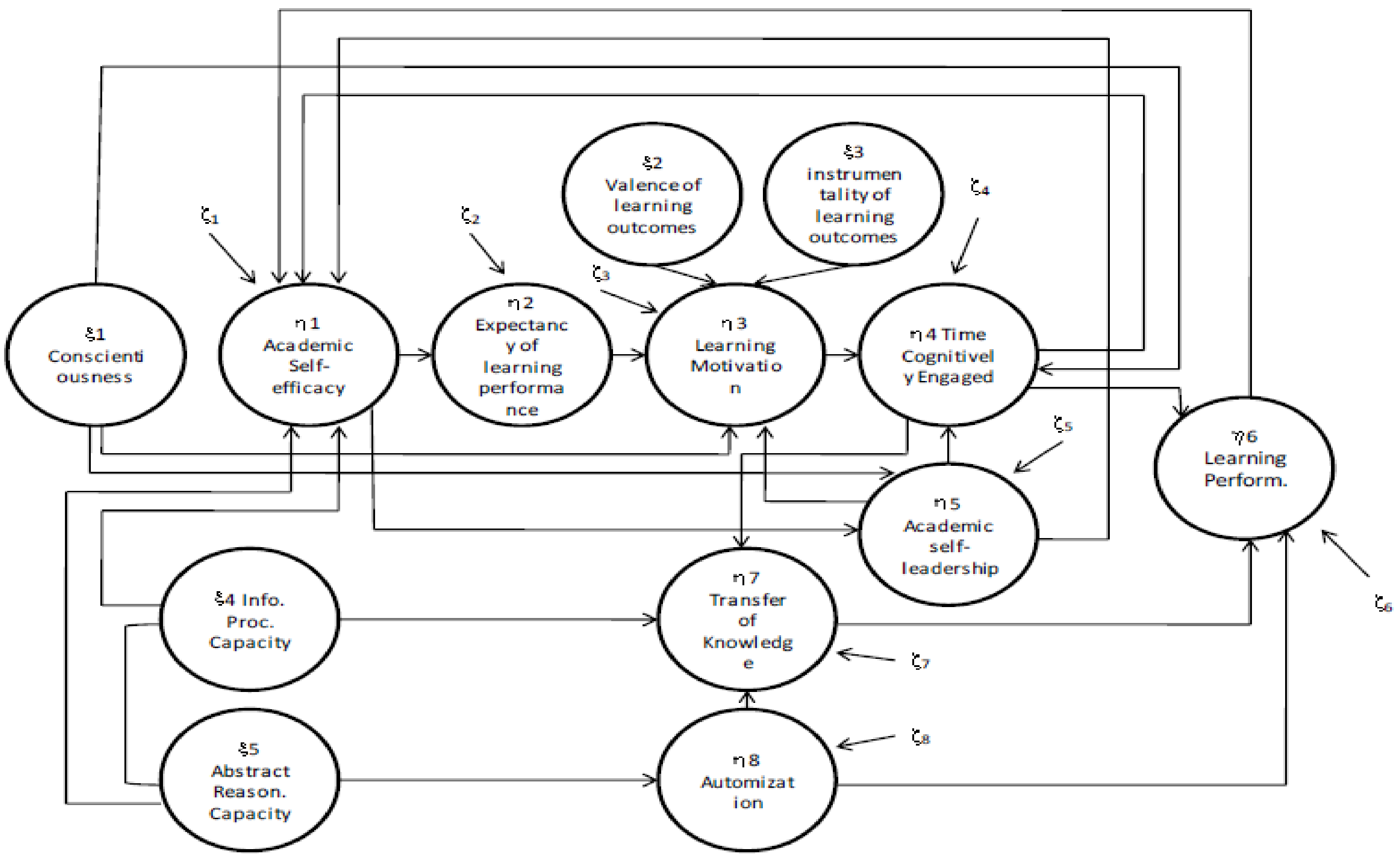

Figure 2.2**: The De Goede - Burger (Burger, 2012, p. 81) expanded structural model**

2.3.5 The Reduced Burger (2012) Learning Potential Structural Model

Burger (2012) realised that the process of empirically testing the proposed expanded model (Figure 2.2) developed through theorising in response to her research initiating question, will present major practical challenges. According to Burger (2012), the most serious challenge is the time research participants will need to invest in order to complete the battery of instruments measuring the constructs comprising the structural model. A further consideration was the realisation that the APIL developed by Taylor (1992; 1994) to measure *transfer of knowledge* and *automisation* was not an appropriate measure of these learning competencies as dimensions of *classroom learning performance*. The APIL measures *transfer of knowledge* and *automisation* based on simulated learning material whereas the evaluation of the expanded De Goede – Burger structural model requires measures of these two competencies in action over time grappling with the learning material covered in the development program. Developing such measures would require a lot of work and the measures in addition would have little or no utility beyond the research study. As a result, Burger (2012) decided to reduce the learning potential structural model depicted in Figure 2.2, to the model presented in Figure 2.3.

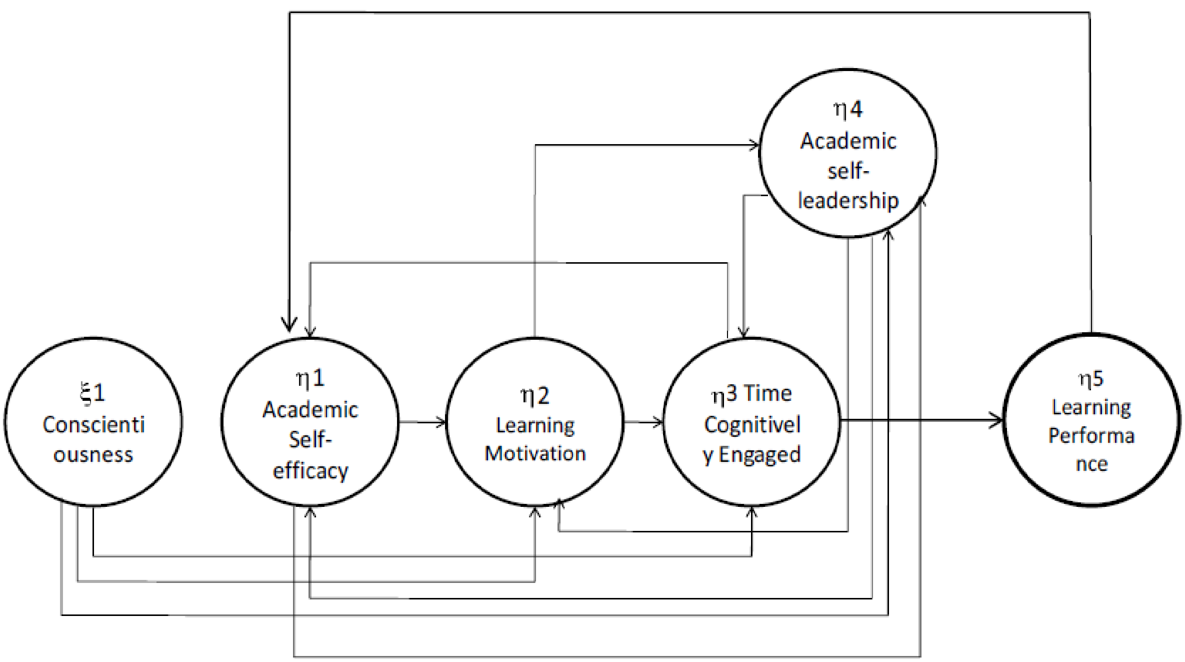

Figure 2.3 **The reduced structural model proposed by Burger (2012, p. 86)**

2.4 THE RESULTS OF THE REDUCED BURGER STRUCTURAL MODEL

When the proposed reduced learning potential structural model depicted in Figure 2.3 was fitted to the data, it initially failed to converge. Burger (2012) reported that the preliminary output delivered by LISREL indicated that the structural error variance estimate linked with the *learning motivation* latent variable 'may not be identified'. Burger (2012), tried to solve this problem, by increasing the number of iterations, but it was unsuccessful. Burger (2012) subsequently decided to delete one of the paths associated with the *learning motivation* latent variable, and decided on the hypothesised impact of *learning motivation* on *academic self-leadership*, as it was seen as the least convincing path. The reduced model successfully converged, and the goodness of fit statistics indicated an RMSEA-value of .0463 ($p > .05$), which implies a good, close fit in the parameter (Burger, 2012). A good fit was also suggested by the RMR-value of .0352, as well as the standardised RMR-value of .0342, since both the values are less than .05, and is therefore regarded as indicative of a model that fits the data well (Burger, 2012).

Burger (2012) reported that the review of the beta matrix revealed no support for the hypothesis that *time cognitively engaged* positively influences *academic self-efficacy*. Consequently, this path was deleted (Burger, 2012). Additionally, the output indicated that the fit of the model would improve by adding a path from *learning performance* to *learning motivation*. This was evident in the large and statistically significant ($p < .01$) modification index value associated with this specific path for the beta matrix. The proposed path made substantive theoretical sense and consequently, this path was included in the model (Burger, 2012). After these two changes were made to the structural model shown in Figure 2.3, the model fit was tested again, and the results indicated an RMSEA-value of .0317 ($p > .05$), which suggested that a good fit was achieved. Burger (2012) also reported that inspection of the data did not reveal any further paths that should be added or removed that would improve the fit of the model. All the paths in the final model were found to be statistically significant ($p < .05$). The proposed expanded Burger – Prinsloo learning potential structural model introduced in this study will be based on the final Burger (2012) learning potential structural model that resulted from the foregoing two modifications made to the model she initially tested (Figure 2.3). The final Burger (2012) learning potential structural model is presented in Figure 2.4.

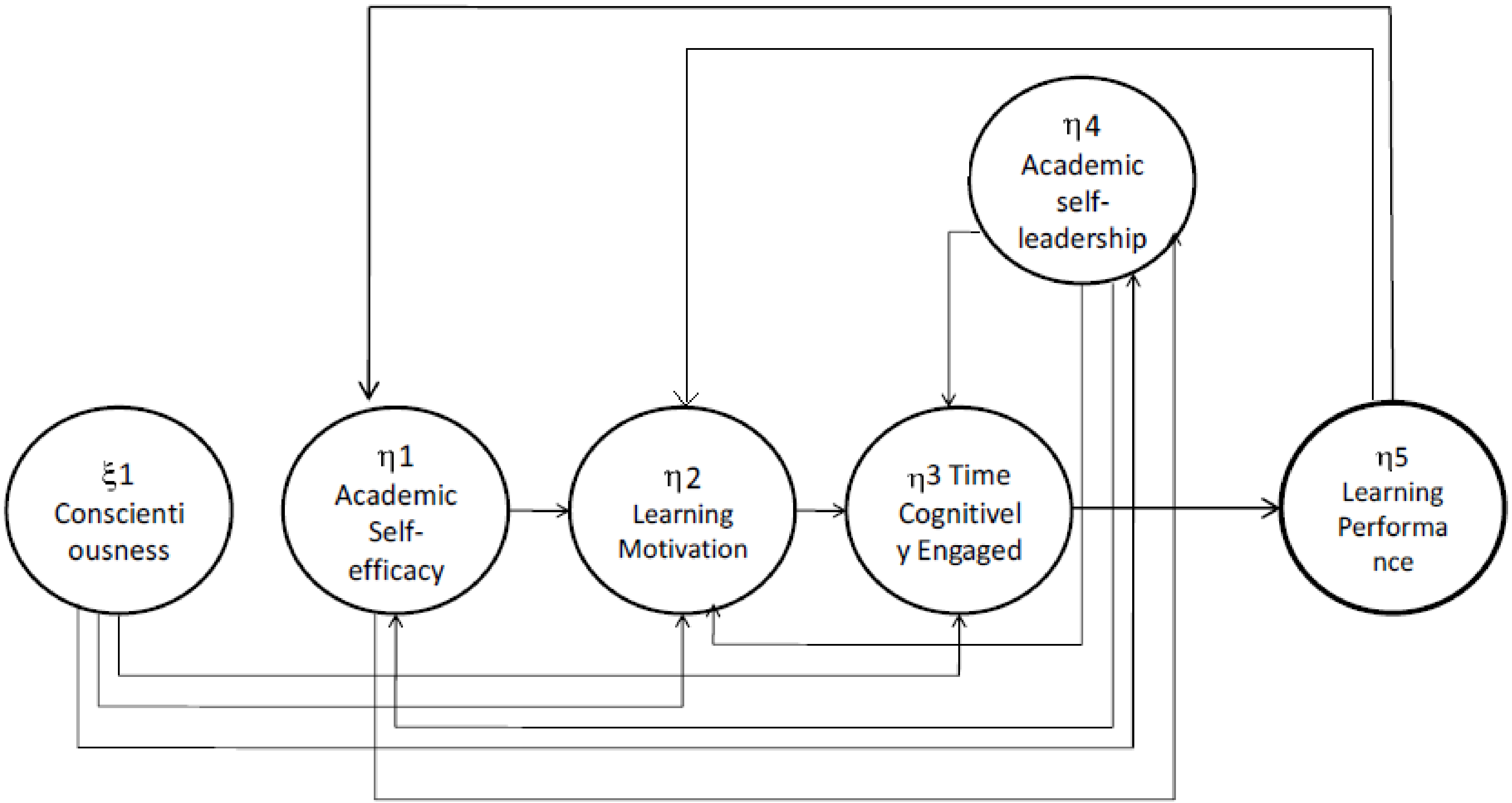

Figure 2.4 **The final structural model presented by Burger (2012)**

2.5 THE CONSTRUCTS TO EXPAND THE PROPOSED BURGER - PRINSLOO LEARNING POTENTIAL STRUCTURAL MODEL

According to Visser (2009, p. 21), the African National Congress (ANC) proclaimed in 1994 that they want to achieve the following:

> *In attacking poverty and deprivation, the ANC aims to set South Africa firmly on the road to eliminating hunger, providing land and housing to all our people, providing access to safe water and sanitation for all, ensuring the availability of affordable and sustainable energy sources, eliminating illiteracy, raising the quality of education and training for children and adults, protecting the environment, and improving our health services and making them accessible to all.*

With the change of government in 1994, the majority of South Africans felt hopeful again, this was due to the “better for all”-prospective, emphasised by the democratically elected government. Since the transition, nineteen years ago, the conditions for some previously disadvantaged[17] individuals has definitely improved, but for most of them life still is a constant struggle. According to Landman, Bhorat, Van der Berg, and Van Aardt (2003), almost 40% of South Africans are living in poverty- with the poorest 15% in a desperate struggle to survive. According to the South African Institute of Race Relations (2012), the poverty rate measures the proportion of households with an income below R800 per month. This Institute (2012) further reported that some provinces in South Africa have a poverty rate of up to 83% (Eastern Cape). Visser (2009) further reported that the 2006 World Development Indicators estimate that 10,7% of South Africans are living on under $1 a day, and 34,1% are living on under $2 per day. These statistics reveal that approximately 18 million out of the 50 million people living in this country have not experienced the benefits of our newly found freedom. Consequently, the ‘better for all’ prospective tends to lean to a ‘better for some’ reality.

[17] In this study the focus will be on the previously disadvantaged group, even though some of the previously advantaged group experience struggle and hardship in terms of poverty, unemployment, and improper living conditions since the election of the new government in 1994.

The South African Institute of Race Relations (2012) highlights the fact that variables such as unemployment, income distribution, education and access to services in the municipalities (water, electricity, sanitation, refuse removal, etc.), all seem to correlate with poverty. Consequently, these poverty statistics[18] are not the only features of the current South Africa that emphasises the battle faced by many; the following statistics further stress the current reality of this rainbow nation. According to the South African Institute of Race Relations (2011), the official unemployment rate of the first quarter of 2010 was 25%. More recently the Institute (2012) reported that the unemployment rate for first quarter of 2011 ranged from 16 - 57% in the respective provinces. The Gini-coefficient, which measures the inequality with reference to income distribution of a country, was 0.65 in 2009, which supports the fact that 4% of the South African population earn almost 40% of the total personal income. In terms of education, the South African Institute of Race Relations (2012) reported that the matric pass rate for 2010 was 68%. They further reported that about 35% of South Africans only have primary level schooling, while 10% on average have no schooling at all. On average between 50% and 75% of South African children have to walk to school on a daily basis (The South African Institute of Race Relations, 2012).

Despite the horrific reality painted by the mentioned statistics, South Africa is also one of the countries where people experience the worst living conditions; about 68% of South Africans do not have access to running water, while some 66% of households do not have electricity for lighting. The South African Institute of Race Relations (2012) further reported that on average between 35% and 45% of South African citizens do not have any sanitation, and 95% do not have their refuse collected by municipalities. Visser (2009) reported that 55 000 woman were raped in 1997, and 40% of rape cases were that of children under the age of 18. From a young age numerous South Africans are faced with murder, crime, rape and sexual abuse. The South African Institute of Race Relations (2012) conveyed the horrific reality that per 100 000 people, some provinces experience a sexual offense rate as high as 87% and murder rates up to 41%.

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[18] The poverty statistics as reported by the Landman et al., (2003), the South African Institute of Race Relations (2012), and Visser (2009) in the previous paragraph.

Such statistics, gives substance to the argument that the majority of children in South Africa run the very real risk of never reaching their full cognitive and socio-emotional potential, because of being victims of poverty and adverse living conditions (Visser, 2009). In this country it is not strange for a child to get up at four in the morning, irrespective of the season, to have enough time to walk to get clean water, before they have to walk to be in time for school, which is a further 10km away. It is not out of the ordinary for a child to beg for food to feed younger brothers and sisters, because they lost their family to HIV/AIDS, drug and alcohol abuse, violence or crime.

Despite the promise of a better future for all, too many previously disadvantaged individuals in South Africa still live in conditions where they are faced with hunger, poor sanitation, violence, inadequate education and improper health services every day. Each day is characterised by a constant struggle, and this applies not only to the people who are worst off, but also those individuals who have experienced some benefits in terms of the newly found freedom[19].

With this more realistic picture of the everyday lives of numerous previously disadvantaged South Africans, it is reasonable to argue that when previously disadvantaged individuals are provided with learning opportunities, their chances of succeeding, will be greatly influenced by both the past as well as the present circumstances facing these individuals. This claim will be supported by mobilising the following two further arguments. Firstly, it can be argued that these individuals' chances of succeeding in a learning opportunity will be negatively influenced because of the constant struggle and poor circumstances, as well as the false hope which the elected government has constantly given them over the past 19 years. They were promised a better future for all, but only a few individuals have actually reaped the promised benefits. The government has constantly created expectations, but very little if anything has come from it. Having had to face these adverse circumstances and the false hope on an everyday basis quite conceivably could have resulted in a state of learned helplessness, self-doubt and self-degradation in many disadvantaged South Africans.

[19] Not only are the poorest individuals in this country negatively affected by the horrific circumstances. The majority of the previously disadvantaged group still struggle to reap the benefits promised by the government. This is especially evident in, for example, the quality of education received.

The adverse living conditions faced by many South Africans would make fruitfully utilising affirmative development opportunities a formidable challenge. The learned helplessness, self-doubt and self-degradation on top of the adversity make it almost unreal to expect of disadvantaged individuals to make a success of an affirmative development opportunity given to them, despite the fact that they actually might have the potential to benefit from it. Can it be expected of them to hope for a better future and show optimism with regard to the opportunity provided to them if no promises made with regards to the future ever came to fruition? Will they be able to believe in themselves and have confidence in themselves to make a success of an affirmative development opportunity that they actually could succeed in, if no one has ever believed in them before? The following quote by Stephen. J Gould (1981, p. 147) captures the severe tragedy of individuals placing an inferiority label on themselves because they fail to appreciate the manner in which their living conditions shaped their individual and collective sense of self.

> *We pass through this world but once. Few tragedies can be more extensive than the stunting of life, few injustices deeper than the denial of an opportunity to strive or even to hope, by a limit imposed from without, but falsely identified as lying within.*

It is also crucial to ask whether these individuals will be able to show resilience when having to study in adverse circumstances, or are they too vulnerable because of the adverse circumstances they faced for such a long period of time. According to Seth-Purdie (2000), adverse circumstances which individual's face literally leave a mark in the form of human capital deficits, including a vulnerability to stress.

Secondly, it can also be argued that because the previously disadvantaged group has been regarded as the protected group[20] since the election of the new government in 1994, a culture of dependency has been created. These individuals are provided with benefits, and empowerment opportunities, but instead of it having only a positive influence on these individual's, it fosters a culture of dependency rather than culture of initiative and self-reliance (Seth-Purdie, 2000).

[20] This argument completely supports the fact that the previously disadvantaged group should be regarded as the protected group, simply because it is the right thing to do. However, the consequences of protecting these individuals are positive and negative.

Will these individual(s) be able to make a success of a provided affirmative development opportunity on their own? Will they have confidence in themselves and their own abilities to make a success of such an opportunity? Will they constantly search for external support, which ironically, despite their need for it, is quite often lacking for these individual's[21], to be successful in the provided learning opportunity?

After considering these two arguments[22], the question should be asked; do previously disadvantaged individuals have the necessary positive human qualities[23] (*hope*, *optimism, self-efficacy*, and *resilience*) to be able to face adverse circumstances? Can it be expected of previously disadvantaged individuals to strive and make a success of affirmative development opportunities despite their circumstances[24]? Lastly, will they adapt to adversity, and cope and even thrive, despite the reality of their lives (Bartley, Schoon, Mitchell & Blane, 2011)? Thus, to better understand the construct of learning potential, especially in the South African context, it is vital to take into consideration the circumstances with which these individuals are faced.

However, when expanding the learning potential structural model, this study will not focus on the South African environment as such, but more on the positive qualities that would be required of learners to the extent that they find themselves in an adverse environment. As a result, even though the adverse environment described is a reflection of the current South African situation, this study will not be exclusively applicable to the South African context alone, but to any environment in which individual's positive qualities are being tested due to adverse conditions. These positive individual qualities cause differences in the manner that individuals react to difficult conditions.

[21] According to Cooper and Crosnoe (2007), individuals who are economically disadvantaged have increased chances of being part of a family with an encompassing family structure, where lower levels of psychological resources, such as parental involvement, exist.

[22] These two arguments point to additional latent variables that can be included in the proposed expanded structural model, including, situational adversity/favorableness, and locus of control from an individual perspective. Even though arguments in favor of the inclusion of these variables do exist, the arguments at present are not persuasive enough to include these variables in the proposed model. However, the possibility of these variables should definitely be considered for future research (Theron, Personal communication, 1 March 2012).

[23] The positive human qualities refer to a person's resources/strengths within themselves to cope with difficult/adverse situations.

[24] A previously disadvantaged individual's circumstances can either refer to their current living arrangements (if they still live in adverse conditions) or it can refer to their upbringing in an adverse environment that has the potential to leave permanent marks as referred to by Seth-Purdie (2000).

It is hypothesised here that these positive individual qualities directly or indirectly affect the range of other latent variables that determine *classroom learning performance* and *learning performance during evaluation* in the training/development process. As mentioned by Burger (2012), individual differences are purported to influence the resource capacity of a person, which affects the amount of resources that can be allocated throughout the task activity. Consequently, it is essential to consider the effect these positive qualities/states have on an individual's potential to learn.

This study will specifically consider positive individual qualities which are malleable, and thus, susceptible to development. More specifically, the qualities that are considered should explain why an individual will flourish, prosper and also thrive, in a challenging, adverse situation. As a result, the expanded Burger - Prinsloo structural model will exclusively focus on constructs proposed by the Positive Psychology movement, which explicitly aims to promote positive human qualities. The Positive Psychology movement places emphasis on building strengths and competencies, rather than merely treating deficits (Herbert, 2011). According to Seligman and Csikszentmihalyi (2000), this movement focuses on the scientific study of optimal human functioning and the variables that promote positive human emotions, traits and institutions.

Based on this movement, Luthans (2002b) introduced the concept of Positive Organisational Behaviour (POB), in an attempt to bring Positive Psychology to the workplace. According to Luthans, Youssef and Avolio (2007), POB is defined as the study and application of positively orientated human resource strengths and psychological capabilities that can be measured, developed and effectively managed. To differentiate POB from other positive approaches, the following criteria were established for the inclusion of constructs in the domain of POB: the constructs must (a) be grounded in theory and research, (b) have valid measurements, (c) be relatively unique to the field of Organisational Behaviour, (d) be state-like and therefore, open for development and change, and (e) have a positive impact on work-related, individual-level performance and satisfaction (Luthans, 2002a).

According to Luthans et al., (2007), the positive psychological constructs that have been determined to meet the inclusion criteria, include; *optimism*, *hope*, *resilience* and *self-efficacy*, and these four constructs represent what has been termed psychological capital. Luthans et al., (2007. p. 13) explain psychological capital, or Psycap, as:

> *Psycap is an individual's positive psychological state of development and is characterised by: (i) having confidence (self-efficacy) to take on and put in the necessary effort to succeed at challenging tasks; (ii) making a positive attribution (optimism) about succeeding now and in the future; (iii) persevering towards goals and, when necessary, redirecting paths to goals (hope) in order to succeed; and (iv) when beset by problems and adversity, sustaining and bouncing back and even beyond (resilience) to attain success.*

Psycap is a higher-order psychological factor of positivity, which comprises of four facet constructs, namely; s*elf-efficacy/confidence*, *optimism*, *hope*, and *resiliency*. Psycap provides positive psychological resources from which an individual can draw to cope with challenges in terms of growth, development, and self-actualisation. These constructs focus on helping healthy people become happier, more productive and actualising their human potential (Luthans et al., 2007). Specifically, Psycap is concerned with "who you are", and in the developmental sense, "who you are becoming" (Herbert, 2011). Psycap recognises moving (developing) from the actual self to the possible self. The main reason why the proposed expanded learning potential structural model will focus on psychological capital is because of the underlying common thread and shared characteristics running through each of the psychological resources capacities. This thread is characterised by positive, intentional striving toward flourishing and success, no matter what changes and challenges arise (Avey, Wernsing & Luthans, 2008).

This study will focus on only the inclusion of three of the four constructs in the expanded Burger – Prinsloo learning potential structural model, namely *optimism*, *hope* and *resilience*, since *self-efficacy/confidence*, was already included and studied by Burger (2012) in the form of *academic self-efficacy*. Therefore, this study will consider the manner in which *optimism*, *hope* and *resilience* should be embedded in the proposed expanded Burger – Prinsloo learning potential structural model.

2.5.1 Optimism

Optimism is one of the most talked about, but least understood psychological strengths. In Positive Psychology, *optimism* has a very specific meaning, based on empirical theory and research (Herbert, 2011). As a result, it carries a far richer meaning than the laymen connotation of anticipating that good things will happen in the future. The connotative meaning of *optimism* is rooted in the reasons and attributions one uses to explain why certain events occur, whether positive or negative, past, present or future (Luthans et al., 2007). This implies that *optimism* refers to an individual's explanatory style, which includes his/her habitual way in which they explain setbacks and failure (Schulman, 1999). According to Snyder (2002), an individual who has an optimistic explanatory style reflects the tendency to make external, variable and specific attributions for negative outcomes rather than internal, stable and global attributions. More specifically, *optimism* is an explanatory style that attributes positive events to personal, permanent and pervasive causes, and as a result takes credit for the positive occurrences in their lives. An optimist will also continue to remain positive and confident about their future despite being faced with undesirable and negative events, because they attribute the causes of such an event to external causes. As a result, they will continue to move forward with positive expectations regardless of past problems (Avey, Wernsing & Luthans, 2008). Consequently, an optimistic individual will thrive and more likely make a success of a developmental opportunity, despite their dreadful circumstances at present or in the past.

To avoid the criticism of false *optimism*, POB emphases the importance of this construct being realistic; which means that even the diehard optimist will occasionally have pessimistic beliefs (Schulman, 1999). An optimist should be a 'flexible optimist', in the sense that their eyes are wide open and they realise that there exist a time and place for pessimism, or at least realism. *Optimism* is not based on an unchecked process that has no realistic assessment (Herbert, 2011). This realistic *optimism* as a state (as opposed to a dispositional trait), involves an objective evaluation of what one can accomplish in a situation, given the available resources and time (Herbert, 2011). Peterson (2000) explains that *optimism* is a dynamic, state-like, yet changeable construct that is amendable to development.

Any successful individual needs both an accurate appreciation of reality and an ability to optimistically dream beyond the present reality (Schulman, 1999). Therefore, in summary, *optimism* is associated with a positive outcome, outlook or attribution of events, which includes positive emotions and motivation, and has the requirement of being realistic (Luthans, 2002a).

Scheier and Carver (1985) refer to *optimism* as a goal-based state, which is especially present when an outcome is very valuable. Individuals who display *optimism* have a generalised expectancy that they will experience good outcomes in life and because of this thought, their *optimism* leads to persistence in their goal-directed striving. Optimists have positive expectancies and specific positively valenced goals in mind. According to the expectancy theory of motivation (Von Haller Gilmer & Deci, 1977), motivation can be conceptualised as the linear combination of the product of expectancies and valences associated with a salient set of outcomes. Motivation can therefore be expected to increase as expectancies increase and as the salient outcome set becomes populated with more positively valenced outcomes. As a result motivation should tend to be lower in the absence of optimistic expectations (Schulman, 1999). As a result, it seems safe to argue that *optimism* positively influences *learning motivation*.

Hypothesis 1: In the proposed learning potential structural model it is hypothesised that *optimism* positively influences *learning motivation*.

According to the model presented by Burger (2012), *learning motivation* positively influences *time cognitively engaged*. It is also argued that *time cognitively engaged* positively influences *learning performance*. When an individual attains success in the learning/developmental opportunity by achieving a high level of *learning performance during evaluation*, this individual would have achieved a desired, positively valenced outcome. Thus, the individual's motivational force which was exerted has caused a desired result to be achieved. By achieving success in the given opportunity, a feedback loop causes an increase in the individual's *learning motivation* for the next opportunity that he/she might face. Consequently, *learning performance* positively influences *learning motivation* through a feedback loop (Burger, 2012). However, the following should also be considered: if an individual achieves a high level of *learning performance*, they will experience a positive event in their life and be filled with positive emotions.

They would also have achieved a valuable goal, and as a result it is safe to argue that this positive occurrence in their lives has the potential to increase their *optimism* regarding their specific learning opportunity. This is based on the argument[25] that *optimism* is a goal-based construct, which becomes present when an individual achieves a valuable goal. Therefore, it can be hypothesised that *learning performance* positively influences *optimism*.

Hypothesis 2: In the proposed learning potential structural model it is hypothesised that *learning performance* positively influences *optimism*.

The first hypothesis presented in this study argued that *optimism* positively influences *learning motivation*. The second hypothesis presented explores the possibility that *learning performance* positively influences *optimism*. However, as hypothesised by Burger (2012), *learning performance* positively influences *learning motivation*. Consequently, this proposal hypothesised that *optimism* mediates the positive effect of *learning performance* on *learning motivation*.

Optimist are individuals that attribute positive events to personal, permanent and pervasive causes, and as a result take credit for the positive events in their lives. They tend to attribute the causes of negative events to external, temporary, and specific situations; thus, they continue to be positive and confident in the future. As a result it can be argued that an optimist will generally display positive cognitive-thought pattern strategies involving the creation and maintenance of functional constructive patterns of habitual thinking (Burger, 2012). These positive cognitive-thought pattern strategies include self-management of beliefs and assumptions. In addition to the above argument, it can also be argued that optimistic individuals also partake in behavioural-focused strategies in the form of repeated practice and self-goal setting. Cognitive-thought patterns and behavioural-focussed strategies, introduced by Burger (2012) are key aspects of *academic self-leadership*. As a result, based on these two arguments, it can be argued that *optimism* positively influences *academic self-leadership*.

Hypothesis 3: In the proposed learning potential structural model it is hypothesised that *optimism* positively influences *academic self-leadership.*

[25] This argument refers to the one presented by Scheier and Carver (1985).

2.5.2 Hope

Hope is a term commonly used in everyday language, but the traditional definition of *hope* in terms of hoping for the best, does not fully capture the rich, positive, psychological process of the latent variable *hope* as a scholarly construct (Luthans, Van Wyk & Walumbwa, 2004). Snyder (2002, p. 250) offered the following comprehensive definition of *hope*:

> *Hope is a positive motivational state that is based on an interactively derived sense of successful (a) agency (a sense of willpower, or determination to begin and maintain the effort needed to achieve goals), and (b) pathway (a sense of waypower, or belief in one's ability to generate successful plans and alternatives when obstacles are met in order to achieve goals).*

This definition clearly emphasises the fact that *hope* consists of a trilogy; goals, pathways, and agency. These willpower (agency) and waypower (pathways) components of *hope* are interrelated and operate in a combined, iterative process to generate *hope* (Luthans & Jensen, 2002). More specifically, agency refers to a person's desire to get started towards a goal as well as the "stick to it" aspect of not prematurely abandoning the attempted journey. Pathways on the other hand, refer to an individual's ability to come up with alternative plans of action should an initial path toward a goal be blocked. According to Snyder (2002), if an individual experience blockages, the agency/willpower component, i.e. the desire to get started on a goal and "stick to it", will help the individual to channel the requisite motivation to the best alternative pathway (waypower). This emphasises the combined, iterative process that generates *hope*.

Before considering the impact of *hope* in the proposed structural model, it is critical to consider the difference between *hope* and *optimism*. Although they both share common perspectives regarding the importance of expectancies and both operate within the context of goal-directed behaviour, the constructs differ in how the expectancies operate. According to Luthans and Jensen (2002), *optimism* is a generalised expectancy that one will experience positively valenced outcomes in life. They also emphasise the fact that *optimism* leads to persistence in goal-directed striving.

This explanation of *optimism* is very similar to the agency (willpower) component of *hope*, as both encourage the individual to start toward a goal and persistently "stick to it". However, the pathway (waypower) component is not explicitly addressed in the conceptualisation of *optimism*. This is due to the fact that even though an optimist may believe that "good things will result", he/she may lack the vital pathway thinking (i.e. the ability to generate alternative paths) needed to overcome barriers and attain desired results. This argument is reinforced in Luthans and Jensen (2002, p. 310), when they refer to a statement made by Admiral Jim Stockdale, who was held prisoner and tortured by the Vietcong for 8 years during the Vietnam War. He was asked who did not make it out of the camps, and he replied with the following:

> *Oh, it's easy. It was the optimists. They were the ones who said we were going to be out by Christmas. And then they'd said we'd be out by Easter and then out by the fourth of July and then out by Thanksgiving, and then Christmas again…You know, I think they died of broken hearts.*

In other words, the optimists are those individuals who had the agency (willpower) component of *hope*, thus, they had the positive expectations and specific goals in mind. However, what mattered more was the fact that they did not have the pathway (waypower) dimension of *hope*, which meant that they were not able to figure out alternative pathways when expectancies did not turn out or the paths were blocked (Luthans & Jensen, 2002). As a result of this systematic analysis of the difference between *optimism* and *hope*, it is apparent that *optimism* is structurally related to one of the two components of *hope*. This conclusion highlights the idea that when an individual's level of *hope* increases, both the agency (willpower) and pathway (waypower) components of *hope* will tend to increase, and therefore it is evident that an individual's *optimism* will also increase[26]. Accordingly, it can be argued that *hope* positively influences *optimism*.

Hypothesis 4: In the proposed learning potential structural model it is hypothesised that *hope* positively influences *optimism*.

However, this relationship between *hope* and *optimism* can go both ways. This becomes clearer when considering the following.

[26] This is due to the fact that *optimism* explains one of the two components of *hope*.

Luthans (2002a) associates *optimism* with a positive outcome, outlook or attribution of events. This association stresses the immense effect of an optimistic attribution style on the perception process and interpretations of an individual. Therefore, the outlook or attribution of a person will determine how they see and interpret external events, which have an unavoidable effect on their behaviour (Herbert, 2011). This is highlighted by Gabris, Maclin and Ihrke (1998), when they explain that *optimism* introduces one to believe, or at least *hope* that through the responsible use of knowledge and reason, mankind can improve existing conditions. Thus, rather than accepting the *status quo*, the optimistic approach asks how things can be improved or made better, and encourage an individual to take control of their own social and material destiny (Herbert, 2011). Based on this argument, it is clear that an individual, who is optimistic, will also have *hope* to strive from where they currently are in their lives to become their best possible self, by taking control of their own destiny. Accordingly, it can be argued that *optimism* will positively influence *hope*.

Hypothesis 5: In the proposed learning potential structural model it is hypothesised that *optimism* positively influences *hope*.

Herbert (2011) summarised the meaning of *hope* by referring to it as a positive motivational state that is based on a collaborative effort of a sense of successful goal-directed energy (agency/willpower) as well as the planning involved in actually meeting the goals (pathway/waypower). From this summary it is evident that the agency/willpower component of *hope* consists of the individual's determination to maintain the effort needed to achieve specific goals. Consequently, this component of *hope* reflects an individual's motivation and determination that goals can be achieved i.e. their ability to "stick to" the goals they wish to attain (Luthans, Van Wyk & Walumbwa, 2004). Avey, Wernsing and Luthans (2008), define *hope* as a positive motivational state, which captures the idea that an individual with a high level of *hope*, structure tasks in a way that keeps them highly motivated to attain success in the task at hand. Consequently, from the above argumentation it is safe to reason that when an individual maintains a high level of *hope*, it is highly possible for them to also have a high level of motivation, as *hope* is described as a positive motivational state. Therefore, it can be argued that *hope* positively influences *learning motivation*.

Hypothesis 6: In the proposed learning potential structural model it was hypothesised that *hope* positively influences *learning motivation*.

Peterson and Luthans (2003) suggest that high *hope* individuals tend to be more certain of their goals and challenged by them. Due to a higher degree of goal certainty, Snyder, Shorey, Cheavens, Pulvers, Adams and Wiklund (2002), explain that high *hope* individuals conceptualise their goals clearer and are better at staying attuned to their goals. Due to the two components of *hope*, they have the tendency to stay focused on their goals, go for it, and also choose an alternative pathway if the existing one gets blocked. Because they are attuned to their goals, they are in control of how they will pursue them; as a result these individuals are intrinsically motivated and perform better. *Hope* is concerned with outcomes and actions initiated by the self (Jensen & Luthans, 2006), and as a result, high *hope* individuals have the ability to influence themselves to achieve self-direction and a high level of motivation that enable them to perform in a desired way (Burger, 2012). Consequently, the two components of *hope* have the potential to enable an individual to control their own behaviour, in addition to influencing and leading themselves. So, in accordance with the arguments provided by Burger (2012), individuals with high levels of *hope* tend to partake in behavioural-focused strategies in the form of self-goal setting, self-observation, and self-corrective feedback. They also partake in natural reward strategies, because they leverage intrinsic motivation to enhance performance (Burger, 2012). Consequently, it can be argued that the level of *hope* of an individual should influence different parts of their *academic self-leadership* as explained in paragraph 2.3.1(b). Thus, it can be hypothesised that *hope* positively influences *academic self-leadership*.

Hypothesis 7: In the proposed learning potential structural model it is hypothesised that *hope* positively influences *academic Self-leadership*.

Burger (2012) introduced the concept of *academic self-efficacy* as an individual's belief in their own capabilities to learn or perform an academic task effectively. *Academic self- efficacy* and self-efficacy are fundamentally similar, as they both strive to answer whether an individual believe that they can successfully and effectively do something. Herbert (2011) explains that individuals who possess a high level of self-efficacy can be distinguished based on five characteristics; (1) they set high goals for themselves and self-select into difficult tasks, (2) they welcome and thrive on challenges, (3) they are highly motivated, (4) they exert the needed effort to accomplish their set goals, and (5) they persist despite being faced with obstacles.

These five characteristics are very similar to the characteristics displayed by a high *hope* individual. They are highly motivated, self-directive; they "stick to" their goals, and find an alternative path when faced with obstacles; thus enabling them to persevere. The following example presented by Luthans et al., (2007, p. 79) further supports the probability of a possible relationship between *academic self-efficacy* and *hope*.

> *In an organisation where the prospect of tuition-reimbursement programs are non-existent, an individual who knows about a possible promotion for which he/she needs additional training/development to qualify and be considered, takes it upon themselves (agency) to move up (be promoted). Thus, this individual uses their self-directive motivation to set a goal to obtain the necessary training/development to be considered for the promotion. After this individual has qualified for the promotion, they have used the components, agency (setting the goal) and pathway (higher education), of Hope in order to reach this challenging goal.*

This example, once again, stresses the fact that an individual will not be able to make a success of their goal-setting if they do not occupy the pathway component of *hope*. More importantly, this example gives credence to the idea that this individual would not have been able to make a success of a pathway that they chose if they were not confident that they will be successful. In simple terms, an individual will not go to all the trouble to take on additional priorities and use of their personal money and time for the training/development, if they were not sure that they will be succeed. Thus, with reference to both the arguments presented above, *academic self-efficacy* in relation to *hope* can be interpreted as the conviction and belief in one's ability to (a) generate multiple pathways, (b) take actions toward the goal, and (c) ultimately be successful in goal attainment. Therefore it can be hypothesised that *academic self-efficacy* positively influences *hope*[27].

Hypothesis 8: In the proposed learning potential structural model it is hypothesised that *academic self-efficacy* positively influences *hope*.

[27]The arguments presented in favour of a positive relationship between *academic self-efficacy* and *hope* may rather seem to suggest that *academic self-efficacy* moderates the effect of *hope* on *learning motivation*. Even though this argument seems possible, it is not persuasive enough to be included in the proposed model as such.

2.5.3 Resilience

Resilience is the positive psychological capacity to rebound or "bounce back" from adversity, uncertainty, conflict, failure, or even positive change, progress and increased responsibility (Avey et al., 2008). Accordingly, *resilience* is characterised as a positive coping and adapting mechanism during times of significant risk or adversity (Herbert, 2011). So, with reference to this proposal, *resilience* is the ability to positively adapt and thrive in very challenging circumstances as well as the ability to be buoyant, flexible and be able to bend without breaking (Hunter & Chandler, 1999). *Resilience* is not just the ability of sustaining and bouncing back, but also the ability to even bounce beyond (Luthans, Vogelgesang & Lester, 2006).

Several factors can be identified as attributing to, or hindering the development of *resilience*. These factors can be classified as either assets, risk factors or values (Luthans et al., 2007). Assets are factors that decrease the negative influences of being at risk, and include examples such as; *optimism*, positive self-esteem, trust, problem-solving abilities, support, and internal locus of control (Stewart, Reid & Mangham, 1997). If an individual has asset factors, they will be better prepared, and more likely to survive adverse circumstances. Individuals with asset factors will be more likely to achieve success in the provided learning opportunity despite the circumstances they are faced with. So, an individual with asset factors are more likely to show high levels of *resilience*. In relation to this study, examples of asset factors will be *optimism* and positive self-esteem. *Academic self-efficacy* can be regarded as a form of positive self-esteem. This is due to the fact that both these represent an individual's belief in their own ability to succeed. As a result, it seems safe to argue that *optimism* and *academic self-efficacy* will positively influence an individual's *resilience*, as both of these constructs serve as asset factors.

Hypothesis 9: In the proposed learning potential structural model it is hypothesised that *optimism* positively influences *resilience*.

Hypothesis 10: In the proposed learning potential structural model it is hypothesised that *academic self-efficacy* positively influences *resilience*.

Risk factors, on the other hand, elevate the probability of an undesirable outcome, and they are referred to by Luthans et al., (2007) as *vulnerability factors*. These may include an experience of trauma, exposure to violence, adverse living conditions or less obvious, gradual, but eventually detrimental factors (e.g. stress). These factors cause an individual to be less prepared to face difficult circumstances and to more likely be unsuccessful in exploiting their learning opportunity. It is important to understand that the presence of risk factors does not automatically result in a lack of *resilience* and neither does it invariably result in failure. Risk factors are inevitable and omnipresent. Completely sheltering someone from risk factors is unrealistic, and the presence of challenges is actually necessary because it is invaluable for growth and self-actualisation opportunities. *Resilience* moreover by definition presupposes the existence of adversity.

When one uses asset factors to overcome the risk factors, it can help individual to overcome complacency, explore new domains, and further exploit their existing talents and strengths. Risk factors are therefore important antecedents for bouncing back and beyond in the resiliency process, and consequently help an individual to take advantage of latent potential that would go undiscovered otherwise (Luthans, Youssef & Avolio, 2007). This argument is extremely relevant within the South African context. In paragraph 2.5 it was argued that previously disadvantaged Black South Africans most likely will have to cope with significant adversity if they would be offered an affirmative developmental opportunity. The current argument suggests that these risk factors can actually assist them in identifying talents and strengths (asset factors) from their vast untapped reservoir of human potential referred to in the introductory argument, and assist them in striving and achieving success in the provided opportunity. Thus, with specific reference to this study, this argument provides further support for Hypothesis 9 and 10 presented above. This is based on the argument that to the extent that a previously disadvantaged individual can draw on their *optimism*, as well as their *academic self-efficacy* (asset factors), they will demonstrate *resilience* and will therefore more likely make a success of the given affirmative development opportunity despite the presence of risk factors (e.g. adverse living conditions).

This argument also introduces the idea that the other positive psychological state i.e. *hope*, may also have a positive effect on *resilience*, as it can also be regarded as an asset factor. This possibility is reinforced when considering the following: *Resilience* can be regarded as patterns of positive adaption in the context of adversity or risk. It includes not only the ability to bounce back from adversity, but also from positive challenging events (e.g. learning/development opportunities) (Luthans et al., 2007). *Resilience* is similar to the pathway/waypower component of *hope*, because the pathway/waypower component includes an individual's ability to find alternative pathways which can be utilised when an individual is faced with obstacles. So, both *resilience* and the pathway/waypower component assist an individual to, despite unfavourable circumstances, strive and make a success. As a result, it is clear that *resilience* explains one of the two components of *hope*, and therefore based on both the arguments presented above, it can be hypothesised that *hope* positively influences *resilience*.

Hypothesis 11: In the proposed learning potential structural model it is hypothesised that *hope* positively influences *resilience*.

The role that values play in the improvement of *resilience* refers to an individual's underlying value- and belief system that guides, shapes, and give consistency and meaning to their cognitions, emotions and actions. Values and beliefs will help individuals to elevate themselves over difficult and overwhelming events. Consequently, the value- and belief system of a person, may cause to either increase or decrease the person's *resilience*, i.e. their ability to "bounce back" despite adverse circumstances. The role which values and beliefs play in enhancing an individual's *resilience* strengthens the arguments for *Hypotheses 9, 10* and *11*. This is grounded on the idea that *optimism*, *academic self-efficacy* and *hope* are all rooted in an individual's belief system, and can consequently affect a person's *resilience* by means of that. Thus, further support is provided for *Hypotheses 9, 10* and *11*.

According to Luthans, Vogelgesang and Lester (2006), *resilience* is reactive, as opposed to the other three positive psychological states (*hope*, *optimism* and *self-efficacy*), which are more proactive. This is due to the fact that *resilience* contains a strong stressor antecedent, which activates the resiliency process. This emphasises the idea mentioned above that *resilience* by definition assumes the existence of adversity.

So, when an individual is confronted with adverse circumstances or positive challenging events (e.g. a learning/development opportunities), their resiliency process is activated which enables them to ‘bounce back’ despite their situation. If an individual achieves success because of their resiliency process providing them with the ability to ‘bounce back’, this success achieved can essentially result in the strengthening of the person’s three proactive Psycap variables (*hope*, *optimism*, and *self-efficacy*). This hypothesis is based on the argument that if a person achieves success due to their ability to ‘survive’ the difficult situation, they will become more optimistic, more hopeful and have more self-confidence to ‘survive’ and be successful in the future. As a result, based on this argument *resilience* could actually serve to restore *hope*, *optimism*, and *self-efficacy*/confidence, after a challenging experience. This suggests that *resilience* is an antecedent to the other positive psychological states.

Based on the above mentioned arguments that *academic self-efficacy* positively influences *hope*, and *hope* positively influences both *resilience* and *optimism*, it therefore seems safe to argue that if *resilience* positively influence an individual’s *academic self-efficacy* it indirectly influence the other two positive psychological states of Psycap (i.e. *hope* and *optimism*). Consequently, it can be argued that *resilience* will have the restoring effect on the other positive psychological capital variables, as emphasised by Luthans, Vogelgesang and Lester (2006). Therefore, it can be hypothesised that *resilience* positively influences *academic self-efficacy*.

Hypothesis 12: In the proposed learning potential structural model it is hypothesised that *resilience* positively influences *academic self-efficacy*.

If an individual is faced with an adverse situation, and they overcome the adversity successfully, a possibility exists that the particular individual will overcome future adversity even quicker. Herbert (2011) supports this notion by explaining that individuals may actually become more resilient to an adverse circumstance each time they effectively “bounce back” from the previous setback. In a study completed by Richardson (2002), it was found that the *resilience* of an individual can increase and even grow when the individual returns to levels above homeostasis after an adverse situation.

Consequently, if an individual is provided with a difficult/challenging learning opportunity, and the individual makes a success of it; their *resilience* will definitely improve and their ability to recover from adversity in the future will advance. Accordingly, if an individual makes a success of the opportunity, and achieve a high level of learning performance, their *resilience* will also improve. Therefore, it can be argued that *learning performance during evaluation* positively influences *resilience*.

Hypothesis 13: In the proposed learning potential structural model it is hypothesised that *learning performance during evaluation* positively influences *resilience*.

The De Goede - Burger (2012) learning potential structural model hypothesised that *learning performance during evaluation* positively influences *academic self-efficacy*. Consequently, based on the arguments presented above, *learning performance during evaluation* positively influences *resilience*, and *resilience* positively influences *academic self-efficacy*. Therefore it can be argued that *resilience* mediates the positive effect of *learning performance during evaluation* on *academic self-efficacy*.

2.6 THE PROPOSED EXPANDED BURGER - PRINSLOO LEARNING POTENTIAL STRUCTURAL MODEL

The research initiating question of this research study asked why variance in learning performance among previously disadvantaged individuals participating in affirmative development opportunities occurs? More specifically, the research initiating question asked how the Burger (2012) learning potential structural model should be expanded to present a better understanding of the psychological process determining the level of learning performance achieved by an individual partaking in a learning opportunity.

The literature study offered a theoretical argument which was presented in an attempt to answer the research initiating question. A response to the question was developed through theorising, and can be summarised in the form of a structural model and portrayed in the form of a path diagram. The proposed expanded Burger - Prinsloo learning potential structural model is presented below in Figure 2.5.

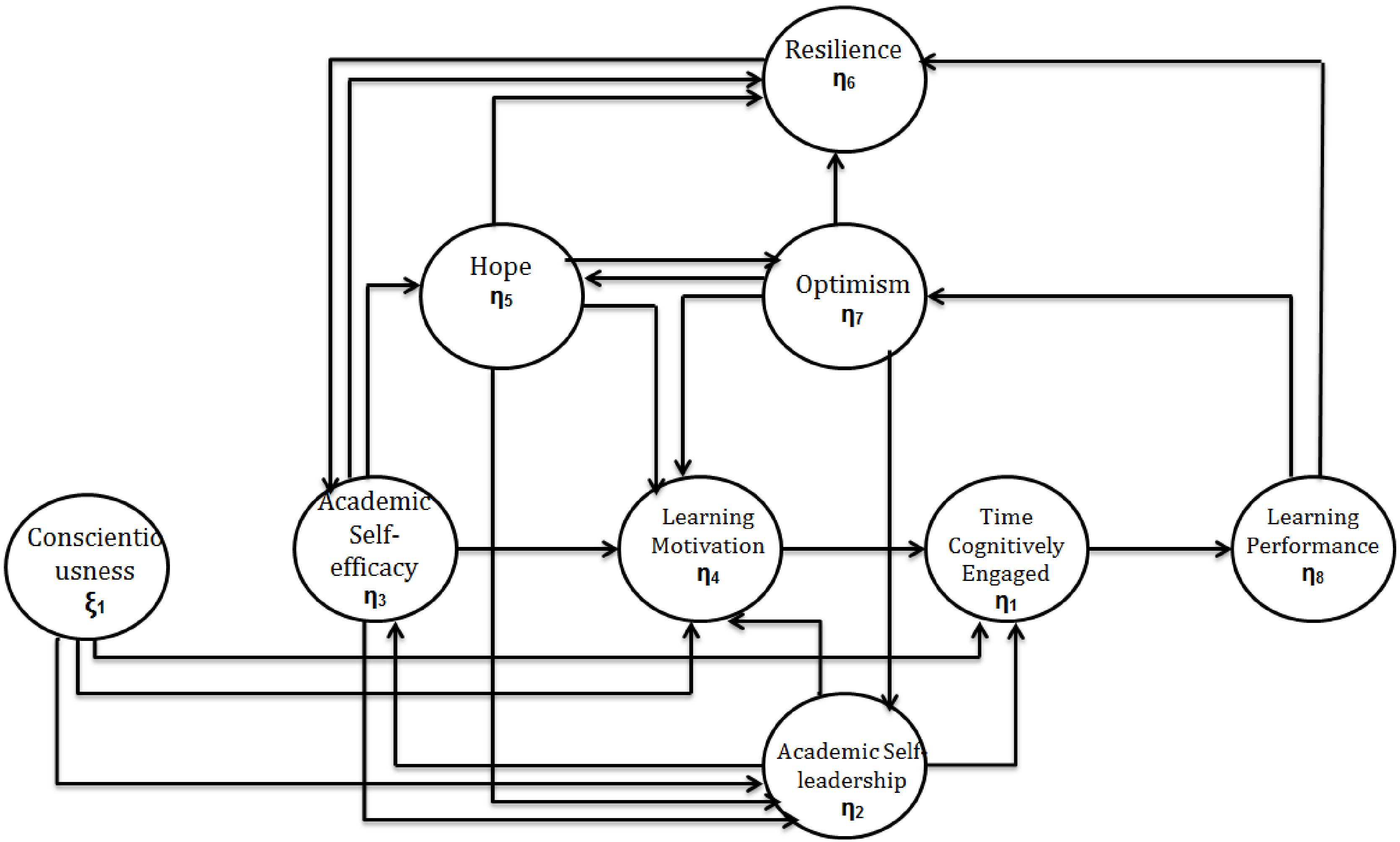

Figure 2.5 **The proposed Burger – Prinsloo learning potential structural model**

CHAPTER 3

RESEARCH METHODOLOGY

3.1 INTRODUCTION

Burger (2012) highlighted the importance of non-cognitive or non-ability variables as predictors of *classroom learning performance* and of eventual *learning performance during evaluation*. This was based on the fact that even though ability tests are useful indicators of what an individual *can* do, non-ability/non-cognitive variables may provide useful information regarding what an individual *will* do (Burger, 2012)[28]. The academic literature presented by Burger (2012) supported the fact that learning potential is a function of both cognitive and non-cognitive variables. It was for this particular reason that Burger (2012) expanded the De Goede (2007) learning potential structural model by adding non-cognitive variables.

As indicated in the introduction of this thesis; a single explanatory research study is unlikely to result in an accurate understanding of the comprehensive nomological network of latent variables that determine *classroom learning performance* and *learning performance during evaluation* (Burger, 2012). Due to the complexity of this phenomenon, the explanatory structural models established through research each succeed in explaining only a portion of this intricate network. Therefore, even though the construct of learning performance has been researched by several others (De Goede, 2007; Burger, 2012; Van Heerden, 2013); meaningful progress will only be achieved if explicit attempts are made at successive research studies, which takes effort in expanding and elaborating the latest version of the learning potential structural model (Smuts, 2011). In addition, partial overlap between the variable sets incorporated into these successive research studies are essential, firstly because of the intention to expand on existing structural models and secondly, to partially replicate and confirm findings of earlier studies. This assists with the "uncovering" of the nomological network of latent variables underpinning learning performance and reveal as much of the complexity that reflects itself in this construct, as is humanly possible.

[28] Chamorro-Premuzic, Furnham and Ackerman (2006) emphasised the importance of studying non-cognitive/non-ability predictors of educational achievement.

Owing to this argument as well as the literature study presented in the previous section, the Burger (2012) learning potential structural model was expanded by including additional non-ability/non-cognitive latent variables. This study tested the expanded Burger – Prinsloo explanatory learning potential structural model depicted in Figure 2.5.

The validity and credibility of the implicit claim of this study that it came to the correct verdict on the fit of the explanatory structural model depended on the methodology used to arrive at the verdict (Burger, 2012). Theron (2009) agrees by emphasising the importance of a meticulous research methodology by stressing the fact that the methods used to derive the conclusions will determine the validity and credibility of the inferences made. This is due to the fact that the methodology of this study is meant to serve the epistemic ideal of science, which means that the methodology of this study is meant to ensure that valid conclusions are reached on the validity of the hypothesised learning potential structural model. Smuts (2011) explained that the explanations will only be considered valid if the explanations closely fit the available data. Babbie and Mouton (2001) further explain that research methodology serves the epistemic ideal through two characteristics of the scientific method; namely, objectivity and rationality. *Objectivity* refers to the conscious, explicit focus on the reduction of error. Science is *rational* if it provides an opportunity for knowledgeable peers to critically evaluate the research findings and the validity of the proposed contribution by assessing the methodological rigour of the processes used to arrive at the conclusions (Babbie & Mouton, 2001).

If very little of the methodology used is made explicit, there is no way of evaluating the merits of the researcher's conclusions. The rationality therefore suffers, as does ultimately the epistemic ideal of science (Babbie & Mouton, 2001). As a result, it is vital to provide a comprehensive description and thorough motivation of how the methodology was approached. This description should specifically focus on the methodological choices that were made at the various critical points in the method where the epistemic ideal is potentially threatened (Smuts, 2011). This will allow knowledgeable peers to identify flaws in the methodology, if they exist, and identify the implications of these for the validity of the conclusion, which assist in the achievement of the epistemic ideal of science.

Consequently, the methodology used in the study will be discussed in sufficient depth in the next section to allow knowledgeable peers to identify flaws in the methodology if they exist and identify the implications of these for the validity of the conclusion.

3.2 THE BURGER-PRINSLOO LEARNING POTENTIAL STRUCTURAL MODEL

The proposed expanded structural model depicted in Figure 2.5 as a path diagram can also be expressed as a set of structural equations:

$\eta_1= \beta_{12}\eta_2+\beta_{14}\eta_4+Y_{11}\xi_1+\zeta_1$..1

$\eta_2=\beta_{23}\eta_3 +\beta_{25}\eta_5+\beta_{27}\eta_7+Y_{21}\xi_1+\zeta_2$..2

$\eta_3= \beta_{32}\eta_2+\beta_{36}\eta_6+\zeta_3$..3

$\eta_4= \beta_{42}\eta_2+\beta_{43}\eta_3+\beta_{45}\eta_5+\beta_{47}\eta_7+Y_{41}\xi_1+\zeta_4$...4

$\eta_5=\beta_{53}\eta_3+\beta_{57}\eta_7+\zeta_5$........ 5

$\eta_6=\beta_{63}\eta_3+ \beta_{65}\eta_5+ \beta_{67}\eta_7+\beta_{68}\eta_8+\zeta_6$...6

$\eta_7= \beta_{75}\eta_5+\beta_{78}\eta_8+\zeta_7$...7

$\eta_8=\beta_{81}\eta_1+\zeta_8$...8

The learning potential structural model expressed as a set of structural equations can be reduced in matrix form to a single matrix equation:

$$\begin{pmatrix}\eta_1\\ \eta_2\\ \eta_3\\ \eta_4\\ \eta_5\\ \eta_6\\ \eta_7\\ \eta_8\end{pmatrix} = \begin{pmatrix} 0 & \beta_{12} & 0 & \beta_{14} & 0 & 0 & 0 & 0\\ 0 & 0 & \beta_{23} & 0 & \beta_{25} & 0 & \beta_{27} & 0\\ 0 & \beta_{32} & 0 & 0 & 0 & \beta_{36} & 0 & 0\\ 0 & \beta_{42} & \beta_{43} & 0 & \beta_{45} & 0 & \beta_{47} & 0\\ 0 & 0 & \beta_{53} & 0 & 0 & 0 & \beta_{57} & 0\\ 0 & 0 & \beta_{63} & 0 & \beta_{65} & 0 & \beta_{67} & \beta_{68}\\ 0 & 0 & 0 & 0 & \beta_{75} & 0 & 0 & \beta_{78}\\ \beta_{81} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix}\eta_1\\ \eta_2\\ \eta_3\\ \eta_4\\ \eta_5\\ \eta_6\\ \eta_7\\ \eta_8\end{pmatrix} + \begin{pmatrix}Y_{11}\\ Y_{21}\\ 0\\ Y_{41}\\ 0\\ 0\\ 0\\ 0\end{pmatrix} \begin{pmatrix}\xi_1\end{pmatrix} + \begin{pmatrix}\zeta_1\\ \zeta_2\\ \zeta_3\\ \zeta_4\\ \zeta_5\\ \zeta_6\\ \zeta_7\\ \zeta_8\end{pmatrix} \quad \ldots 9$$

The single matrix equation expressed as equation 9 can in turn be reduced to equation 10:

$\eta = B\eta + \Gamma\xi + \zeta$……………………………………………………………..........10

Equations 9 and 10, however as yet do not fully specify the hypothesised Burger – Prinsloo learning potential structural model. The nature of the variance-covariance matrix Ψ defining the variances in and the covariances between the structural error terms ζ needed to be specified as well. Ψ was defined as a diagonal matrix thereby expressing the assumption that the structural error terms are considered to be uncorrelated. No common source of structural error variance was therefore assumed. Since the hypothesised Burger – Prinsloo learning potential structural model only contains a single exogenous latent variable the definition Φ was not relevant.

3.3 SUBSTANTIVE RESEARCH HYPOTHESIS

The proposed research methodology served the objective of the study. The objective of this study was to elaborate the learning potential structural model proposed by Burger (2012) and to empirically test the validity of the hypothesised Burger – Prinsloo learning potential structural model.

The argument presented in the literature study resulted in the inclusion of non-cognitive learning potential latent variables and the modification of some of the causal paths. Three non-cognitive variables were included in the expanded model presented in Figure 2.5. All but one of the original paths in the Burger (2012) model was retained, and one of them was modified. The hypothesised positive relationship that *learning performance during evaluation* had on *academic self-efficacy* was modified by hypothesising that *resilience* mediates the effect of *learning performance during evaluation* on *academic self-efficacy.* The modification allowed for a replacement of the hypothesis originally presented by Burger (2012) with the two hypotheses that *learning performance during evaluation* positively feeds back onto *resilience* and that *resilience* positively affects *academic self-efficacy*.

The overarching substantive research hypothesis of this study (*Hypothesis 1*) is that the structural model depicted in Figure 2.5 provided a valid account of the psychological process that determined the level of *learning performance during evaluation* achieved by an individual presented with an affirmative developmental learning opportunity[29]. *Hypothesis 1* was dissected into twenty-three more detailed path-specific substantive research hypotheses.

Hypothesis 2: In the proposed learning potential structural model it was hypothesised that *time cognitively engaged* positively influences *learning performance during evaluation*.

Hypothesis 3: In the proposed learning potential structural model it was hypothesised that *conscientiousness* will positively influence *time cognitively engaged*.

Hypothesis 4: In the proposed learning potential structural model it was hypothesised that *learning motivation* will positively influence *time cognitively engaged*.

Hypothesis 5: In the proposed learning potential structural model it was hypothesised that *conscientiousness* will positively influence *learning motivation*.

Hypothesis 6: In the proposed learning potential structural model it was hypothesised that *academic self-leadership* will positively influence *learning motivation*.

Hypothesis 7: In the proposed learning potential structural model it was hypothesised that *academic self-efficacy* positively influences *academic self-leadership.*

Hypothesis 8: In the proposed learning potential structural model it was hypothesised that *academic self-leadership* will positively influence *time cognitively engaged.*

Hypothesis 9: In the proposed learning potential structural model it was hypothesised that *academic self-leadership* positively influences *academic self-efficacy*.

[29] Burger (2012) explained that even though this study is motivated by the need for a structural model that explicates the determinants of learning performance from the perspective of affirmative development, the value of this model extends to all forms of training/development and teaching. This is due to the fact that the psychological dynamics underlying the learning performance in affirmative development programs do not differ considerable from those that underlie learning performance in other training/development and teaching situations (Burger, 2012). The assumption underlying the sample strategy in the Burger (2012) model, that will also be applicable in this proposed expanded model, entails that the same complex nomological network of latent variables that determine learning in affirmative development programs will also determine learning performance in school learners. However, the only difference will most likely involve the level of latent variables that will possible vary across the different teaching contexts.

Hypothesis 10: In the proposed learning potential structural model it was hypothesised that *conscientiousness* positively influences *academic self-leadership*.

Hypothesis 11: In the proposed learning potential structural model it was hypothesised that *academic self-efficacy* positively influences *learning motivation*.

Hypothesis 12: In the proposed learning potential structural model it was hypothesised that *optimism* positively influences *learning motivation*.

Hypothesis 13: In the proposed learning potential structural model it was hypothesised that *learning performance during evaluation* positively influences *optimism*.

Hypothesis 14: In the proposed learning potential structural model it was hypothesised that *optimism* positively influences *academic self-leadership*.

Hypothesis 15: In the proposed learning potential structural model it was hypothesised that *hope* positively influences *optimism*.

Hypothesis 16: In the proposed learning potential structural model it was hypothesised that *optimism* positively influences *hope*.

Hypothesis 17: In the proposed learning potential structural model it was hypothesised that *hope* positively influences *learning motivation*.

Hypothesis 18: In the proposed learning potential structural model it was hypothesised that *hope* positively influences *academic self-leadership*.

Hypothesis 19: In the proposed learning potential structural model it was hypothesised that *academic self-efficacy* positively influences *hope.*

Hypothesis 20: In the proposed learning potential structural model it was hypothesised that *optimism* positively influences *resilience*.

Hypothesis 21: In the proposed learning potential structural model it was hypothesised that *academic self-efficacy* positively influences *resilience*.

Hypothesis 22: In the proposed learning potential structural model it was hypothesised that *hope* positively influences *resilience*.

Hypothesis 23: In the proposed learning potential structural model it was hypothesised that *resilience* positively influences *academic self-efficacy.*

Hypothesis 24: In the proposed learning potential structural model it was hypothesised that *learning performance during evaluation* positively influences *resilience.*

3.4 RESEARCH DESIGN

The overarching research hypothesis presented in the previous section (3.3), made specific claims with regards to the hypothesised learning potential structural model.

The model presented in Figure 2.5 hypothesised specific structural relations between the various latent variables included in the expanded model. To empirically evaluate the merit of the overarching substantive research hypothesis and the array of path-specific substantive research hypotheses, a strategy was required that will guide the process of gathering the empirical evidence to test the operational hypotheses (Smuts, 2011). The strategy was presented in the form of a research design, which can be described as the plan, guideline or blueprint on how the research will be conducted (Babbie & Mouton, 2001).

The design that best fitted the intended research depended mainly on the research problem and the type of evidence necessary to address the problem. According to Burger (2012), the research design is used to obtain an answer to the research initiating question and to also control variance. Through the control of variance, the research design attempts to ensure empirical evidence that can be interpreted unambiguously for or against the overarching substantive research hypothesis and the array of path-specific substantive research hypotheses as answers to the research initiating question. More specifically, the research design has to maximise systematic variance, minimise error variance and control extraneous variance (Kerlinger & Lee, 2000).

In this particular study an *ex post facto* correlation design was used. The design used is schematically depicted in Figure 3.1.

[X_{11}]	[X_{12}]	..	Y_{11}	Y_{12}	..	Y_{1i}	..	Y_{117}
[X_{21}]	[X_{22}]	..	Y_{21}	Y_{22}	..	Y_{2i}	..	Y_{217}
:	:	..	:	:	..	:	..	:
[X_{j1}]	[X_{j2}]	..	Y_{j1}	Y_{j2}	..	Y_{ji}	..	Y_{j17}
:	:	..	:	:	..	:	..	:
[X_{n1}]	[X_{n2}]	..	Y_{n1}	Y_{n2}	..	Y_{ni}	..	Y_{n17}

***Figure 3.1 Ex post facto* correlational design**

This research design is a systematic empirical inquiry in which the researcher does not have direct control of the independent variables, as their manifestations have already occurred or because they fundamentally do not allow being manipulated (Burger, 2012). Because experimental manipulation and random assignment were not possible it was decided to use an *ex post facto* correlational research design. The aim of this design was to discover what happened to one variable as the other variables changed. According to Burger (2012), inferences about the hypothesised relation existing between the latent variables ξj and η_i and between η_j and η_i are made from associated variation in independent and dependant variables. The nature of this specific research design precluded the drawing of casual inferences from significant path coefficients, as correlations do not suggest causation (Burger, 2012).

The *ex post facto* correlational design tested the validity of the hypothesised structural model through the following logic. Measures were obtained on the observed variables and the observed *n x p* covariance matrix was calculated (Kerlinger & Lee, 2000). Estimates for the freed structural and measurement model parameters were obtained in an iterative way, with the objective of reproducing the observed covariance matrix as precisely as possible (Diamatopoulos & Sigauw, 2000). If the fitted model fails to reproduce the observed covariance matrix sufficiently accurately, it would inevitable mean that the proposed expanded learning potential structural model does not offer an acceptable explanation for the observed covariance matrix (Smuts, 2011). This would lead to the necessary conclusion that the structural relationships hypothesised by the proposed model fail to provide an accurate portrayal of the psychological processes shaping an individual's learning performance.

Smuts (2011) states that the opposite is not true, thus emphasising that if the fitted covariance matrix obtained from the estimated structural and measurement model parameters agrees with the observed covariance matrix, it would not imply that the psychological dynamics postulated by the structural model necessarily produced the observed covariance matrix. Burger (2012) explained that it can therefore *not* be concluded that psychological processes depicted in the model necessarily must have produced the levels of *learning performance during evaluation* observed in the individual's sampled for this study. A high level of fit between the observed and estimated covariance matrices would only imply that the psychological processes portrayed in the structural model provided one plausible explanation for the observed covariance matrix (Smuts, 2011).

The value of this research design lies in the fact that most research in the social sciences fail to lend itself to experimentation. Therefore, even though controlled inquiry is possible in a limited number of cases (Kerlinger & Lee, 2000); experimentation was not a feasible option in this case. The *ex post facto* correlational design was therefore extremely valuable in this case despite its problems in controlling extraneous variance.

3.5 STATISTICAL HYPOTHESES

The statistical hypotheses were formulated in a way that depicted the logic underlying the proposed research design, as well as the nature of the envisioned statistical analyses. The proposed learning potential structural model consisted of a single exogenous and a number of endogenous latent variables and the model further introduced causal paths between these latent variables. Burger (2012) explained that structural equation modelling (SEM) offered the only possibility of testing the proposed structural model as an integrated, complex hypothesis. The reason why this was so important was due to the fact that the explanation as to why individuals vary with regards to their level of learning performance is not located in a specific part of the proposed model, but rather it is spread over the whole, complex network of relationships. Therefore, if multiple regression would be used to test the proposed paths, it will result in a dissection of the model into as many sub-models as there are endogenous latent variables. This would result in an invariable loss of meaning.

The notational system used in the formulation of the respective statistical hypotheses followed the SEM convention associated with LISREL (Burger, 2012).

Diamantopoulos and Siguaw (2000) clarifies that in order to estimate the hypothesised model's fit, the extent to which the model is consistent with the obtained empirical data should be tested. To investigate the hypothesised model's fit, an exact fit and a close fit null hypothesis was tested.

The overarching substantive research hypothesis stated that the structural model depicted in Figure 2.5 provides a valid account of the psychological process that determines the level of *learning performance during evaluation* achieved by an individual who is presented with an affirmative development opportunity. If the overarching substantive research hypothesis would be interpreted to mean that the structural model provides a perfect explanation for the psychological dynamics underlying *learning performance during evaluation*, then the substantive research hypothesis could be expressed in terms of the following exact fit null hypothesis:

H_{o3}: RMSEA=0[30]

H_{a3}: RMSEA>0

The probability of an exact fit is highly unlikely, because according to Burger (2012), models are only approximations of reality and, as a result, an exact fit in the population would be rarely found. Consequently, the close fit null hypothesis was considered as it takes the error of approximation into account and therefore displays a more realistic picture of reality (Diamantopoulos & Siguaw, 2000). If the error due to approximation in the population is equal to or less than .05, the model can be said to fit closely. Therefore, if the overarching substantive research hypothesis would be interpreted to mean that the structural model provided an approximate description of the psychological dynamics underlying *learning performance during evaluation* the research hypothesis would be expressed in terms of the following close fit null hypothesis:

H_{o4}: RMSEA $\leq$ 0.05

H_{a4}: RMSEA >0.05

[30] The subscript numbering of the statistical hypothesis implies that the exact and close fit null hypotheses will also be tested in terms of the measurement model, thus enabling an evaluation of the success with which the latent variables in the structural model have been operationalised.

The overarching substantive research hypothesis was dissected into twenty-three more detailed substantive research hypotheses. These hypotheses translated into path coefficient statistical hypotheses as summarised below and in Table 3.1.

Hypothesis 2: In the proposed learning potential structural model it was hypothesised that *time cognitively engaged* positively influences *learning performance*.

$$H_{o5}: \beta_{81}=0$$

$$H_{a5}: \beta_{80}>0$$

Hypothesis 3: In the proposed learning potential structural model it was hypothesised that *conscientiousness* will positively influence *time cognitively engaged*.

$$H_{o6}: \gamma_{11}=0$$

$$H_{a6}: \gamma_{11}>0$$

Hypothesis 4: In the proposed learning potential structural model it was hypothesised that *learning motivation* will positively influence *time cognitively engaged*.

$$H_{o7}: \beta_{14}=0$$

$$H_{a7}: \beta_{14}>0$$

Hypothesis 5: In the proposed learning potential structural model it is hypothesised that *conscientiousness* will positively influence *learning motivation*.

$$H_{o8}: \gamma_{41}=0$$

$$H_{a8}: \gamma_{41}>0$$

Hypothesis 6: In the proposed learning potential structural model it was hypothesised that *academic self-leadership* will positively influence *learning motivation*.

$$H_{o9}: \beta_{42}=0$$

$$H_{a9}: \beta_{42}>0$$

Hypothesis 7: In the proposed learning potential structural model it was hypothesised that *learning motivation* positively influences *academic self-leadership.*

$$H_{o10}: \beta_{23}=0$$

$$H_{a10}: \beta_{23}>0$$

Hypothesis 8: In the proposed learning potential structural model it was hypothesised that *academic self-leadership* will positively influence *time cognitively engaged.*

$$H_{o11}: \beta_{12}=0$$

$$H_{a11}: \beta_{12}>0$$

Hypothesis 9: In the proposed learning potential structural model it was hypothesised that *academic self-efficacy* positively influences *academic self-leadership*.

$$H_{o12}: \beta_{32}=0$$

$$H_{a12}: \beta_{32}>0$$

Hypothesis 10: In the learning potential structural model it was hypothesised that *conscientiousness* positively influences *academic self-leadership*.

$$H_{o13}: \gamma_{21}=0$$

$$H_{a13}: \gamma_{21}>0$$

Hypothesis 11: In the learning potential structural model it was hypothesised that *academic self-efficacy* positively influences *learning motivation*.

$$H_{o14}: \beta_{43}=0$$

$$H_{a14}: \beta_{43}>0$$

Hypothesis 12: In the proposed learning potential structural model it was hypothesised that *optimism* positively influences *learning motivation*.

$$H_{o15}: \beta_{47}=0$$

$$H_{a15}: \beta_{47}>0$$

Hypothesis 13: In the proposed learning potential structural model it was hypothesised that *learning performance* positively influences *optimism*.

H_{o16}: $\beta_{78}=0$

H_{a16}: $\beta_{78}>0$

Hypothesis 14: In the proposed learning potential structural model it was hypothesised that *optimism* positively influences *academic self-leadership*.

H_{o17}: $\beta_{27}=0$

H_{a17}: $\beta_{27}>0$

Hypothesis 15: In the proposed learning potential structural model it was hypothesised that *hope* positively influences *optimism*.

H_{o18}: $\beta_{75}=0$

H_{a18}: $\beta_{75}>0$

Hypothesis 16: In the proposed learning potential structural model it was hypothesised that *optimism* positively influences *hope*.

H_{o19}: $\beta_{57}=0$

H_{a19}: $\beta_{57}>0$

Hypothesis 17: In the proposed learning potential structural model it was hypothesised that *hope* positively influences *learning motivation*.

H_{o20}: $\beta_{45}=0$

H_{a20}: $\beta_{45}>0$

Hypothesis 18: In the proposed learning potential structural model it was hypothesised that *hope* positively influences *academic self-leadership.*

H_{o21}: $\beta_{25}=0$

H_{a21}: $\beta_{25}>0$

Hypothesis 19: In the proposed learning potential structural model it was hypothesised that *academic self-efficacy* positively influences *hope*.

H_{o22}: $\beta_{53}=0$

H_{a22}: $\beta_{53}>0$

Hypothesis 20: In the proposed learning potential structural model it was hypothesised that *optimism* positively influences *resilience*.

H_{o23}: $\beta_{67}=0$

H_{a23}: $\beta_{67}>0$

Hypothesis 21: In the proposed learning potential structural model it was hypothesised that *academic self-efficacy* positively influences *resilience*.

H_{o24}: $\beta_{36}=0$

H_{a24}: $\beta_{36}>0$

Hypothesis 22: In the proposed learning potential structural model it was hypothesised that *hope* positively influences *resilience*.

H_{o25}: $\beta_{65}=0$

H_{a25}: $\beta_{65}>0$

Hypothesis 23: In the proposed learning potential structural model it is hypothesised that *resilience* positively influences *academic self-efficacy.*

H_{o26}: $\beta_{36}=0$

H_{a26}: $\beta_{36}>0$

Hypothesis 24: In the proposed learning potential structural model it was hypothesised that *learning performance during evaluation* positively influences *resilience.*

H_{o27}: $\beta_{68}=0$

H_{a27}: $\beta_{68}>0$

Table 3.1
Path coefficient statistical hypotheses

Hypothesis 2:	**Hypothesis 7:**	**Hypothesis 12:**	**Hypothesis 17:**	**Hypothesis 22:**
H_{o5}: β_{81}=0	H_{o10}: β_{23}=0	H_{o15}: β_{47}=0	H_{o20}: β_{45}=0	H_{o25}: β_{65}=0
H_{a5}: β_{81}>0	H_{a10}: β_{23}>0	H_{a15}: β_{47}>0	H_{a20}: β_{45}>0	H_{a25}: β_{65}>0
Hypothesis 3:	**Hypothesis 8:**	**Hypothesis 13:**	**Hypothesis 18:**	**Hypothesis 23:**
H_{o6}: γ_{11}=0	H_{o11}: β_{12}=0	H_{o16}: β_{78}=0	H_{o21}: β_{25}=0	H_{o26}: β_{36}=0
H_{a6}: γ_{11}>0	H_{a11}: β_{12}>0	H_{a16}: β_{78}>0	H_{a21}: β_{25}>0	H_{a246} β_{36}>0
Hypothesis 4:	**Hypothesis 9:**	**Hypothesis 14:**	**Hypothesis 19:**	**Hypothesis 24:**
H_{o7}: β_{14}=0	H_{o12}: β_{32}=0	H_{o17}: β_{27}=0	H_{o22}: β_{53}=0	H_{o27}: β_{68}=0
H_{a7}: β_{14}>0	H_{a12}: β_{32}>0	H_{a17}: β_{27}>0	H_{a22}: β_{53}>0	H_{a27}: β_{68}>0
Hypothesis 5:	**Hypothesis 10:**	**Hypothesis 15:**	**Hypothesis 20:**	
H_{o8}: γ_{1}=0	H_{o13}: γ_{21}=0	H_{o18}: β_{75}=0	H_{o23}: β_{67}=0	
H_{a8}: γ_{1}>0	H_{a13}: γ_{21}>0	H_{a18}: β_{75}>0	H_{a23}: β_{67}>0	
Hypothesis 6:	**Hypothesis 11:**	**Hypothesis 16:**	**Hypothesis 21:**	
H_{o9}: β=0	H_{o14}: β_{43}=0	H_{o19}: β_{57}=0	H_{o24}: β_{36}=0	
H_{a9}: β>0	H_{a14}: β_{43}>0	H_{a19}: β_{57}>0	H_{a24}: β_{36}>0	

3.6 RESEARCH PARTICIPANTS

The units of analysis for this study were grade 11 pupils (who have completed their first and second term i.e. first semester), from seven different schools within the Western Cape. In collaboration with the *Division of Community Interaction* at Stellenbosch University, a few schools were approached, from which seven schools agreed to participate in the study. These schools vary in terms of their residential area, and as a result, the schools are different with reference to their gender-, age-, home language-, racial- and income demographics. The seven schools represented a non-probability, convenience sample from all schools in the Western Cape resorting under the Western Cape Department of Education (DOE). The DOE as well as the principles from the respective schools were contacted (*See Appendix 1)* and permission for the study was obtained. Due to the fact that this study worked with school children i.e. minors, both informed assent from the learners, along with informed consent from the parents/guardians of the learners were obtained. All the learners who had presented signed informed assent and informed consent forms were included in the study. Beforehand, the purpose, and possible consequences of this study were clearly explained to the learners as well as to their parents/guardians. They were also informed that they are not obliged to complete the questionnaire and could withdraw at any time prior, during or after the study.

3.6.1 Sample and Sample Design

It is not always possible to obtain measurements from each and every subject in a target population (containing N final sampling units (FSU)), and as a result, the more practical option will be to focus on obtaining a representative sample (containing a subset of N FSU's) of the target population. De Goede and Theron (2010) further explained that the extent to which observations can or may be generalised to the target population depends on the number of subjects in the chosen sample, as well as the representation of the sample, while the power of inferential statistics tests also depend on the sample size.

The motivation for this study, similar to the Burger (2012) study, presented the need to develop a structural model that explained the determinants of learning performance from the perspective of affirmative development. Despite the known importance of such a model in the affirmative development context, the value of this model extends to all forms of training, development and teaching.

This is based on the assumption that the psychological dynamics underlying learning performance in affirmative development programs do not differ significantly from those governing learning performance in other learning contexts. The same complex nomological network of latent variables that determine learning performance in affirmative development programs will also determine learning performance in grade 11 learners (Burger, 2012). What might be different across different teaching contexts is the *level* of latent variables needed by the learner. This line of reasoning suggests that testing the hypothesised learning potential structural model on a sample of non-disadvantaged learners would be warranted. Based on this conclusion, and following the lead of the Burger (2012) study, this study empirically evaluated the structural model on a sample of non-previously disadvantaged learners in addition to previously disadvantaged learners who have enrolled for a teaching/training program that cannot be classified as an affirmative development program.

The decision regarding the specific sample size of this study was reliant on three considerations. These three issues were especially important to consider due to the intention of this study to use structural equation modelling (SEM) (Smuts, 2011).

The first consideration was the ratio of the sample size to the number of parameters to be estimated. Smuts (2011) explained that one would not regard a situation desirable in which more freed parameters have to be estimated than there are observations in the sample. Elaborate measurement and structural models contain more variables, and as a result, more freed parameters have to be estimated, which causes an increase in the required sample size (Burger, 2012). Bentler and Chou (as cited in Kelloway, 1998), suggested that the ratio of sample size to estimated parameters, should range between 5:1 and 10:1. Therefore, based on the proposed expanded structural model (Figure 2.5), the proposed procedure for operationalizing the latent variables, considering the Bentler and Chou (as cited in Kelloway, 1998) guideline; a sample of 305-610 learners were required to provide a convincing test of the structural model (61 freed parameters).

The second consideration that was taken into account referred to the statistical power associated with the test of the hypothesis of close fit (H_0: RMSEA ≤ .05) against the alternative hypothesis of mediocre fit (H_a: RMSEA > .05). Smuts (2011) explained that the statistical power in the SEM context refers to the probability of rejecting the null hypothesis of close fit i.e. H_0: RMSEA ≤ .05, when in fact it should be rejected (i.e., the model actually shows mediocre fit; RMSEA = .08). Too high statistical power would cause any attempt to obtain formal empirical proof for the validity of the model to be futile. Burger (2012) explained that even a small deviation from the close fit will result in the rejection of the close fit hypothesis. On the other hand, if the statistical power is too low, and the model fails to fit closely, the null hypothesis would still not be rejected. Burger (2012) argued that by not rejecting the close fit under low power conditions, will not provide very convincing evidence on the validity of the model.

MacCullum, Browne, and Sugawara (1996), developed power tables that are used to derive sample size estimates for the test of close fit. It is derived based on the effect size assumed above, a significant level (α) of .05, a power level of .80, and degrees of freedom (v).

$$
\begin{aligned}
Df &= (½[(p+q]\ [p+q+1]-t) \\
&= 190-61 \\
&= 129
\end{aligned}
$$

For this particular study, the MacCullum et al. (1996) table indicated that a sample of less than 115 observations would be required to ensure statistical power of .80 in testing the hypothesis of close fit for the expanded learning potential structural model.

The third and last consideration involved any practical and logistical considerations with reference to this specific study. These may include considerations of the costs involved, availability of suitable respondents, as well as the willingness of the employer (the school principals in this study) to commit a large number of employees (school learners) to this study.

After taking into account all three of the above considerations, a sample of 200-250 individuals was considered optimal for this study to succeed, where all of the learners signed an informed assent (*See Appendix 2*) form and all of their parents/guardians signed an informed consent form (*See Appendix 3*). After the completion of the study, the following profile of the sample of grade 11 learners were established (Table 3.2):

Table 3.2
Profile of the sample of Grade 11 learners

SCHOOL		
SCHOOL	**FREQUENCY**	**PERCENTAGE**
SCHOOL 1	102	36.4%
SCHOOL 2	18	6.4%
SCHOOL 3	49	17.5%
SCHOOL 4	46	16.4%
SCHOOL 5	23	8.2%
SCHOOL 6	13	4.7%
SCHOOL 7	29	10.4%
GENDER		
GENDER	**FREQUENCY**	**PERCENTAGE**
FEMALE	156	55.7%
MALE	124	44.3%
RACE		
RACE	**FREQUENCY**	**PERCENTAGE**
COLOURED	243	86.7%
WHITE	29	10.4%
BLACK	8	2.9%

AGE		
AGE	**FREQUENCY**	**PERCENTAGE**
16	75	26.8%
17	190	67.8%
18	12	4.3%
19	3	1.1%

HOME LANGUAGE		
HOME LANGUAGE	**FREQUENCY**	**PERCENTAGE**
AFRIKAANS	267	95.3%
ENGLISH	10	3.6%
XHOSA	3	1.1%

The sample profile presented in Table 3.2 shows that the sample for this study consisted of 280 grade 11 school learners from seven different schools in the Western Cape. The seven schools in this sample represented different residential areas and consisted of individuals with different gender-, age-, income-, and racial demographics. School 5 and School 6 were predominantly White schools where the children were seemingly from advantaged backgrounds, while the other five schools (School 1,2,3,4 and 7) were predominantly Coloured/Black schools where the children were predominantly from previously disadvantaged backgrounds and still living in adverse circumstances. Eighty seven percent (87%) of the sample consisted of individuals from previously disadvantaged backgrounds while 13% were not. However, it should be taken note of that the schools that are regarded as previously advantaged schools also consist of learners with previously disadvantaged status, and vice versa.

With regards to the gender of the sample; about 55,7% of the individuals were female, and 44,3% were male. The sample, therefore, provided an almost 50/50 split between male and female. In terms of race, the sample consisted predominantly of Coloured learners, however, a few White (10.4%) and Black (2.9%) learners also took part in the study. The age of the learners varied from 16 years old to 19 years old. Most of the learners, about 67.8% of the sample, were 17 years of age. Furthermore, it was also evident that the majority of the sample's home language was Afrikaans (95.3%), while 3.6% indicated English as their home language and 1.1% indicated that Xhosa was their home language.

3.7 MEASURING INSTRUMENTS/OPERATIONALISATION

The fit of the proposed learning potential structural model can only be evaluated if measures exist that would allow the evaluation of the relationships postulated by the model. As a result, specific measures of the various endogenous and exogenous latent variables presented in the proposed model were selected. To come to a valid and credible conclusion of the ability of the model to explain variance in learning performance, evidence was needed that these indicators were indeed valid and reliable measures of the latent variables that they are linked to (Burger, 2012). Diamantopoulos and Siguaw (2000) emphasised that if we cannot trust the quality of the measures used, then any evaluations of the relationships presented in the model will be problematic. Consequently, literature was reviewed on the reliability and validity of the selected instruments, to justify the selection of these specific measures.

The existing research evidence that supports the psychometric integrity of each measure is presented below. Additionally, the successes with which the indicator variables represent the latent variables comprising the structural model in this specific study were empirically evaluated via item analysis, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) (Section 3.9).

Firstly, item analyses were performed to determine whether the items of each measure reflect a common underlying variable and that all the items of each measure sensitively differentiate between the different states of the latent variable being measured. Poor items were either deleted or considered for revision.

Secondly, EFA was performed to determine whether the unidimensionality assumption was served in the case of those subscales that were designed and developed to measure a unidimensional latent variable.

Lastly, the CFA was performed to evaluate the degree to which the design intention underlying the operationalisation of the latent variables contained in the proposed structural model succeeded (Burger, 2012)[31]. The results of these analyses will be presented in Chapter 4.

[31] CFA was also separately performed on two of the measures that consisted of more than one subscale. These measures were the Psycap Questionnaire and the Revised Academic Self-leadership Questionnaire. These results will be discussed, in detail, in Chapter 4.

The Learning Potential Questionnaire (LPQ) originally developed by Burger (2012) formed the basis of the Revised Learning Potential Questionnaire (RLPQ), used to assess the latent variables comprising the proposed expanded learning potential structural model. The RLPQ differs from the LPQ in that it also included subscales measuring psychological capital; specifically *hope*, *resilience*, and *optimism*.

3.7.1 Time Cognitively Engaged

Linnebrank, Pistrich and Arbor (2003) explained that learners need to think critically, deeply and creatively about the content of the material they are studying. Burger (2012) continued with this line of reasoning by explaining that when a learner becomes more deeply engaged in the content of the material they are studying, the probability of them gaining a better understanding of the material increases. For most teachers, understanding serves as a better indicator of learning, more than just simple memory of the material studied (Burger, 2012). This is based on the idea that when a learner truly understands the material they are studying, there exists a greater probability of them having insight into the work. Insight has the potential to result in an improvement in their chances of successful transfer of knowledge, which will result in enhanced learning performance (Theron, personal communication, 1 March 2012).

The Academic Engagement Scale for Grade School Students (AES-GS) was adapted to measure *time cognitively engaged*. Engagement was associated with how much the individuals invest in their learning and the AES-GS was devised to measure the level of engagement of an individual in his/her education (Burger, 2012). Burger (2012) obtained excellent reliability statistics indicated by a Cronbach alpha of .936. However, two poor items were detected (CE11 and CE14), which showed the lowest squared multiple correlation and corrected item-total correlation values. The results indicated that these two poor items, if deleted, would increase the Cronbach's alpha. As a result, they were deleted in the Burger (2012) study, and a Cronbach alpha of .940 was obtained (Burger, 2012). In the Burger (2012) study this scale was therefore reduced from 17 to 15 items. In the RLPQ all 17 items were, however, initially retained.

When item analysis was conducted on the 17 item *time cognitively engaged* scale, this study[32] achieved an initial Cronbach alpha of .913. However, through the analysis of the various item statistics three poor items were identified, i.e. TCE9, TCE11 and TCE14. Two of the poor items identified in this study corresponded to the problematic items identified by Burger (2012). All three of the items were deleted and a Cronbach alpha of .916 was obtained for this measure. The scale therefore was reduced from 17 to 14 items. Two item parcels were calculated, without the three poor items, by taking the mean of the even and uneven numbered items of the AES-GS, to form two composite indicator variables for the *time cognitively engaged* latent variable in the Burger – Prinsloo structural model.

3.7.2 Conscientiousness

In this study the alphabetical Index of 204 labels for 269 International Personality Item Pool (IPIP) Scales was used. Burger (2012) explained that it is based on the revised version of the NEO Personality Inventory (NEO-PI-R) and contains 20 items. Despite the fact that the 20 item scale defined *conscientiousness* the same way as presented in this study, some items have been deleted and others were adapted for the purpose of this study.

In the Burger (2012) study the Cronbach alpha of this instrument was reported to be .90. Burger's (2012) item analysis results indicated a Cronbach alpha for the conscientiousness scale of .890. Item C3 showed the lowest inter-item correlations (-.038 to -.166), and was the only item where the squared multiple correlation was smaller than .30. Burger (2012) decided to first reflect the negatively worded and potentially poor item, C3. After C3 was reflected, the inter-item correlations did increase, but were still low (.125 to .337). Even though the Cronbach alpha increased from .890 to .920, the item-total statistics revealed that the Cronbach alpha would increase to .927 if item C3 were to be deleted. After the item was deleted a Cronbach alpha of .927 was obtained.

Despite the fact that the inter-item correlations matrix further revealed that a few items had correlations lower that .50, the item-total statistics indicated that none of the items, if deleted, would further increase the Cronbach alpha (Burger, 2012). As a result, only item C3 was deleted, decreasing the scale from 12 to 11 items.

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[32] This section only provides a summary of the results to provide a comparison with the results found in the Burger (2012) study. The item analysis and EFA results will be discussed in more detail in Chapter 4.

This study[33] achieved an initial Cronbach alpha of .861 when conducting item analysis on the 12 item measure. However, through the analysis of the various item statistics one poor item was detected, i.e. CON3, which was in line with the results found by Burger's (2012) study. This item was also first revised, after which it was deleted, and a Cronbach alpha of .90 was obtained for this measure. The scale therefore was reduced from 12 to 11 items. Two item parcels were calculated, without the poor item, using the mean of the even and uneven numbered items of this scale to form two composite indicator variables for the *Conscientiousness* latent variable in the proposed Burger - Prinsloo structural model.

3.7.3 Learning Motivation

Nunes (as cited in Burger 2012), developed a questionnaire that measures both an individual's motivation to learn and intention to learn. The Motivation to Learn Questionnaire (MLQ) consists of three sections: Section B (Motivation to learn) provides an assessment of *learning motivation*. *Learning motivation*, according to this instrument, refers to the specific desire to learn the content of the training program, which agrees with the way it is presented in this study. Section B, was therefore used in this study, to assess the motivation of an individual to learn.

According to Burger (2012) the measure revealed a Cronbach alpha of .940 with a sample of 114 in the original Nunes study. Burger (2012) herself, obtained a Cronbach alpha of .899 for this scale, which was the lowest reliability coefficient value she obtained for all the scales used. The results obtained by Burger (2012) revealed no poor items. As a result, none of the items were flagged as problematic, and therefore all the items of this scale were retained.

The item analysis conducted during this study[34] resulted in an initial Cronbach alpha of .854 for this 6 item measure. This was also one of the lowest Cronbach alpha values obtained in this study. However, the analysis of the various item statistics indicated no poor items which precluded any possibility of improving the internal consistency of the scale through the deletion of poor items.

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[33] This section only provides a summary of the results to provide a comparison with the results found in the Burger (2012) study. The item analysis and EFA results will be discussed in more detail in Chapter 4.
[34] This section only provides a summary of the results to provide a comparison with the results found in the Burger (2012) study. The item analysis and EFA results will be discussed in more detail in Chapter 4.

Consequently, two item parcels were calculated containing six items each, by using the mean of the even and uneven numbered items to form two composite indicator variables for the *learning motivation* latent variable in the hypothesised structural model.

3.7.4 Academic Self-leadership

The Revised Self-leadership Questionnaire (RSLQ) (Houghton & Neck, 2002) will be used in this study to assess the individual's *academic self-leadership*. According to Burger (2012), the RSLQ comprises of nine first-order self-leadership factors, namely; *self-goal setting*, *self-reward*, *self-punishment*, *self-observation*, *self-cueing*, *natural rewards*, *visualising successful performance*, *self-talk* and *evaluating belief and assumptions*. All nine of these were discussed in the section on *academic self-leadership* in the literature study, and is thus ideal for this study. According to Burger (2012), the reliabilities of these nine subscales ranged from .74 to .93. Houghton and Neck (2002) tested the reliability and construct validity of the RSLQ, and found significantly better reliability and factor stability in comparison with other existing self-leadership measures. It can therefore be concluded that the RSLQ measures self-leadership in accordance with the constitutive definition of self-leadership provided by Houghton and Neck (2002).

Burger (2012) obtained an initial Cronbach alpha of .923 for the scale. After items SL8 and SL9 were deleted, due to lower inter-item correlations and lower squared multiple correlations, the Cronbach alpha slightly increased to .925, which was regarded as satisfactory.

The item analysis conducted on the entire 23 item measurement[35] during this study[36] achieved a Cronbach alpha of .913. No poor items were identified, which led to the creation of two item parcels by using the mean of the even and uneven numbered items to form two composite indicator variables for the *academic self-leadership* latent variable in the Burger - Prinsloo structural model.

[35] Burger (2012) adapted the original Revised Self-leadership Questionnaire (RSLQ) from a 35-item questionnaire to a 23-item questionnaire. The revised version was used for this study. The reason for and precise nature of the scale adjustment was not clear. Burger (2012, p. 97) only stated that: 'In adapting the scale some items were deleted and all the items were adapted. In addition items 6, 15, 24 and 30 from the self-punishment scale were excluded from the self-punishment scale as advised by Jeffery Houghton (J. Houghton, personal communication, 18 February 2011)'.

[36] This section only provides a summary of the results to provide a comparison with the results found in the Burger (2012) study. The item analysis and EFA results will be discussed in more detail in Chapter 4.

3.7.5 Academic Self-efficacy

Academic self-efficacy is explained as an individual's beliefs in their own capabilities to perform academic tasks effectively. Consequently, *academic self-efficacy* focuses on gaining information about a person's beliefs about achieving academic/learning success (Burger, 2012). In order to achieve this, Burger (2012) obtained and adapted academic self-efficacy items from three different scales; the Morgan-Jinks Student Efficacy Scale (MJSES), the Self-efficacy for Learning Form (SELF) Questionnaire, and the scale developed by Vick and Packard (2008).

From the MJSES, only the talent items were used and adapted, and the Cronbach alpha for the talent subscale was .78 (Jinks & Morgan, 1999). Self-reported marks/grades are dependent variables in the MJSES scale, and items pertaining to this were also excluded from the *academic self-efficacy* scale by Burger (2012), as actual school marks was used in the study. The SELF scale focuses on capturing a students' certainty about coping with challenging academic problems or academic contexts. This scale comprised of 57 items and obtained a Cronbach alpha of .96. This scale also obtained a high level of validity in predicting students' college-reported grade point average, GPA (r=.68). Some items from this scale were adapted and included in the *academic self-efficacy* scale. Vick and Packard (2008) developed an *academic self-efficacy* scale from the Motivated Strategies for Learning Questionnaire (MSLQ) developed by Pintrich and De Groot (1990). This subscale consists of 9 items measured on a 7-point scale. This scale obtained a Cronbach alpha of .90. All the items comprising this scale were included in the construction of the *academic self-efficacy* scale by Burger (2012).

The results of Burger's (2012) study, revealed an initial Cronbach alpha of .906. After an inspection of the item analysis results, item ASE3 came to the fore as problematic, and was deleted. After the deletion of item ASE3, some other items revealed themselves to be to some degree problematic. However, it was indicated that none of the items, if deleted, would result in a further increase in the Cronbach alpha. As a result, the increase in the Cronbach alpha from .906 to .933, after the deletion of ASE3, was regarded as satisfactory (Burger, 2012). Despite the deletion of ASE3, the complete 12-item scale used by Burger (2012) was included in the Revised Learning Potential Questionnaire (RLPQ), without any reduction in items.

This study[37] achieved an initial Cronbach alpha of .895 when conducting item analysis on the 12 item *academic self-efficacy* measure. ASE3 was, however, again identified as a poor item and therefore deleted, which caused an increase in the Cronbach alpha to .910. The 12 item measure was consequently reduced to 11 items. Two item parcels were calculated by taking the mean of the even and uneven numbered items of the *academic self-efficacy* scale. This resulted in the formation of two composite indicator variables for the *academic self-efficacy* latent variable in the proposed expanded structural model.

3.7.6 Psychological Capital (Self-efficacy, Hope, Resilience, Optimism)

For the purpose of this study, the Psycap Questionnaire (PCQ), which was developed from recognised, published measures of *efficacy*, *hope*, *optimism* and *resilience*, was used (Luthans et al., 2007). When the measure was developed, the team selected different scales for each of the four facets of Psycap. The selection criteria for the different scales, included; reliability and validity in the published literature, relevance to the workplace and it had to be developed as, or capable of, measuring the state-like constructs making up Psycap (Luthans, Avolio, Avey & Norman, 2007). The four selected measures provided the foundation for the pool of items from which the research group developed the PCQ. According to Luthans et al. (2007), two major criteria were used to construct the PCQ; firstly, all four constructs were to have equal weight. Consequently, the best six items of each scale were selected. Secondly, the selected items should have face and content validity with being state-like and relevant to the workplace or adaptable to wording changes to make them relevant. The 24 items were placed on a 6-point Likert scale (1 = *strongly disagree*, 2 = *disagree*, 3 = *somewhat disagree*, 4 = *somewhat agree*, 5 = *agree*, 6 = *strongly agree*) (Luthans et al., 2007).

The PCQ in its entirety can be found in Luthans et al., 2007). Some sample items from the PCQ include: (a) *efficacy*: “I feel confident in presenting my work to my teacher” and “I feel confident helping to set targets/goals in my schoolwork”; (b) *hope*: “Right now I see myself as being pretty successful at school” and “If I should find myself in a jam at school, I could think of many ways to get out of it”; (c) *resilience*: “When I have a setback at school, I have trouble recovering from it,

[37] This section only provides a summary of the results to provide a comparison with the results found in the Burger (2012) study. The item analysis and EFA results will be discussed in more detail in Chapter 4.

moving on" and "I usually take stressful things at school in stride"; and (d) *optimism*: "I always look on the bright side of things regarding school things" and "If something can go wrong for me school-wise, it will."

The PCQ has undergone extensive psychometric analysis, which resulted in support from four samples representing service, manufacturing, education, and military sectors (Luthans et al., 2007). The Cronbach alpha for each of the six-item subscales and the overall Psycap measures for the four samples were as follows: *hope* (.72, .75, .80, .76); *resilience* (.71, .71, .66, .72); *self-efficacy* (.75, .84, .85, .75); *optimism* (.74, .69, .76, .79); and the overall Psycap (.88, .89, .89, .89). Although the *optimism* scale in the second sample (.69) and the *resilience* scale in the third sample (.66) did not reach generally acceptable levels of internal consistency, the reliability of the overall Psycap measure in all four samples was consistently above conventional standards (Luthans et al., 2007). Only the overall Psycap measure, however, sufficiently met the reliability criterion set in this study.

The Burger (2012) measure for *academic self-efficacy* will still be used, even though the PCQ includes a measure on self-efficacy. This is based on the fact that *academic self-efficacy* and generalised self-efficacy are viewed as two related but distinct constructs. Therefore, the score obtained for self-efficacy provided by the PCQ, was not used in this study. The learner's *academic self-efficacy* was measured by the *academic self-efficacy* subscale of the LPQ as discussed in the previous section (Section 3.7.5).

Item analysis was conducted on each of the subscales of the Psycap Questionnaire, and the following results were achieved during this study[38]. The six item *hope* subscale revealed a Cronbach alpha of .766. During the analysis two items were identified as poor items, i.e. PC7 and PC9. After conservative contemplation it was decided to delete these two items, and the *hope* subscale diminished from six to four items. With the deletion of the two items the Cronbach alpha increased to .846, which was regarded as satisfactory.

[38] This section only provides a summary of the results to provide a comparison with the results found in the Burger (2012) study. The item analysis and EFA results will be discussed in more detail in Chapter 4.

The *resilience* subscale revealed an initial Cronbach alpha of .537, which was not regarded as satisfactory. After the deletion of PC13, which was regarded as a poor item, the Cronbach alpha increased to .670 which was still not regarded as really satisfactory. The *optimism* subscale revealed an initial Cronbach alpha of .456, which was not regarded as satisfactory. However, after the deletion of PC20 and PC23 the Cronbach alpha increased to .652, which was still not regarded as really satisfactory.

Two item parcels per Psychological Capital-variable were calculated to represent the three Psycap latent variables in the proposed structural model. This was calculated by using the mean of the even and uneven numbered items of the scale, to form the two composite indicator variables per Psychological Capital variable in the proposed structural model.

3.7.7 Learning Performance

Given their informed assent and parental/guardian consent, all Grade 11 learners from the seven schools were included in the study. Their academic marks in a number of specific subjects were used as indicators of their *learning performance during evaluation*.

To maximise the size of the sample, the marks in the subjects which are taken by most Grade 11 students were used in the study. Based on the profile presented by the schools, there exist four subjects taken by majority of Grade 11 students in all seven schools. These are; Afrikaans, English, Mathematics and Life Orientation. Prior to the study it was decided that only three of the four subjects will be included in the calculation of the *learning performance during evaluation* construct. This decision was based on the fact that the *learning performance during evaluation* of a learner should be measured by subjects where insight and *transfe*r of knowledge is required to perform well in the evaluation. Subjects that could be passed based on memory alone will not provide a sufficient indication of learners' *learning performance during evaluation*, as successful *transfer of knowledge* does not play such a decisive role in the level of learning performance achieved. As a result the study only included Afrikaans, English and Mathematics as indicators of *learning performance during evaluation.*

The new educational system expect of all Grade 11's to take Mathematics up to Grade 12, but nonetheless make provision for two types of mathematical subjects namely, Mathematics and Mathematics literacy. Mathematics refers to the old Mathematics higher grade (HG) and Mathematics literacy refers to the old Mathematics standard grade (SG). This study only included students who offered Mathematics as a subject and did not include learners that offered Mathematics literacy as a subject. This decision was yet again based on the argument that in this study *learning performance during evaluation* was conceptualised in terms of essentially the same learning competencies that constitute *classroom learning performance*. Of these learning competencies *transfer of knowledge* was regarded as the principal learning competency. To obtain a valid operationalisation of this construct therefore required that only the subjects where insight plays a deciding role and where *transfer of knowledge* was needed for the learner to achieve a certain level of learning performance were taken into consideration.

The average of the Grade 11's first and second term subject marks for each respective subject served as criterion measures for this particular study. These formed three composite indicator variables for the *learning performance during evaluation* latent variable in the structural model presented.

3.7.8 Method Bias

Method bias refers to the presence of nuisance variables due to method-related factors (Van der Vijver, 2002). Three types of method bias can be identified; *sample bias* (incomparability of samples on aspects other than the target variable), *instrument bias* (problems due to measurement instrument characteristics), and *administration bias* (due to administration problems, i.e. communication between testers and testees) (Van der Vijver, 2002). Foxcroft and Roodt (2009) stated that especially in the context of where measures are developed for the use of multi-cultural test takers, the possibility of method bias should be taken into consideration. Based on the literature, as well as the self-reporting nature of the instruments utilised for this study, the threat of method bias in the form of instrument bias was a possibility. This was due to the fact that the learner completed all the measures (but the *learning performance during evaluation* measures) in the form of a self-report, fill-in questionnaire. This meant that information on all the latent variables, but for one, was obtained from the same person.

According to Meade, Watson and Kroustalis (2007), research that involves self-report measures should be considered as a source of concern, based on the potential inflation of correlations between measures assessed via the same method (e.g. self-report). The possibility of method bias in this study could have been reduced by involving the teachers or principles in the assessment of the learners. However, to expect a teacher or principle to assess each learner in their class or school on each of the constructs seemed practically somewhat unrealistic. The practical feasibility of obtaining multi-rater assessments for each learner from their teachers and/or their principal was compromised by the size of the sample (280 Grade 11 learners) as well as the fact that the teachers and/or principals did not possess adequate knowledge of any of the learners to be able to accurately complete the RLPQ questionnaire. Despite this possible threat of method bias, this study also made use of each participant's academic marks for three of their subjects to measure the *learning performance during evaluation* of each learner. The use of academic marks served as a method to decrease the potential threat of method bias to some degree.

3.8 MISSING VALUES

Multivariate data sets more often than not contain missing values due to either non-responses or absenteeism (Mels, 2003). This issue was dealt with before analyses of the data commenced. If this practice was not followed, and the composite indicator variables were calculated without the treatment of missing values, it may have resulted in seemingly adequate, but in reality deficient indicator variables (Burger, 2012).

Five options that could assist in the treatment of missing values were identified (Du Toit & Du Toit, 2001; Mels, 2003):

1. List-wise deletion
2. Pair-wise deletion
3. Imputation by matching
4. Multiple imputations
5. Full information maximum likelihood imputation

The method used to assist in treating the missing values depended on the number of missing values, as well as the nature of the data, i.e. whether the data followed a multivariate normal distribution (Burger, 2012). Once the nature and extent of the missing values in the data of this particular study was determined, a final decision was made on the approach to use to treat the missing-values issue. In this study the missing value issue was treated by using multiple imputation. The choice of procedure will be more thoroughly discussed and motivated in Chapter 4.

3.9 DATA ANALYSIS

The data collected from the measurements was analysed using a range of different techniques. These included the following: item analysis, exploratory factor analysis (EFA), and structural equation modelling (SEM). The objective of the data analyses was to test the elaborated learning potential structural model as depicted in Figure 2.5.

3.9.1 Item Analysis

The various scales used to measure the latent variables contained in the structural model depicted in Figure 2.5, were developed with the specific intention to measure a specific construct or a specific dimension of a construct carrying a specific constitutive definition. All the scales in the RLPQ are multi-indicator measures of the latent variables they were developed to reflect. According to Smuts (2011), the items comprising these scales have been specifically developed to indicate an individual's standing on these specific dimensions of the latent variables. The items were developed to function as stimuli to which the test taker responds with specific behaviour that serves as a fairly uncontaminated expression primarily of the specific underlying latent variable.

Item analysis was used to determine the internal consistency of the responses of respondents to items of the measuring instruments utilised to test the proposed structural model (Burger, 2012). Since the items comprising the various scales were designed and developed to reflect learner's standing on the various unidimensional latent variables, the learners' responses to the items of each scale should reflect a reasonable degree of consistency if this design intention succeeded.

The main reason why item analysis was conducted was to establish whether the items successfully reflect the intended latent variable[39]. Although item analysis cannot conclusively establish that the items of a specific subscale do in fact reflect the latent variable of interest successfully it can conclusively establish the failure of the items of a specific subscale to reflect a common underlying latent variable. If variance in and covariance between the items of a subscale cannot be explained in terms of a common underlying latent variable then by implication the items of that subscale do not reflect the latent variable of interest. Items will in addition be considered to be poor items if they failed to discriminate between the different levels of a latent variable.

Items that did not contribute to the internal consistency of the scales were identified and considered for elimination (Smuts, 2011). Considerations for elimination involved either transforming or completely deleting the items from the respective scales. The decision was based on the basket of evidence presented in the item statistics provided by the item analysis. The classical measurement theory item statistics that was considered included the following; the item-total correlation, the squared multiple correlation, the change in subscale reliability when the item were to be deleted, the change in subscale variance when the items were to be deleted, the inter-item correlations and the item mean and the item standard deviation (Burger, 2012).

The *learning performance during evaluation* measures were not item analysed nor subjected to explanatory factor analysis. They were, however included in the final confirmatory factor analysis used to evaluate the success with which the latent variables in the Burger – Prinsloo learning potential structural model were operationalised. This decision was taken because no item scores were available for the Afrikaans, English and Mathematics scores that were obtained from the participating schools. The inability to perform these analyses is recognised as a methodological weakness in the study.

[39] Neither the item analysis nor the exploratory factor analysis (EFA) of the different scales can deliver sufficient evidence to permit a conclusive finding on the success with which the specific latent variable, as constitutively defined, are measured. To obtain more conclusive evidence on the construct validity of the various scales, the measurement models mapping the items on the latent variables would have to be elaborated into fully fledged structural models that also mapped the latent variables onto outcome latent variables in accordance with the directives of the constitutive definitions of the latent variables (Smuts, 2011).

Item analysis was performed on the data before and after the missing values was treated. This practice was followed, as it allowed the assessment of the impact of the chosen procedure on the quality of the item level measurements. SPSS version 19 (SPSS, 2012) was utilised to perform the item analysis.

3.9.2 Exploratory Factor Analysis

The architecture of each of the scales and subscales used to operationalise/measure the latent variables comprising the learning potential structural model reflects the intention to construct essentially one-dimensional sets of items. These items are intended to operate as stimulus sets to which the learners respond with observable behaviour, which is primarily an expression of the specific uni-dimensional underlying latent variable (Theron, 2011). The behavioural response to every item is however not only dependant on the latent variable of interest, but also influenced by numerous other non-relevant latent variables and random error influences that are not relevant to the measurement objective (Guion, 1998). Systematic non-relevant latent variables that influence a learner's reaction to item *i* do not necessarily operate to affect the learner's reaction to item *j* (Burger, 2012). Consequently, the assumption is that only the pertinent latent variable is a common source of variance across all the items comprising a subscale. Accordingly, the assumption is that if the latent variable of interest would be statistically controlled, the partial correlation between items will approach zero (Hulin, Drasgow, & Parson, 1983). This will prove the existence of a single underlying common factor. The intention is to acquire sufficiently uncontaminated measures of the specific underlying latent variable of interest via the items comprising the scale.

The uni-dimensionality assumption as well as the assumption that the target latent variable explains a considerable proportion of the variance observed in each item, was examined by conducting an exploratory factor analysis on each of the subscales (presented in Section 3.7). Principle axis factor (PAF) analysis was used as extraction technique, and is preferred over principal component factor (PCA) analysis, as the former only analyses common variance shared between the items comprising a subscale, whereas PCA analyses all variance. In the case of factor fission, the extracted solution was subject to oblique rotation.

Despite the fact that oblique rotation provides a slightly more difficult solution to interpret than the solution obtained from the orthogonal rotation, the former solution was more realistic in that it made provision for the possibility that, if factor fission did occur, the extracted factors could be correlated (Tabachnick & Fidell, 2001). A factor loading was considered acceptable if $\lambda_{ij} > .50$. Hair, Black, Babin, Anderson, and Tatham (2006), recommended in the context of confirmatory factor analysis that factor loadings should be considered satisfactory if $\lambda_{ij} > .71$. This cut-off value was regarded as rather stringent in the case of individual items, but was used when interpreting the factor loadings of the item parcels in the measurement model fitted before the evaluation of the fit of the structural model.

The objective of these analyses was to confirm the uni-dimensionality of each subscale and to remove items with inadequate factor loadings. In the (unforeseen) event of factor fission the possibility was considered of making adjustments to the measurement and structural models prior to the evaluation for the structural model. The dimensionality analyses were conducted by making use of SPSS version 19.

The Revised Self-leadership Questionnaire (RSLQ) used to assess learner's *academic self-leadership* constitutively defined the construct in terms of nine first-order self-leadership factors, namely; self-goal setting, self-reward, self-punishment, self-observation, self-cueing, natural rewards, visualising successful performance, self-talk and evaluating belief and assumptions. The factorial validity of the RSLQ was assessed by utilizing confirmatory factor analysis (CFA) rather than exploratory factor analysis EFA. A nine-factor measurement model was firstly fitted to the item data. This consisted of a process where the RLPQ item data were fitted to each of the nine first - order factors as defined in section 3.7.4. After which, the initial fitted model were loaded on to single factor, i.e. *academic self-leadership*. This process will be graphically displayed in section 4.6.1.

A similar procedure was also implemented with the Psycap Questionnaire (PCQ). However, with the Psycap Questionnaire both EFA and CFA were conducted. The EFA was conducted on all the subscales of this model, after which CFA was performed on the three dimensional Psycap model used for this particular study, i.e. *hope*, *resilience* and *optimism*. The results of these analyses will be fully discussed in Chapter 4.

3.9.3 Structural Equation Modelling

3.9.3.1 Variable type

The measurement level on which the indicator variables were measured was the deciding factor in choosing the appropriate moment matrix to analyse, as well as choosing the appropriate estimation technique to use to estimate freed model parameters. Section 3.7 indicated that two or more linear composites of individual items were formed to represent each of the latent variables when evaluating the fit of the proposed structural model. Apart from simplifying the task of fitting the proposed structural model, the creation of the linear composite indicator variables for each latent variable had the additional advantage of creating more reliable indicator variables (Nunnally, 1978). Marsh, Hau, Balla and Grayson (1998) (as cited in Smuts, 2011), however, explained that solutions in confirmatory factor analyses tend to improve when the number of indicator variables per factor increased. When individual items are used as indicator variables, the LISREL model becomes extremely complex. This complexity requires an extremely large sample, to ensure credible parameter estimates. As a result, it was decided to make use of composite indicator variables. This allowed for the assumption that the indicator variables were continuous variables, measured on an interval level (Jöreskog & Sörbom, 1996a, 1996b). The covariance matrix was thus analysed with maximum likelihood estimation provided that the multivariate normality assumption was met.

3.9.3.2 Multivariate Normality

The maximum likelihood estimation that LISREL uses by default, assumed that the indicator variables used to operationalise the latent variables in the proposed structural model, followed a multivariate normal distribution. The null hypothesis that this particular assumption was satisfied was tested in PRELIS. If the data did not follow a multivariate normal distribution, normalisation was attempted.

The success of the attempt to normalise the data was evaluated by testing the null hypothesis that the normalised indicator variable distribution followed a multivariate normal distribution. If the attempt was unsuccessful, robust maximum likelihood estimations were used (Jöreskog & Sörbom, 1996a).

3.9.3.3 Confirmatory Factor Analysis

The comprehensive LISREL model (comprising both the measurement model describing the structural relations between the latent variables and the indicator variables as well as the structural model describing the structural relations between the various latent variables) fit indices could only be interpreted unambiguously for or against the fitted structural model, if it could be shown that the indicator variables used to operationalise the latent variables when fitting the structural model successfully reflected the latent variables they were assigned to represent. As a result, the measurement model fit had to be evaluated prior to fitting the comprehensive LISREL model.

The fit of the measurement model was done through the analysis of the covariance matrix. If the multivariate normality assumption was satisfied, before or after normalisation, maximum likelihood estimation would be used. If normalisation failed to achieve multivariate normality in the observed data, then robust maximum likelihood estimation would be used. The confirmatory factor analysis (CFA) was performed by using LISREL 8.8 (Du Toit & Du Toit, 2001).

Decisions with regards to the operationalisation of the latent variables in the structural model were taken as described in Section 3.7. In order to permit the evaluation of the fit, the model implied a specific measurement model. The measurement model described the way in which the latent variables expressed themselves in indicator variables.

Even though the comprehensive LISREL model comprised of an exogenous and endogenous measurement model, a single exogenous measurement model was fitted to assess the success of the operationalisation of the latent variables, where all 9 latent variables, as shown in Figure 2.5 were treated as exogenous.

The exogenous measurement model matrix is depicted as equation 11.

11

$$
\begin{pmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \\ X_6 \\ X_7 \\ X_8 \\ X_9 \\ X_{10} \\ X_{11} \\ X_{12} \\ X_{13} \\ X_{14} \\ X_{15} \\ X_{16} \\ X_{17} \\ X_{18} \\ X_{19} \end{pmatrix}
=
\begin{pmatrix}
\lambda_{11} & & & & & & & & \\
\lambda_{21} & & & & & & & & \\
 & \lambda_{32} & & & & & & & \\
 & \lambda_{42} & & & & & & & \\
 & & \lambda_{53} & & & & & & \\
 & & \lambda_{63} & & & & & & \\
 & & & \lambda_{74} & & & & & \\
 & & & \lambda_{84} & & & & & \\
 & & & & \lambda_{95} & & & & \\
 & & & & \lambda_{10,5} & & & & \\
 & & & & & \lambda_{11,6} & & & \\
 & & & & & \lambda_{12,6} & & & \\
 & & & & & & \lambda_{13,7} & & \\
 & & & & & & \lambda_{14,7} & & \\
 & & & & & & & \lambda_{15,8} & \\
 & & & & & & & \lambda_{16,8} & \\
 & & & & & & & & \lambda_{17,9} \\
 & & & & & & & & \lambda_{18,9} \\
 & & & & & & & & \lambda_{19,9}
\end{pmatrix}
\begin{pmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \\ \xi_5 \\ \xi_6 \\ \xi_7 \\ \xi_8 \\ \xi_9 \end{pmatrix}
+
\begin{pmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \\ \delta_7 \\ \delta_8 \\ \delta_9 \\ \delta_{10} \\ \delta_{11} \\ \delta_{12} \\ \delta_{13} \\ \delta_{14} \\ \delta_{15} \\ \delta_{16} \\ \delta_{17} \\ \delta_{18} \\ \delta_{19} \end{pmatrix}
$$

Equation 11 can be expressed as a single matrix equation presented as equation 12

$\mathbf{X=\Lambda_x\xi+\delta}$..12

Equations 11 and 12, however as yet do not fully specify the hypothesised measurement model. To fully specify the measurement model the variance-covariance matrices Θ_δ and Φ describing the variance in and covariance between the measurement error terms δ and describing the variance in and covariance between the latent variables needed to be specified. Θ_δ was defined as a diagonal matrix. Only the measurement error variances were freed to be estimated. The measurement error terms were assumed to be uncorrelated. All off-diagonal elements in Φ were freed to be estimated. In the measurement model the latent variables were allowed to correlate.

The measurement hypothesis that was evaluated suggested that the measurement model expressed in equation 12 provided a valid account of the process that produced the covariance matrix (Hair et al., 2006).

If the measurement model hypothesis were to be interpreted to mean that the learning potential measurement model provided a perfect account of the way in which the latent variables manifest themselves in the indicator variables, the measurement hypothesis translated into the following exact fit null hypothesis:

$$H_{01}: RMSEA=0$$

$$H_{a1}: RMSEA>0$$

If measurement model hypothesis were to be interpreted to mean that the measurement model provided an approximate description of the way in which the latent variables manifest themselves in the indicator variables, the substantive measurement hypothesis translated into the following close fit null hypothesis:

$$H_{02}: RMSEA \leq 0.05$$

$$H_{a2}: RMSEA >0.05$$

Successful operationalisation could be concluded if the measurement model fitted the data closely, the estimated factor leadings were all statistically significant ($p < .05$), the completely standardised factor loadings were large and the measurement error variance was statistically significant ($p < .05$) and small.

3.9.3.4 Interpretation of Measurement model fit and parameter estimates

The ability of the measurement model to reproduce the observed covariance matrix was reflected in the measurement model fit. According to Burger (2012), the model is said to fit well if the reproduced covariance matrix approximates the observed covariance matrix. The measurement model fit was interpreted by considering the full range of fit indices provided by LISREL (Diamantopoulos & Siguaw, 2000). In addition to these, the magnitude and distribution of the standardised residuals, as well as the magnitude of the model modification indices calculated for $\mathbf{\Lambda}^X$ and $\mathbf{\Theta}_\delta$, were considered to assist in the evaluation of the fit of the measurement model. Larger modification index values gave an indication of the existence of measurement model parameters, that if set free, will improve the fit of the model. Large numbers of large and significant modification index values will comment negatively on the fit of the measurement model in the sense that it will suggest numerous possibilities to improve the proposed model.

The model modification indices for the aforementioned matrices were inspected for the sole purpose of commenting on the fit of the proposed model. If close model fit were to be obtained (i.e. H_{02} failed to be rejected), or at least reasonable model fit, the significance of the estimated factor loadings was determined by testing $H_{0p:}$ $\lambda_{ij} = 0$; p = 28, 29, … , 46[40]; i = 1, 2, … , 19; j = 1, 2, … , 9 against H_{ap}: $\lambda_{ij} > 0$; p = 28, 29, … , 46; j = 1, 2, … , 19; j = 1, 2, … , 9.

Where the completely standardised factor loading estimates exceeded .71; the factor loadings were considered satisfactory (Hair et al., 2006). Satisfaction of this criterion implied that at least 50% of the variance in the indicator variables was explained by the latent variable they were assigned to represent.

3.9.3.4.1 Discriminant Validity

The nine latent variables used in the hypothesised learning potential structural model were regarded as distinct but causally related constructs. However, the question did arise whether the manner in which the RLPQ measured these constructs reflected/acknowledged this assumption. Discriminant validity basically refers to the degree to which latent variables that are conceptualised to be qualitatively distinct but inter-related (i.e., correlated) constructs actually are measured as distinct constructs. So, in a study where more than one measurement is utilized, as in this particular study, discriminant validity refers to the fact that the latent variables should be measured in manner that does not imply that two or more different latent variables correlate perfectly, and are therefore by implication essentially a single construct. Each measure of a construct used in this study, could be to some degree related to measures of another construct, but the measures of each construct should nonetheless measure something distinct. The correlations between latent variables should not have been excessively high as this would have served as evidence that the scales successfully discriminated between distinct constructs. In the case of high discriminant validity, it would have entailed that the correlations between the latent variables were sufficiently low to warrant the conclusion that the latent variables were successfully operationalised as qualitatively distinct constructs.

---

[40] There are 19 factor loadings freed in the 19 × 9 $\mathbf{\Lambda}^X$ factor loading matrix.

The aim of this study was to achieve high levels of discriminant validity. In addition to an inspection of the Φ matrix the 95% confidence intervals were calculated for each of the ϕ_{ij} estimates in Φ. Discriminant validity would be indicated if all the ϕ_{ij} estimates are smaller than .90 and none of the confidence intervals include unity.

3.9.3.5 Fitting of the comprehensive LISREL model

If close measurement model fit was obtained (i.e. H_{02} failed to be rejected), or if at least reasonable measurement model fit was obtained, if H_{028} - H_{046} were rejected and if the completely standardised factor loading estimates were considered to be satisfactory, H_{01} and H_{02} would be tested by fitting the comprehensive LISREL model comprising both the measurement model and the structural model. This would be done by analysing the covariance matrix.

Maximum likelihood estimation would be used if the multivariate normality assumption was satisfied (before or after normalisation). If normalisation failed to achieve multivariate normality in the observed data, then robust maximum likelihood estimation would be utilized. Therefore, if H_{02} failed to be rejected and H_{028} - H_{046} were rejected it would warrant the fitting of the comprehensive LISREL model. The structural equation analysis was performed by using LISREL 8.8 (Du Toit & Du Toit, 2001).

3.9.3.6 Interpretation of the structural model fit and parameter estimates

In this study, the fit of the comprehensive model was interpreted by considering the full range of fit indices provided by LISREL (Diamantopoulos & Siguaw, 2000). The magnitude and distribution of model modification indices calculated for **Γ**, **B** and **Ψ**, were also considered. Where a large modification index was discovered, it indicated that structural model parameters, if set free, would improve the fit of the proposed model. If a range of large and significant modification index values were discovered, it would comment negatively on the fit of the model, as it would suggest that many possibilities exist to improve the fit of the proposed model. The model modification indices for the **Γ** and **B** matrices were not evaluated solely to comment on the model fit, but also to explore possible modifications to the current structural model if such modifications make substantive theoretical sense (Smuts, 2011).

If the proposed model achieved close fit, which meant that H_{02} failed to be rejected, or at least reasonable model fit was obtained, then H_{05}- H_{027} was tested. The magnitude of the direct completely standardised path coefficients was interpreted for all significant (direct effect) path coefficients.

Additionally, the significance and magnitude of the indirect and total effects for each influence[41] in the proposed model[42], was also examined. The variance explained in each endogenous latent variable in the proposed model, was also interpreted.

Finally, the psychological explanation for *learning performance during evaluation* as it was expressed in the proposed model depicted in Figure 2.5, was considered satisfactory if the comprehensive model fitted the data well, the measurement model fitted the data well, the path coefficients for the hypothesised structural relations were significant, and the proposed model was found to explain a substantial segment of the variance in each of the endogenous latent variables (especially the learning competency variables).

3.9.3.7 Considering possible structural model modification

Prior to the study, and in accordance with guidelines from Diamantopoulos and Siguaw (2000), it was decided that the modification indices and completely standardised expected change values calculated for **Γ** and **B** matrices, would be evaluated to determine whether any meaningful possibilities existed to improve the fit of the proposed model. The possibilities could include the adding of additional paths to the proposed model. However, it is important to take note of the fact that the modification of the model would only be contemplated if the proposed changes made theoretically sense and were able to be theoretically validated (Diamantopoulos & Siguaw, 2000; Henning, Theron & Spangenberg, 2004). As a result, it was decided that correlated structural error terms, and correlated measurement error terms, were not allowed even if statistically significant modification indices were obtained in $\boldsymbol{\Psi}$ or $\boldsymbol{\Theta}_\delta$.

[41] Influence, in this case, referred to the indirect and total effects of ξ_i on η_i as well as the effects of η_i on η_i.
[42] Strictly speaking, formal statistical hypothesis should have been explicitly stated for both the indirect and total effects presented in the proposed model.

3.10 SUMMARY

Chapter 3 provided the hypotheses relevant to this study, as well as the research methodology that was used to test the proposed hypotheses. An overview of the research design, sampling techniques, and resultant sample measuring instruments and statistical techniques was provided. A comprehensive discussion of the research methodology in this chapter was regarded as crucial, as it is regarded as a necessary prerequisite to the achievement of the epistemic ideal of science.

CHAPTER 4

RESEARCH RESULTS

4.1 INTRODUCTION

Chapter 4 presents and discusses the statistical results obtained via the various statistical analyses discussed in Chapter 3. This chapter will focus on discussing the whole process of data analyses conducted in this study.

It will start with an in-depth discussion of the treatment of the missing values in the initial data set, after which it will focus on explaining the item analyses performed on each measurement's scale and each subscale of the multi-dimensional measurements, i.e. the Revised Self-Leadership Questionnaire and the Psycap Questionnaire. This discussion will assist in determining the psychometric integrity of the indicator variables that were designed to represent the various latent variables. Subsequently an evaluation of the extent to which the data satisfied the statistical data assumptions relevant to the data analysis techniques that were implemented, will be discussed. The fit of the measurement model will also be evaluated in this chapter as well as the adequacy of the measurement model parameter estimates.

4.2 ANALYSES PRIOR TO TREATMENT OF MISSING VALUES

Prior to initiating the process of treating the missing values, the item analyses and exploratory factor analyses were conducted. The decision to also perform these analyses prior to treating the missing values was based on the notion that if the analyses resulted in the almost similar output before and after imputation, the credibility of and faith in the imputation procedure and the resultant data set would increase. This is based on the fact that if similar results were found, the integrity of the data set would increase, as it would show that the process of treating the missing values did not influence the data in any significant way (Görgens, personal communication, 26 March 2013). Consequently, these analyses were conducted before and after the treatment of the missing values.

The results of these analyses, however, will not be explained in this section, but rather in the section 4.4, where the results of the item analyses after imputation will be discussed. The reason for this is, the results obtained of the item and EFA analyses prior to and after the treatment process were similar. Therefore, it can be concluded that the treatment of missing values did not adversely influence the data set, and therefore confidence in the integrity of the data set has been bolstered.

4.3 MISSING VALUES

A few missing values occurred on the items comprising the Revised Learning Potential Questionnaire (RLPQ). Each questionnaire consisted of 100[43] items. The sample consisted of 280 learners. Consequently, the final data set consisted of a total of 28000[44] potential item responses. Of these 28000 potential item responses, a total of 104 values were missing from the final data set. The 104 missing values only comprise .37% of the potential data set. The output further revealed that there were 44 missing-value patterns and that under list-wise deletion the total effective sample size would be 229. The distribution of missing values across the different measurement scales is described in Table 4.1 and the distribution of missing values across the items of the RLPQ is indicated in Table 4.2.

Table 4.1
Distribution of missing values across measurement scales

INSTRUMENTS	# MISSING VALUES
Time Cognitively Engaged (17 item scale)	18
Academic Self-leadership (23 item scale)	12
Learning Motivation (6 item scale)	3
Academic Self-efficacy (12 item scale)	4
Conscientiousness (12 item scale)	4
Total Psycap Questionnaire (PCQ) (24 item scale)	25
Optimism (PCQ) (6 item subscale)	5
Resilience (PCQ) (6 item subscale)	13
Hope (PCQ) (6 item subscale)	5
Learning Performance (Academic marks of three subjects)	0

[43] The 100 items were made up of the different items for each scale added to the two items per academic subject (Mathematics, Afrikaans and English) for each learner. Consequently the calculation was as follows: Number of items per learner = 17+ 23+ 6 + 12+ 12+ 24 + (2marks*3subjects) = 100

[44] The sample consisted of 280 learners and each filled in a questionnaire of 94 items and provided another 6 items with their academic marks for the three chosen subjects.

Table 4.2
Distribution of missing values across items

TCE1	*TCE2*	*TCE3*	*TCE4*	*TCE5*	*TCE6*	*TCE7*	*TCE8*
0	3	0	1	1	5	1	2
TCE9	*TCE10*	*TCE11*	*TCE12*	*TCE13*	*TCE14*	*TCE15*	*TCE16*
1	1	1	1	2	1	0	1
TCE17	*ASL1*	*ASL2*	*ASL3*	*ASL4*	*ASL5*	*ASL6*	*ASL7*
0	1	1	1	0	1	0	1
ASL8	*ASL9*	*ASL10*	*ASL11*	*ASL12*	*ASL13*	*ASL14*	*ASL15*
0	0	4	2	1	1	3	1
ASL16	*ASL17*	*ASL18*	*ASL19*	*ASL20*	*ASL21*	*ASL22*	*ASL23*
1	1	2	2	1	1	0	0
ASE1	*ASE2*	*ASE3*	*ASE4*	*ASE5*	*ASE6*	*ASE7*	*ASE8*
0	0	1	0	2	0	0	1
ASE9	*ASE10*	*ASE11*	*ASE12*	*CON1*	*CON2*	*CON3*	*CON4*
0	0	0	0	0	0	0	0
CON5	*CON6*	*CON7*	*CON8*	*CON9*	*CON10*	*CON11*	*CON12*
0	0	0	1	1	0	2	1
LM1	*LM2*	*LM3*	*LM4*	*LM5*	*LM6*	*PC1*	*PC2*
1	0	1	1	1	1	2	2
PC3	*PC4*	*PC5*	*PC6*	*PC7*	*PC8*	*PC9*	*PC10*
5	2	0	1	0	2	2	2
PC11	*PC12*	*PC13*	*PC14*	*PC15*	*PC16*	*PC17*	*PC18*
1	1	0	4	5	3	0	2
PC19	*PC20*	*PC21*	*PC22*	*PC23*	*PC24*	*ENG1*	*ENG2*
1	3	2	2	1	1	0	0
AFR1	*AFR2*	*MATH1*	*MATH2*				
0	0	0	0				

The treatment of these missing values consisted of the process of actually dealing with the incomplete responses. The calculation of composite indicator variables without appropriately treating these missing values would have resulted in what seemed as adequate but in reality, deficient indicator variables. The method used to actually deal with these incomplete responses depended on the number of missing values as well as the nature of the data, especially whether the data followed a normal distribution. So, even though only a few missing values were observed, it needed to be addressed before the statistical analyses could commence. A range of methods exist that could assist in dealing with the missing values in a data set. These include the following (Du Toit & Du Toit, 2001; Mels, 2003):

- *List-wise deletion*
- *Pair-wise deletion*
- *Multiple imputation*
- *Full information maximum likelihood imputation*
- *Imputation by matching*

List-wise deletion is the default method used to treat the problem of missing values (Du Toit & Du Toit, 2001). This method relies on the deletion of the complete case where a missing value existed. According to Myburgh (2013) and Burger (2012), this process can lead to a dramatic reduction in sample size. Du Toit and Du Toit (2001) also mentioned that the danger of such a reduction in sample size is the increased possibility of sampling bias. Due to the small sample size of this study (N = 280), this option was immediately rejected as a possible method to solve the missing value problem.

Pair-wise deletion offered another possible method of treating the missing value problem. According to Dunbar-Isaacson (2006) this method focuses on deleting cases only for analysis on variables where values are missing. This method presented difficulties, seeing that the deletion will cause problems in the calculation of the observed covariance matrix when the effective sample size for the calculation of the various covariance terms differ substantially. This method is also not a feasible solution when aiming to calculate item parcels; considering that the problem would simple perpetuate on the item parcel level (Burger, 2012). This procedure therefore also did not present an adequate solution for the missing value problem in this research study.

Multiple imputation assumes that the items are missing at random, and that the observed data follows a normal distribution (Du Toit & Du Toit, 2001). This method also assumes that the data set has less than 30% missing values, and that the responses of the participants are measured on a Likert Scale with 5 or more points. Both the two multiple imputation procedures presented by LISREL, has the advantage of developing estimates of missing values for all cases in the initial sample. This entails that no cases with missing values are deleted and that the whole data set is available for subsequent item analysis, dimensionality (EFA) analysis and the formation of item parcels (Du Toit & Du Toit, 2001; Mels, 2003). The multiple imputation procedure conducts several imputations for each missing value, after which it creates a complete data set for each imputation. Raghunatha and Schafer (as cited in Dunbar-Isaacson, 2006) explained that the data set created for each imputation can be analysed separately to assist in obtaining multiple estimates of the parameters of the model.

Du Toit and Du Toit (2001) explain that in LISREL the missing values for each case are substituted with the average values imputed in each of the data sets. Consequently, plausible values are created whilst also reflecting the uncertainty in estimates (Smuts, 2011).

Full information maximum likelihood (FIML), uses a repetitive approach, the expectation-maximisation (EM) algorithm, which computes a case-wise likelihood function using only the variables that are observed for a specific cases (Burger, 2012). Enders and Bandalos (as cited in Dunbar-Isaacson, 2006) explain that estimates of missing values are obtained based on the incomplete observed data to maximise the observed data likelihood. This process directly returns a covariance matrix calculated from the imputed data, and therefore separate imputed data is not created. So, the FIML process prevents the calculation of item parcels and consequently hinders item and dimensionality analyses. This procedure was for this reason not considered adequate for this research study.

Imputation by matching is a process that makes less stringent assumptions than Multiple Imputation. Similarly to multiple imputation, this procedure also assumes that the data values are missing at random. However, this process substitutes the missing values with real values. These values are derived from one or more cases that follow the same response pattern over a set of matching variables (Jöreskog & Sörbom, 1996b). A minimisation criterion is applied on a set of matching variables, and imputation does not occur where this criterion was not satisfied. Imputation will also refrain from occurring if no observation exists that has complete data on the set of matching variables, as explained by Enders et al (as cited in Dunbar-Isaacson, 2006). The cases with missing values after imputation are deleted by default. Consequently, due to the already small sample size, this was also not considered as the best method to solve the missing values problem in this research study.

With careful consideration, *multiple imputation* was chosen as the best possible solution to treat the missing value problem in this particular study. Even though this procedure has very strict assumptions, this specific study did comply with these requirements. Firstly, far less than 30% of the data comprised missing values (0.37%). Secondly, the individual responses to the items were measured on a six- and seven-point Likert scale and could therefore be permissibly treated as continuous variables (Muthén & Kaplan, 1985).

Lastly, even though the assumption of multivariate normality was not satisfied, the observed item variables were not excessively skewed. It was also important to choose a method where cases would not be deleted from the already small sample (N=280). Consequently, the latter feature of this method that protected against the possibility of deleting any of the cases was a crucial reason for the selection of this procedure. Consequently, multiple imputation was used to impute the 104 missing values, and all 280 cases were retained in the imputed sample.

4.4 ITEM ANALYSIS

The intention of the RLPQ was to reflect one - dimensional sets of items that could explain variance in each of the latent variables. Consequently, the objective was that the learners should respond to the items with behaviour that is primarily an expression of the underlying dimension that each set of items intend to measure (Myburgh, 2013). Descriptive item statistics were generated via the SPSS reliability procedure, to identify how well these items reflect the content of the underlying dimension, and therefore, to identify and possible delete poor items. Poor items were defined as those items that fail to discriminate between the different states of the latent variable as well as those items that do not reflect a common latent variable. The rationale behind performing these analyses is that item analysis is very informative when a scale is unreliable or fails to show expected levels of validity. This procedure not only identifies unreliability, but also suggests ways for improvement, i.e. identifying and removing bad items (Burger, 2012).

Item analyses was conducted on each of the latent variable scales included in the Revised Learning Potential Questionnaire (RLPQ), as well as on each subscale of the latent variable multi-dimensional scales, used to measure the latent variables included in the learning potential structural model depicted in Figure 2.5. The goal of this procedure was to investigate: (i) the reliability of indicators of each latent variable; (ii) the homogeneity of each subscale, and (iii) and screen for poor items prior to their inclusion in composite item parcels representing the latent variables (Burger, 2012). This procedure was performed with the help of the reliability procedure of SPSS version 19 (SPSS, 2011) on the data before and after imputation.

The results of the analyses conducted prior to and after imputation were similar, and therefore, only the results of the item analyses performed after imputation will be discussed in this section. However, to emphasise the similarity and increase the credibility of the imputation process, the results of the item analysis before imputation is presented in Table 4.3.

Table 4.3
Reliability results of learning potential latent variable scales before imputation

SCALE	SAMPLE SIZE	NUMBER OF ITEMS	MEAN	VARIANCE	STANDARD DEVIATION	CRONBACH ALPHA
TCE	280	17	68.29	186.821	13.668	.911
ASE	280	12	51.68	101.228	10.061	.896
CON	280	12	40.30	134.720	11.607	.859
LM	280	6	32.21	38.557	6.209	.856
ASL	280	23	92.46	451.133	21.240	.915
PSYCAP	280	24	101.98	179.031	13.380	.838
HOPE	280	6	27.01	20.603	4.539	.768
RES	280	6	25.06	17.199	4.147	.537
OPT	280	6	24.73	13.619	3.690	.452

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

4.4.1 Item Analysis Findings

Table 4.4, presented below, depicts a summary of the final item analysis results for each of the latent variable scales, after imputation. In addition, for the Psycap Questionnaire (PCQ)[45], the results of the three subscales, i.e. *hope*, *optimism* and *resilience*, which are individually presented in the proposed structural model, are also presented. These results presented in Table 4.4, will be discussed in greater detail in the next few sections.

Table 4.4
Reliability results of learning potential latent variable scales after imputation

SCALE	SAMPLE SIZE	NUMBER OF ITEMS	MEAN	VARIANCE	STANDARD DEVIATION	CRONBACH ALPHA
TCE	280	14	56.068	130.085	111.405	.916
ASE	280	11	48.007	94.867	9.739	.910
CON	280	11	38.604	141.495	11.895	.900
LM	280	6	32.171	38.315	6.189	.854
ASL	280	23	92.268	437.666	20.920	.913
PSYCAP	280	24	102.000	176.344	13.279	.836
HOPE	280	4	17.378	13.655	3.695	.846
RES	280	4	21.414	11.598	3.405	.670
OPT	280	5	21.718	15.988	3.998	.547

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

[45] The item analyses results for the complete Psycap Questionnaire, as well as for the three subscales individually included in the proposed structural model, are presented in the summary provided in Table 4.4.

4.4.2 Time Cognitively Engaged

The *time cognitively engaged* scale comprised of 17 items (*See Appendix 4*). The item analysis was conducted and the results, as depicted in Table 4.5, indicated a Cronbach alpha value of .916 for the 17 item measure. The Cronbach alpha indicates the item homogeneity found for each subscale. This obtained value fell above the critical cut-off value of .80 set for this study[46].

Table 4.5
Initial item analysis results for the 17 item time cognitively engaged scale

Cronbach's Alpha	Cronbach's Alpha Based on Standardised items	N of items
.913	.919	17

Item	Mean	Std Deviation	N
TCE1	3.56071	1.192822	280
TCE2	3.58214	1.087747	280
TCE3	4.20000	1.207503	280
TCE4	4.49643	1.097401	280
TCE5	4.11429	1.037544	280
TCE6	3.56786	1.183384	280
TCE7	3.95714	1.335329	280
TCE8	4.03571	1.169571	280
TCE9	4.35000	1.385667	280
TCE10	3.61429	1.273303	280
TCE11	3.95000	1.516102	280
TCE12	4.12857	1.093106	280
TCE13	4.27857	1.104360	280
TCE14	3.65714	1.787136	280
TCE15	4.47500	1.203080	280
TCE16	3.93929	1.145300	280
TCE17	4.11786	1.307698	280

[46] Setting a definitive and single cut-off value with regards to the adequacy and reliability of a set of measures; is at best debatable and contentious. Various contextual factors like scale length, sample homogeneity, and the purpose of the assessment, need to be taken into consideration. Despite these reservations the internal consistency/reliability of the measure of a subscale will be considered acceptable if the Cronbach Alpha value exceeds .80 (Myburgh, 2013). This would entail that 80% and more of the variance in the items is systematic/true score variance; while the rest is random error variance.

Table 4.5 (Continue)

Initial item analysis results for the 17 item time cognitively engaged scale

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TCE1	64.46429	168.049	.691	.626	.906
TCE2	64.44286	170.728	.666	.572	.907
TCE3	63.82500	170.976	.583	.405	.908
TCE4	63.52857	172.630	.590	.489	.908
TCE5	63.91071	173.057	.612	.497	.908
TCE6	64.45714	171.131	.591	.442	.908
TCE7	64.06786	169.196	.572	.416	.909
TCE8	63.98929	169.358	.661	.535	.906
TCE9	63.67500	172.586	.448	.318	.913
TCE10	64.41071	166.816	.681	.645	.906
TCE11	64.07500	169.933	.471	.336	.913
TCE12	63.89643	170.409	.674	.620	.906
TCE13	63.74643	170.369	.668	.610	.906
TCE14	64.36786	165.861	.473	.318	.915
TCE15	63.55000	168.635	.664	.584	.906
TCE16	64.08571	168.831	.695	.607	.906
TCE17	63.90714	170.766	.537	.329	.910

TCE= Time Cognitively Engaged

When considering the item statistics, presented in Table 4.5, the means fell in a range from 3.56071 to 4.49643 (on a 7-point Likert scale). The standard deviations ranged from 1.037544 to 1.787136. The absence of extreme means and small standard deviations showed the absence of insensitive or range restricted items[47]. The inter-item correlations for this scale showed that most of the items correlated above .50 with one or more of the other items in the scale. However, some of the items, i.e. TCE9, TCE11 and TCE14 correlated with values below .50. These items can possibly be poor items, as they do not correlate well with the other items. This might be an indication that these items do not reflect the same underlying factor as the remaining items. However, further results must be considered.

The corrected item-total correlation for all the items except for TCE9 (.448), TCE11 (.471), and TCE14 (.473), were above .50. The squared multiple correlations were above .30 for all the items. However, TCE9 (.318), TCE11 (.336) and TCE14 (.318) again provided indication that these items might be poor items, seeing that it is very close to .30. The results also showed that if items TCE9, TCE11 and TCE14, were to be deleted, the Cronbach alpha would either remain unaffected (TCE9 and TCE11) or increase (TCE14). Based on the basket of results indicating that these items are poor items, it was decided to delete all three of them from the scale.

[47] The other results obtained from the item analyses must first be considered before a final decision with regards to poor items and the possible deletion of items can be made.

The item analysis was subsequently re-run without these three items (TCE9, TCE11 and TCE14).The results are displayed in Table 4.6 and show that a Cronbach alpha of .916 was obtained for the reduced scale. The item statistics showed no extreme means or small standard deviations, and none of the remaining items, if deleted, would result in an increase in the existing Cronbach alpha. This scale was therefore reduced from 17 items to 14 items. In comparison to the results obtained by Burger (2012) this study obtained a marginally lower reliability coefficient than the reliability coefficient value (.940) obtained in the Burger study. Burger (2012) also deleted TCE11 and TCE14, however, TCE9 was not found to be a problematic item in the Burger research, and was therefore not deleted.

Table 4.6
Final item analysis results for the 14 Item time cognitively engaged scale

Cronbach's Alpha	Cronbach's Alpha Based on Standardised items	N of items
.916	.918	14

Item	Mean	Std Deviation	N
TCE1	3.56071	1.192822	280
TCE2	3.58214	1.087747	280
TCE3	4.20000	1.207503	280
TCE4	4.49643	1.097401	280
TCE5	4.11429	1.037544	280
TCE6	3.56786	1.183384	280
TCE7	3.95714	1.335329	280
TCE8	4.03571	1.169571	280
TCE10	3.61429	1.273303	280
TCE12	4.12857	1.093106	280
TCE13	4.27857	1.104360	280
TCE15	4.47500	1.203080	280
TCE16	3.93929	1.145300	280
TCE17	4.11786	1.307698	280

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TCE1	52.50714	110.982	.703	.624	.908
TCE2	52.48571	113.398	.669	.565	.909
TCE3	51.86786	113.957	.569	.384	.913
TCE4	51.57143	114.848	.597	.487	.912
TCE5	51.95357	115.464	.607	.479	.911
TCE6	52.50000	113.713	.593	.439	.912
TCE7	52.11071	112.084	.574	.406	.913
TCE8	52.03214	112.160	.668	.531	.909
TCE10	52.45357	110.263	.681	.619	.909
TCE12	51.93929	113.383	.666	.598	.909
TCE13	51.78929	112.977	.677	.605	.909
TCE15	51.59286	111.561	.672	.568	.909
TCE16	52.12857	112.177	.684	.584	.909
TCE17	51.95000	113.453	.536	.326	.914

4.4.3 Academic Self-efficacy

The *academic self-efficacy* scale initially comprised of 12 items (*See Appendix 4*). The item analysis was conducted and the results, as depicted in Table 4.6, indicated a Cronbach alpha value of .895 for the 12 item measure. This fell above the critical cut-off value of .80 set for this study.

Table 4.7
Initial item analysis results for the 12 item academic self-efficacy scale

Cronbach's Alpha	Cronbach's Alpha Based on Standardised items	N of items
.895	.896	12

Item	Mean	Std Deviation	N
ASE1	4.34643	1.159960	280
ASE2	4.82857	1.178924	280
ASE3	3.58214	1.281395	280
ASE4	4.16071	1.289283	280
ASE5	4.29286	1.226917	280
ASE6	4.61786	1.182475	280
ASE7	4.37500	1.240917	280
ASE8	4.11071	1.266565	280
ASE9	4.15357	1.270561	280
ASE10	3.93929	1.269956	280
ASE11	4.11786	1.279996	280
ASE12	5.06429	1.055525	280

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ASE1	47.24286	87.116	.561	.362	.889
ASE2	46.76071	87.659	.524	.445	.891
ASE3	48.00714	94.867	.165	.120	.910
ASE4	47.42857	84.597	.605	.461	.887
ASE5	47.29643	82.897	.726	.607	.880
ASE6	46.97143	84.200	.692	.587	.882
ASE7	47.21429	82.276	.746	.660	.879
ASE8	47.47857	82.344	.725	.591	.880
ASE9	47.43571	82.777	.702	.589	.881
ASE10	47.65000	83.311	.677	.574	.883
ASE11	47.47143	83.813	.647	.465	.884
ASE12	46.52500	88.365	.561	.435	.889

ASE= Academic Self-efficacy

When considering the item statistics, presented in Table 4.7, the means ranged from 3.58214 to 5.06429 (on a 7-point Likert scale). The standard deviations ranged from 1.055525 to 1.289283. When considering the range of means; no extreme means were evident. Although the mean of ASE3 (3.58214) can be considered to be slightly different from the other item means, the mean is not low enough to curtail the distribution of responses on this item.

There consequently does not exist sufficient evidence to label this item as a poor item at this stage. The inter-item correlations for this scale showed that most of the items correlated adequately with the other items in the scale. However, ASE3 did not correlate satisfactorily with the other items; with inter-item correlations all below .50. This item could possibly be a poor item, seeing that it did not correlate well with the other items.

The corrected item-total correlation for all the items except for ASE3 (.165), was above .50. The squared multiple correlation was above .30 for all the items, except for ASE3 (.120). The results also showed that if item ASE3 was deleted, the Cronbach alpha would increase from .895 to .910. Based on these results, ASE3 was considered a problematic item, and was deleted. The analysis was re-run without this item (ASE3), and the results displayed in Table 4.8 showed that a Cronbach alpha of .910 was obtained. The recalculated item statistics showed no extreme means or small standard deviations, and none of the remaining items, if deleted, would result in an increase in the existing Cronbach alpha value. This scale was therefore reduced from 12 items to 11 items. The reliability coefficient obtained in this study is marginally lower than was achieved by Burger (2012) (.933). However, Burger (2012) also found ASE3 to be problematic, and as a result this item was also deleted in the Burger (2012) study.

Table 4.8
Final item analysis results for the 11 item academic self-efficacy scale

Cronbach's Alpha	Cronbach's Alpha Based on Standardised items	N of items
.910	.909	11

Item	Mean	Std Deviation	N
ASE1	4.34643	1.159960	280
ASE2	4.82857	1.178924	280
ASE4	4.16071	1.289283	280
ASE5	4.29286	1.226917	280
ASE6	4.61786	1.182475	280
ASE7	4.37500	1.240917	280
ASE8	4.11071	1.266565	280
ASE9	4.15357	1.270561	280
ASE10	3.93929	1.269956	280
ASE11	4.11786	1.279996	280
ASE12	5.06429	1.055525	280
ASE1	4.34643	1.159960	280

Table 4.8 (Continue)

Final item analysis results for the 11 item academic self-efficacy scale

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ASE1	43.66071	81.494	.574	.358	.906
ASE2	43.17857	82.678	.504	.420	.909
ASE4	43.84643	79.285	.606	.453	.904
ASE5	43.71429	77.423	.738	.607	.897
ASE6	43.38929	78.748	.701	.587	.899
ASE7	43.63214	76.714	.764	.654	.896
ASE8	43.89643	77.140	.725	.583	.898
ASE9	43.85357	77.244	.717	.586	.898
ASE10	44.06786	77.999	.680	.574	.900
ASE11	43.88929	78.371	.656	.465	.901
ASE12	42.94286	83.137	.552	.430	.906
ASE1	43.66071	81.494	.574	.358	.906

4.4.4 Conscientiousness

The *conscientiousness* scale originally comprised of 12 items (*See Appendix 4*). The item analysis was conducted and the results, as depicted in Table 4.9, indicated a Cronbach alpha value of .861 for the 12 item measure. This value was above the critical cut-off value of .80 set for this study.

Table 4.9

Initial item analysis results for the 12 item conscientiousness scale

Cronbach's Alpha	Cronbach's Alpha Based on Standardised items	N of items
.861	.867	12

Item	Mean	Std Deviation	N
CON1	3.62500	1.275106	280
CON2	4.05000	1.269013	280
CON3	1.62143	1.667603	280
CON4	4.26071	1.157751	280
CON5	3.78929	1.435055	280
CON6	3.53929	1.375109	280
CON7	3.14286	1.790342	280
CON8	3.64643	1.194366	280
CON9	4.28929	1.343467	280
CON10	2.73929	1.902618	280
CON11	2.64286	1.837762	280
CON12	2.87857	1.954566	280

Table 4.9 (Continue)
Initial item analysis results for the 12 item conscientiousness scale

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
CON1	36.60000	117.072	.603	.555	.847
CON2	36.17500	117.536	.588	.558	.848
CON3	38.60357	141.495	-.225	.147	.900
CON4	35.96429	120.630	.526	.527	.852
CON5	36.43571	117.014	.524	.485	.851
CON6	36.68571	115.026	.624	.480	.845
CON7	37.08214	104.993	.740	.624	.834
CON8	36.57857	116.302	.684	.554	.843
CON9	35.93571	120.182	.453	.415	.855
CON10	37.48571	104.036	.713	.808	.836
CON11	37.58214	104.000	.746	.772	.834
CON12	37.34643	103.639	.700	.747	.837

CON= Conscientiousness

When considering the item statistics, presented in Table 4.9, the means ranged from 1.62143 to 4.05000 (on a 7-point Likert scale). The standard deviations ranged from 1.157751 to 1.954566. The mean of item CON3 (1.62143) was much lower than any of the other means, but could still not be regarded as extreme. The distribution of the responses on this item has not been curtailed by the location of the CON3 distribution on the lower end of the 7-point scale.

This was evident from the fact that the standard deviation of the CON3 distribution indicated that this item discriminated as well between respondents as any of the other items in the scale. The inter-item correlations for this scale showed that most of the items correlated adequately with the other items in the scale. However, CON3 correlated negatively and low with all the other items. This item's correlations ranged from -.092 to -.295. Prior to making a final decision on this potentially poor item, the other results were also evaluated.

The corrected item-total correlation for all the items except for CON3 (-.225), was above .50 and positive. The squared multiple correlation was above .30 for all the items, except for CON3 (.147). The results also showed that if item CON3 was deleted, the Cronbach alpha would increase from .861 to .900. Despite the fact that the results strongly indicated that CON3 was a poor item, the possibility was considered whether CON3 could possibly still be salvaged. The fact that the results showed CON3 to correlate negatively with the remaining items in the scale, pointed towards the fact that the item was negatively phrased. This pointed to the possibility that the item should be reflected.

The rather low to modest magnitude of the correlations on the other hand argued against any attempt to salvage the item. To guard against a premature, overly rash response, it was decided to rather reflect[48] this negatively worded and potentially poor item.

After item CON3 was reflected, and the item analysis performed again, the Cronbach Alpha did increase from .861 to .888. The inter-item correlation matrix showed that the correlations of this item with the other items in the scale showed an increase; however, the values were still low and ranged from .068 to .303. The corrected item-total correlation of item CON3 (.225) was still below .50, and the squared multiple correlation of this item (.147) was far below .30. The results also indicated that if CON3 was deleted, the Cronbach alpha would increase to .900. Subsequently, it was decided to delete CON3, which reduced the *conscientiousness* scale from 12 to 11 items.

Following the deletion of item CON3, the item analysis was conducted again. The results are depicted in Table 4.10. A Cronbach alpha of .900 was achieved, and the inter-item correlations between the remaining items were satisfactory. There existed no extreme means or small standard deviations, and none of the remaining items, if deleted, would result in an increase in the Cronbach alpha. The reliability coefficient obtained in this study is again marginally lower than the value that was obtained by Burger (2012) (.927).

Burger (2012) also found CON3 to be problematic, and as a result this item was also firstly reflected, and after evaluating the results of the subsequent analysis, also finally deleted.

[48] When an item is reflected it entails mathematical recoding of the item responses through the subtraction of the current response score from a constant one numerical value higher than the highest scale score. Consequently, due to the 7-point nature of this Conscientiousness scale, the constant in this case was 8 (Burger, 2012)

Table 4.10
Final item analysis results for the 11 item conscientiousness scale

Cronbach's Alpha	Cronbach's Alpha Based on Standardised items	N of items
.900	.903	11

Item	Mean	Std Deviation	N
CON1	3.62500	1.275106	280
CON2	4.05000	1.269013	280
CON4	4.26071	1.157751	280
CON5	3.78929	1.435055	280
CON6	3.53929	1.375109	280
CON7	3.14286	1.790342	280
CON8	3.64643	1.194366	280
CON9	4.28929	1.343467	280
CON10	2.73929	1.902618	280
CON11	2.64286	1.837762	280
CON12	2.87857	1.954566	280

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
CON1	34.97857	121.978	.635	.539	.891
CON2	34.55357	122.692	.612	.558	.892
CON4	34.34286	125.617	.560	.519	.895
CON5	34.81429	122.066	.548	.482	.895
CON6	35.06429	120.562	.631	.478	.891
CON7	35.46071	110.500	.738	.624	.884
CON8	34.95714	121.912	.688	.551	.889
CON9	34.31429	125.406	.475	.412	.899
CON10	35.86429	109.559	.711	.807	.886
CON11	35.96071	109.744	.737	.770	.884
CON12	35.72500	109.197	.697	.747	.888

4.4.5 Learning Motivation

The *learning motivation* scale comprised of 6 items (*See Appendix 4*). The item analysis was conducted and the results, as depicted in Table 4.11, indicated a Cronbach alpha of .854 for the 6 item measure. This value was above the critical cut-off value of .80 set for this study.

Table 4.11
Item analysis results for the 6 item learning motivation scale

Cronbach's Alpha	Cronbach's Alpha Based on Standardised items	N of items
.854	.855	6

Item	Mean	Std Deviation	N
LM1	5.33929	1.301733	280
LM2	5.25000	1.484085	280
LM3	5.16786	1.263083	280
LM4	5.48929	1.393749	280
LM5	5.26071	1.411636	280
LM6	5.66429	1.273444	280

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
LM1	26.83214	29.015	.542	.346	.847
LM2	26.92143	26.517	.628	.464	.833
LM3	27.00357	27.244	.719	.570	.816
LM4	26.68214	26.483	.689	.511	.820
LM5	26.91071	26.648	.664	.510	.825
LM6	26.50714	28.401	.611	.403	.835

LM= Learning Motivation

When considering the item statistics, presented in Table 4.11, the means ranged from 5.16786 to 5.48929 (on a 7-point Likert scale). The standard deviations ranged from 1.263083 to 1.484085. No extreme means were therefore evident and none of the item distributions were therefore curtailed to reduce the ability of the items to discriminate. The inter-item correlations for this scale showed that all of the items correlated adequately with the other items in the scale, ranging from .346 to .654.

The corrected item-total correlations for all the items was above .50 and therefore satisfactory. The squared multiple correlations were above .30 for all the items and therefore also acceptable. The results also showed that none of the remaining items, if deleted, would result in an increase in the Cronbach alpha of .854.

Consequently, none of the items were flagged as problematic, and therefore all 6 items were retained in the scale. The reliability coefficient obtained in this study is marginally lower than the value that was obtained by Burger (2012) (.899). However, Burger (2012) also found no poor items in the *learning motivation* scale, and therefore also retained the scale in its original form.

4.4.6 Academic Self-leadership

Burger (2012), in accordance with research presented by Houghton, and Neck (2002), defined e academic self-leadership as a multi-dimensional construct that consists of nine subscales. These subscales, with the corresponding items are presented in Table 4.12.

Table 4.12
RSLQ subscales

Subscale	Scale items	Factor number
Visualising successful performance	1,2,3	1
Self-goal setting	4,5	2
Self-talk	6,7	3
Self-reward	8,9	4
Evaluating beliefs and assumptions	10,11	5
Self-punishment	12,13,14	6
Self-observation	15,16,17	7
Focusing thoughts on natural rewards	18,19,20,21	8
Self-cuing	22,23	9

Adapted from Houghton & Neck (2002)

It consequently would have been ideal to do item analysis on each of these nine subscales; however, some of these factors are only measured by two items, which makes it impossible to conduct item analysis. Consequently, it was decided to conduct item analysis on the whole scale, and to analyse the reliability of this construct in this manner. The *academic self-leadership* scale comprised of 23 items (*See Appendix 4*). The item analysis was conducted and the results, as depicted in Table 4.13, indicated a Cronbach alpha of .913 for the 23 item measurement scale. This value is far above the critical cut-off value of .80 set for this study. Consequently indicating that approximately 91% of the variance in the items is systematic/true score variance, while only 9% is random error variance.

Table 4.13
Item analysis results for the 23 Item academic self-leadership scale

Cronbach's Alpha	Cronbach's Alpha Based on Standardised items	N of items
.913	.917	23

Item	Mean	Std Deviation	N
ASL1	4.35000	1.475851	280
ASL2	4.18214	1.395989	280
ASL3	3.79286	1.414195	280
ASL4	3.20357	1.744830	280
ASL5	3.98214	1.589516	280
ASL6	4.66429	1.429894	280
ASL7	4.35000	1.521294	280
ASL8	3.76071	1.848149	280
ASL9	3.67857	1.838528	280
ASL10	3.70357	1.264906	280
ASL11	3.93929	1.335976	280
ASL12	4.38929	1.534044	280
ASL13	4.04643	1.633428	280
ASL14	4.64286	1.457013	280
ASL15	3.94286	1.405424	280
ASL16	4.12857	1.374853	280
ASL17	4.14286	1.347087	280
ASL18	4.15000	1.395975	280
ASL19	3.86786	1.613241	280
ASL20	4.13929	1.492596	280
ASL21	4.32500	1.340605	280
ASL22	3.51071	1.972906	280
ASL23	3.37500	1.981659	280

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ASL1	87.91786	408.362	.455	.600	.911
ASL2	88.08571	404.717	.552	.694	.909
ASL3	88.47500	401.247	.608	.543	.908
ASL4	89.06429	397.308	.536	.434	.909
ASL5	88.28571	396.413	.612	.474	.908
ASL6	87.60357	402.470	.578	.650	.909
ASL7	87.91786	400.126	.579	.640	.908
ASL8	88.50714	395.928	.521	.702	.910
ASL9	88.58929	395.956	.524	.709	.910
ASL10	88.56429	404.369	.623	.571	.908
ASL11	88.32857	410.042	.478	.488	.910
ASL12	87.87857	400.458	.568	.651	.909
ASL13	88.22143	401.951	.505	.667	.910
ASL14	87.62500	406.106	.501	.532	.910
ASL15	88.32500	401.267	.611	.482	.908
ASL16	88.13929	405.317	.550	.471	.909
ASL17	88.12500	402.862	.610	.537	.908
ASL18	88.11786	405.330	.541	.451	.909
ASL19	88.40000	400.305	.538	.432	.909
ASL20	88.12857	409.876	.423	.310	.912
ASL21	87.94286	402.656	.617	.483	.908
ASL22	88.75714	398.120	.453	.768	.912
ASL23	88.89286	395.264	.488	.781	.911

ASL= Academic Self-leadership

When considering the item statistics, presented in Table 4.13, the means ranged from 3.20357 to 4.66429 (on a 7-point Likert scale). The standard deviations ranged from 1.2649894 to 1.848149. No extreme means were evident. The inter-item correlations for this scale showed that all of the items correlated acceptable with the other items in the scale. The corrected item-total correlations for all the items were satisfactory. The squared multiple correlations were above .30 for all the items and therefore also acceptable. The results also showed that none of the remaining items, if deleted, would result in an increase in the Cronbach alpha of .913. Consequently, none of the items were flagged as problematic, and therefore all 23 items were retained.

The reliability coefficient obtained in this study is only marginally lower than the value obtained by Burger (2012) (.925). In contrast to the current study Burger (2012) found ASL8 and ASL9 to be poor items, and these were subsequently deleted from the scale. However, in this study the *academic self-leadership* scale was not reduced, and remained with 23 items.

4.4.7 Psychological Capital

The Psycap questionnaire consists of four subscales measuring four different constructs that together form the construct of psychological capital. The subscales and the respective items are displayed in Table 4.14 presented below.

Table 4.14
Psycap subscales

Subscale	Scale items	Factor number
Self-efficacy	1,2,3,4,5,6	1
Hope	7,8,9,10,11,12	2
Resilience	13,14,15,16,17,18	3
Optimism	19,20,21,22,23,24	4

Adapted from Luthans, Avolio & Avey (2007)

The 24 item scale is divided into 4 subscales, each containing 6 items, measuring *self-efficacy*, *hope*, *resilience* and *optimism*. Thus, the Psycap scale actually consists of four distinct scales. Although these scales are expected to correlate to some degree they do measure qualitatively distinct latent variables. Respondents that score high on one dimension of Psycap therefore do not necessarily have to score high on another dimension of Psycap.

To conduct item analysis on the whole scale and especially to calculate a coefficient of internal consistency would imply that the expectation is that there should be high consistency in item responses across all the items of the scale. A more theoretically justified expectation is that there should be high consistency in item responses across all the items of each of the four subscales. Therefore, it was decided not to conduct item analysis on the whole Psycap scale, but only on the three separate subscales[49] that measure the constructs presented in the structural model.

4.4.8 Hope

The *hope* subscale initially comprised of 6 items (*See Appendix 4*). The item analysis was conducted and the results, as depicted in Table 4.15, indicated a Cronbach alpha of .766 for the 6 item measure. This fell just below the critical cut-off value of .80 set for this study.

Table 4.15
Initial item analysis results for the 6 item hope subscale

Cronbach's Alpha	Cronbach's Alpha Based on Standardized items	N of items
.766	.769	6

Item	Mean	Std Deviation	N
PC7	4.59286	1.193750	280
PC8	4.38571	1.084830	280
PC9	5.00714	.998181	280
PC10	4.37500	1.214643	280
PC11	4.62143	.990766	280
PC12	3.99643	1.165509	280

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PC7	22.38571	16.725	.239	.095	.802
PC8	22.59286	14.221	.622	.449	.702
PC9	21.97143	16.824	.326	.192	.773
PC10	22.60357	13.222	.655	.500	.689
PC11	22.35714	14.410	.677	.499	.692
PC12	22.98214	13.960	.593	.523	.708

PC= Psychological Capital

When considering the item statistics, presented in Table 4.15, the means ranged from 3.99643 to 5.00714 (on a 6-point Likert scale). The standard deviations ranged from .998181 to 1.193750. When considering the range of means and the standard deviations; no extreme means or small standard deviations were evident.

[49] These include the subscales for *hope*, *resilience* and *optimism*. *Self-efficacy* was not included in the structural model, seeing that *academic self-efficacy* was already included.

The inter-item correlations for this subscale showed that most of the items correlated adequately with the other items in the scale, however, PC7 and PC9 did show relatively low correlations. The corrected item-total correlation for all the items except for PC7 (.239) and PC9 (.326), was above .50. Also, the squared multiple correlation was above .30 for all the items, except for PC7 (.095) and PC9 (.192). The results also showed that if item PC7 was deleted, the Cronbach alpha would increase from .766 to .802 and if PC9 was deleted, the Cronbach alpha would increase from .766 to .773. However, it was first decided to only delete PC7, seeing that the Cronbach alpha would increase more if this item were to be deleted.

The subscale is already very short; therefore, it would not be a fruitful decision to delete items unnecessarily. Nevertheless, the subsequent results showed that PC9 correlated low with the remaining items of the subscale, returned a low squared multiple correlation (.162), and that if deleted the Cronbach alpha would increase to .846. Consequently, after careful consideration, it was also decided to delete PC9. Item analysis was repeated without these two items (PC7 and PC9), and the results displayed in Table 4.16, showed that a Cronbach alpha of .846 was obtained. The item statistics showed no extreme means or small standard deviations, and none of the remaining items, if deleted, would result in an increase in the Cronbach alpha already obtained. This scale was therefore reduced from 6 items to 4 items.

Table 4.16
Final item analysis results for the 4 item hope subscale

Cronbach's Alpha	Cronbach's Alpha Based on Standardized items	N of items
.846	.847	4

Item	Mean	Std Deviation	N
PC8	4.38571	1.084830	280
PC10	4.37500	1.214643	280
PC11	4.62143	.990766	280
PC12	3.99643	1.165509	280

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PC8	12.99286	8.337	.661	.438	.814
PC10	13.00357	7.523	.699	.489	.799
PC11	12.75714	8.751	.669	.450	.813
PC12	13.38214	7.692	.712	.508	.791

4.4.9 Resilience

The *resilience* subscale initially comprised of 6 items (*See Appendix 4*). The item analysis was conducted and the results, as depicted in Table 4.17, indicated a highly unsatisfactory Cronbach alpha of .537 for the 6 item subscale. This value fell well below the critical cut-off value of .80 set for this study. Consequently, the results of the item analysis had to be carefully evaluated for the possible presence of poor items.

Table 4.17
Initial item analysis results for the 6 item resilience subscale

Cronbach's Alpha	Cronbach's Alpha Based on Standardised items	N of items
.537	.867	6

Item	Mean	Std Deviation	N
PC13	3.29643	1.457150	280
PC14	4.40000	1.102620	280
PC15	4.42500	1.264946	280
PC16	3.92857	1.216039	280
PC17	4.69643	1.318732	280
PC18	4.26786	1.177615	280

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PC13	21.71786	15.988	-.072	.047	.670
PC14	20.61429	12.704	.426	.263	.431
PC15	20.58929	11.849	.439	.240	.412
PC16	21.08571	12.681	.359	.137	.455
PC17	20.31786	12.175	.365	.221	.449
PC18	20.74643	13.222	.311	.145	.479

When considering the item statistics, presented in Table 4.17, the means ranged from 3.29643 to 4.69643 (on a 6-point Likert scale). The standard deviations ranged from 1.102620 to 1.318732. The mean of item PC13 (3.29643) was much lower than any of the other means, but still could not be regarded as an extreme mean. This was evidenced by the fact that PC13's standard deviation was on par with those obtained for the other items. The inter-item correlations for this subscale also showed that item PC13 correlated negatively and extremely low with all the other items, ranging from -.026 to -.126. In addition, the corrected item-total correlation of item PC13 was -.072. The squared multiple correlation was also below .30 for this item (.047). The results also showed that if item PC13 were to be deleted, the Cronbach alpha would increase from .537 to .670, which constituted a much desired improvement.

Despite the fact that the results strongly indicated that PC13 is a poor item, it more importantly indicated that PC13 correlated negatively with the other items. PC13 is a negatively worded item. This indicated that this item should be reflected. The fact that the magnitude of the correlations between PC13 and the other items in the subscale were rather low argued in favour of deleting PC13. After item PC13 was reflected, and the item analysis was performed again, the Cronbach alpha did increase from .537 to .596. The inter-item correlations matrix for this item showed an increase; however, the values were still quite low. The corrected item-total correlation of item PC13 (.072) was still below .50, and the squared multiple correlation of this item (.047) was far below .30.

The results also indicated that if PC13 was to be deleted from this subscale, the Cronbach alpha would increase to .670. Therefore, it was decided to delete this item, and reduce the length of the *resilience* scale from 6 to 5 items. Subsequent to the deletion of item PC13, the item analysis was conducted again, and the results obtained are depicted in Table 4.18. A Cronbach alpha of .670 was achieved, and the inter-item correlations between the remaining items did not suggest any additional poor items. There existed no extreme means or small standard deviations, and none of the remaining items, if deleted, would result in an increase in the Cronbach alpha. The internal consistency of the scale, however, still remained unsatisfactory.

Table 4.18
Final item analysis results for the 5 item resilience subscale

Cronbach's Alpha	Cronbach's Alpha Based on Standardised items	N of items
.670	.671	5

Item	Mean	Std Deviation	N
PC14	4.40000	1.102620	280
PC15	4.42500	1.264946	280
PC16	3.92857	1.216039	280
PC17	4.69643	1.318732	280
PC18	4.26786	1.177615	280

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PC14	17.31786	11.092	.501	.257	.588
PC15	17.29286	10.473	.478	.239	.592
PC16	17.78929	11.765	.329	.116	.660
PC17	17.02143	10.408	.451	.212	.606
PC18	17.45000	11.646	.368	.143	.643

4.4.10 Optimism

The *optimism* subscale initially comprised of 6 items (*See Appendix 4*). The item analysis was performed and the results, as depicted in Table 4.19, indicated a highly unsatisfactory Cronbach alpha value of .456 for the 6 item measure. This fell far below the critical cut-off value of .80 set for this study, and implied that less than 50% of the variance in these items is systematic/true score variance, while more than 50% is error variance.

Table 4.19
Initial item analysis results for the 6 item optimism subscale

Cronbach's Alpha	Cronbach's Alpha Based on Standardised items	N of items
.456	.481	6

Item	Mean	Std Deviation	N
PC19	3.97857	1.113410	280
PC20	3.56429	1.216439	280
PC21	4.55000	1.162897	280
PC22	4.96071	1.130496	280
PC23	3.35000	1.403656	280
PC24	4.36071	1.085202	280

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PC19	20.78571	10.484	.274	.181	.385
PC20	21.20000	10.376	.235	.165	.405
PC21	20.21429	10.233	.284	.252	.377
PC22	19.80357	10.452	.270	.191	.387
PC23	21.41429	11.598	.014	.155	.547
PC24	20.40357	10.156	.342	.220	.349

The item statistics, presented in Table 4.19, show the means ranging from 3.35000 to 4.96071 (on a 6-point Likert scale). The standard deviations ranged from 1.085202 to 1.216439. These results fail to show any extreme means or small standard deviations. Overall the inter-item correlations for this sub

scale were low, but were nonetheless regarded as acceptable. However, item PC23 correlated very low and negatively with the other items (ranging from -.66 to -.352). The corrected item-total correlation for all the items were regarded as acceptable (ranging from .235 to .342), except for PC23 (.014). Also, the squared multiple correlation for item PC23 was the lowest among all the items (.155). Despite the general poor results achieved by this subscale, the results indicated that the deletion of only item PC23 will result in an increase in the Cronbach Alpha.

The results showed that if item PC23 was deleted, the Cronbach alpha would increase from .456 to .547. Based on this, it was decided to delete item PC23. Item PC20 also showed a very low squared multiple correlation (.165). However, the Cronbach alpha will not increase with the deletion of this item; therefore, it was decided to maintain this item in the *optimism* subscale. Item analysis was performed again without item PC23, and the results portrayed in Table 4.20 showed that a Cronbach alpha of .547 was achieved. This was still lower that the critical cut-off value (.80), however, much higher than the initial item analysis. The recalculated item statistics showed no extreme means or small standard deviations, and none of the remaining items, if deleted, would result in an increase in the Cronbach alpha already obtained. This *optimism* subscale was therefore reduced from 6 items to 5 items.

Table 4.20
Final item analysis results for the 5 item optimism subscale

Cronbach's Alpha	Cronbach's Alpha Based on Standardised items	N of items
.547	.554	5

Item	Mean	Std Deviation	N
PC19	3.97857	1.113410	280
PC20	3.56429	1.216439	280
PC21	4.55000	1.162897	280
PC22	4.96071	1.130496	280
PC24	4.36071	1.085202	280

Item	Scale Mean if Item deleted	Scale variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PC19	17.43571	8.168	.344	.174	.470
PC20	17.85000	9.476	.086	.035	.623
PC21	16.86429	7.630	.407	.244	.429
PC22	16.45357	8.141	.338	.188	.474
PC24	17.05357	7.908	.412	.219	.431

4.4.11 Summary of Item Analysis Results

This section of the results chapter reported on the results obtained from the item analyses conducted. Myburgh (2013) explains that the design and development intention of a questionnaire, like the Revised Learning Potential Questionnaire, was to construct essentially one-dimensional sets of items to reflect variance in each of the constructs presented in the learning potential structural model. The purpose of the analyses was, therefore, to gather evidence on the extent to which the intention succeeded.

Based on the results presented in this section, as well as the final results depicted in Table 4.21; it is evident that satisfactory reliability results was obtained for each of the scales and the subscales presented in the RLPQ with the exception of the *resilience* and *optimism* subscales of the Psycap scale.

The reliability coefficient value reported in Table 4.21 for the Psycap subscale was calculated via the formula proposed by Nunnally (1978)[50]. It is therefore not the reliability coefficient that would have been obtained if item analysis would have been performed on all the Psycap items simultaneously.

Table 4.21
Reliability results of learning potential latent variable scales

SCALE	SAMPLE SIZE	NUMBER OF ITEMS	MEAN	VARIANCE	STANDARD DEVIATION	CRONBACH ALPHA
TCE	280	14	56.068	130.085	111.405	.916
ASE	280	11	48.007	94.867	9.739	.910
CON	280	11	38.604	141.495	11.895	.900
LM	280	6	32.171	38.315	6.189	.854
ASL	280	23	92.268	437.666	20.920	.913
PSYCAP	280	24	102.000	176.344	13.279	.836
HOPE	280	4	17.378	13.655	3.695	.846
RES	280	5	21.414	11.598	3.405	.670
OPT	280	5	21.718	15.988	3.998	.547

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The reliability co-efficient for most of the scales/subscales, except for *resilience* and *optimism*, were above .80. As already explained, this is the critical cut-off value for this study. However, the *resilience* subscale achieved a Cronbach alpha of .670, while the *optimism* subscale achieved .547. These findings were very disconcerting. Nevertheless, these results are in accordance with the results obtained by Luthans in a numbered of studies on the Psycap scale (e.g. Avolio & Avey, 2007[51]; Avey et al., 2010). A similar trend has been noted in South African Psycap research (Görgens-Ekermans & Herbert, 2013).

[50] Nunnally (1978) proposed that the reliability of linear composites should be calculated using the formula $r_{tt} = \frac{\sum r_{tti} - \sum S^2{}_i r_{tti}}{S^2{}_t}$.

[51] Luthans et al., (2007) reported that the Cronbach alpha for each of the six-item subscales and the overall Psycap measures for the four samples were as follows: *hope* (.72, .75, .80, .76); *resilience* (.71, .71, .66, .72); *optimism* (.74, .69, .76, .79); and the overall Psycap (.88, .89, .89, .89)(Luthans et al., 2007).

Luthans et al., (2007), the developers of this instrument, mentioned that the *optimism*- and the *resilience* scale did not reach generally acceptable levels of internal consistency, and have less internal consistency than the other two scales in the Psycap Questionnaire. However, they explained that the reliability of the overall Psycap measures was consistently above conventional standards, which was also achieved in this study. So, even though these two subscales and especially the *optimism* subscale (.547) provided reason for concern, they were nonetheless included in the subsequent analyses.

It should be emphasised that prior to the fitting of the proposed learning potential measurement and structural model, these items comprising the respective scales and subscales underwent additional analyses; including exploratory factor analysis and confirmatory factor analysis. The *academic self-leadership*- and the P*sycap* multi-dimensional scales underwent individual confirmatory factor analysis to ensure that these instruments displayed satisfactory reliability and validity statistics.

4.5 DIMENSIONALITY ANALYSIS

Specific design intentions guided the development and construction of the various scales used to operationalise the latent variables in the structural model depicted in Figure 2.5. The architecture of each of these scales reflected the design intention to primarily reflect one-dimensional latent variables. So, each measurement item should reflect only its associated latent construct without significantly reflecting any of the other construct (Gefen, 2003). Consequently, the design intention was that a response to an indicator variable should be an expression of the specific underlying variable being measured (Myburgh, 2013). Van Heerden (2013) emphasised this by explaining that the purpose was to obtain a relatively uncontaminated measure of the specific latent variables included in the study. If this is accomplished, Gefen (2003) explains that unidimensional validity is achieved.

Unidimensional validity is assessed with means of exploratory factor analysis (EFA). Factor analysis refers to a family of multivariate statistical procedures that seeks to condense a large number of observed variables (i.e. items) into highly correlated groups that measure a single underlying construct (Allen & Yen, 1979).

In the context of this study, the observed variables (i.e. the items) represented the extent of agreement with specific behavioural statements. Byrne (2001) further explains that a factor analytical model constitutes a valid description of the mechanism through which values on the observed variables were generated by underlying latent variables or factors. The factor loading patterns and the parameters characterising the regression paths from the factors to the observed variables (i.e. factor loadings), are therefore of primary interest. Allen and Yen (1979) describes factor loadings as the slope of the regression of an observed variable on the underlying factor that it represents. Although inter-factor relations are of interest, any regression structure amongst them is not considered in the factor-analytic model. Consequently, factor analysis assumes that each observed variable is a linear combination of some number of common factors and a unique factor (Byrne, 2001).

All the scales, except for the *academic self-leadership* questionnaire and the *psycap* questionnaire were designed and developed to measure unidimensional constructs[52]. All the items in these scales are therefore expected to load on a single underlying factor. In the case of the *academic self-leadership* questionnaire and the *psycap* questionnaire this expectation only exists with regards to the subscales. Both these scales are multi-dimensional scales that consist of one or more subscales, which all measure their own individual construct. These are depicted in Table 4.22.

Table 4.22
Multi-dimensional constructs

Scale	First-order dimensions
Revised Academic Self-leadership Questionnaire	1. Visualising successful performance 2. Self-goal setting 3. Self-talk 4. Self-reward 5. Evaluating beliefs and assumptions 6. Self-punishment 7. Self-observation 8. Focusing thoughts on natural rewards 9. Self-cuing
Psychological Capital Questionnaire	1. Hope 2. Optimism 3. Resilience

[52] The situation with regards to the *hope* subscale of the Psycap questionnaire is a little bit ambiguous. The constitutive definition of *hope* clearly acknowledges two dimensions, namely agency and pathway. The Psycap questionnaire, however, does not formally make provision for such a distinction in its scoring key.

So, due to these measures' multi-dimensional nature, it would not be appropriate to conduct factor analysis (EFA) on the whole measure seeing that they do not represent one dimension. So, with reference to the Psycap Questionnaire, factor analysis will be conducted on each of the three subscales, i.e. *hope*, *optimism* and *resilience*. However, the Revised Academic Self-leadership Questionnaire posed a unique situation. This measure consists of nine factors, as presented in Table 4.22. Even though it would be the best to do factor analysis on each of the nine factors, this was not feasible seeing that some of these factors have only two items. Thus, the attainment of useful results would not be possible. Consequently, factor analysis was conducted on the complete Revised Academic Self-leadership Questionnaire[53].

Unrestricted principal axis factor analysis with oblique rotation was performed on each scale and each of the subscales to evaluate the uni-dimensionality assumption (i.e. the success with which each item, along with the rest of the items in the particular scale, measure the specific latent variable it was designed to reflect). The results of the item analysis were taken into consideration prior to the performance of these analyses. This entails that the decisions made during those analyses (i.e. deletion of items), were honoured in the factor analyses. Thus, the items presented in Table 4.23 were excluded from the factor analyses.

Table 4.23
***Items excluded* from EFA**

Scale/Subscale	Items Deleted
Time Cognitively Engaged	TCE9, TCE11, TCE14
Academic Self-efficacy	ASE3
Conscientiousness	CON3
Hope	PC7, PC9
Resilience	PC13
Optimism	PC23

The correlation matrix was considered for each scale/subscale, and should contain statistically significant ($p < .05$) correlations larger than .30 for the correlation matrix to be factor analysable. The Kaiser-Meyer-Olkin (KMO) statistic for each scale/subscale should approach unity (> .60), to improve the factor analysability of the correlation matrix (Tabachnick & Fidell, 2007). The final criterion that was considered to determine the factor analysability of each scale/subscale was the decision on the null hypothesis tested via Bartlett's test of sphericity.

[53] Confirmatory factor analysis was also conducted on both the Academic Self-leadership- and the Psycap Questionnaires, and these results will be discussed in the next section. These were conducted to strengthen the support for these measures.

This test proposes that the correlation matrix is an identity matrix in the parameter. The decision with regards to the number of factors to extract to explain the observed correlation matrix was based on the eigenvalue-greater-than-one rule[54] as well as the scree test[55] (Tabachnick & Fidell, 2007). Factor loadings were considered acceptable if they were greater than .50 and satisfactory if the exceeded .71 (Hair et al., 2006). Table 4.24 provides a summary of the results of the factor analyses.

Table 4.24
Factor analyses results for the Revised Learning Potential Questionnaire (RLPQ) scales

Scales/Subscales	KMO	Bartlett's Test	Maximum Loading	Minimum Loading	Number of factors extracted
TCE	.921	2016.703	.735	.560	2
ASE	.914	1606.660	.809	.527	2
CON	.891	1948.302	.524	.767	2
LM	.840	686.205	.592	.785	1
ASL	.859	3452.286	.011	.654	6
HOPE	.822	522.428	.731	.780	1
RES	.767	193.039	.408	.647	1
OPT	.652	191.548	.422	.661	1

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

Below follows a more detailed account of the results obtained for each scale and each subscale.

4.5.1 Time Cognitively Engaged

The item analyses denoted that items TCE9, TCE11 and TCE14 were poor items, and these were subsequently deleted from the *time cognitively engaged* scale. The dimensionality analysis was therefore conducted on the 14-item scale. All the items in the correlation matrix obtained correlations exceeding the .30 cut-off value, except for TCE3 and TCE7, as well as the correlation between TCE5 and TCE17 and TCE6 and TCE17.

[54] This method is known as the Kaiser method (Kaiser, 1960). Eigenvalue or latent root is the amount of variance accounted for by a factor, i.e. the sum of variances for each variable (Hardy & Brown, 2004). This rule assists in determining the number of factors to extract by computing eigenvalues for the correlation matrix. Myburgh (2013) explains that in this process of calculating eigenvalues; eigenvalues less than 1.00 are ignored; seeing that they do not contribute as much in the variance of the variable. Therefore, eigenvalues greater than 1 are retained. The disadvantage of this method is that factors can fall close to the cut-off value of 1.00. A factor with an eigenvalue of 1.01 would be retained, while a factor with a value of .99 would be rejected.

[55] The scree test is the graph of the eigenvalues of the extracted factors plotted against the number of factors extracted. In this plot, researchers look for the 'break' between factors with large eigenvalues and factors with small eigenvalues (Cattell, 1966). Scree refers to the factors that can be ignored after a substantial drop in the eigenvalues. Myburgh (2013) explained that the number of factors to be extracted is shown by the number of factors before the 'break' in the scree plot.

Despite this, all the correlations in the correlation matrix were statistically significant ($p < .05$). The *time cognitively engaged* scale obtained a KMO-value[56] of .921, providing sufficient evidence that this scale was factor analysable (> .60). The Bartlett test of sphericity ($p = .00$) indicated that the null hypothesis stating that the correlation matrix is an identity matrix in the population could be rejected ($p < .05$), providing further support that this matrix is factor analysable (Hair et al., 2006). The eigenvalue-greater-than-one rule and the scree plot suggested the extraction of two factors. Therefore, even though, the *time cognitively engaged* latent variable was conceptualised as a uni-dimensional construct, two factors had to be extracted to adequately explain the observed correlation matrix. This was evident from the pattern matrix[57] presented in Table 4.25.

Table 4.25

Rotated factor structure for the time cognitively engaged scale

	Factor	
	1	2
TCE1	**.847**	-.067
TCE2	**.679**	.064
TCE3	.101	**.561**
TCE4	-.047	**.764**
TCE5	.067	**.649**
TCE6	.332	**.341**
TCE7	**.608**	.028
TCE8	**.663**	.079
TCE10	**.922**	-.161
TCE12	-.046	**.848**
TCE13	.031	**.777**
TCE15	**.550**	.198
TCE16	**.706**	.054
TCE17	**.376**	.224

The EFA finding in this study indicated that the *time cognitively engaged* scale measured two underlying factors. Consequently, the results obtained in this study were, therefore, in conflict with the original design intention of the scale.

Table 4.25 shows that seven of the fourteen items loaded acceptable on Factor 1 (> .50). Whereas five factors loaded acceptable on Factor 2 (> .50). Items TCE6 and TCE17 did not load satisfactory (> .50) onto any of the two factors, and rather loaded relatively strongly onto both factors.

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[56] The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy reflects the ration of the sum of the squared inter-item correlations to the sum of the squared inter-item correlations plus the sum of the squared partial inter-item correlations. When this value approaches unity (at least >.06), the correlation matrix can be considered as factor analyzable (Hair et al., 2006).

[57] The pattern matrix reflects the unique relationship between the items and the underlying factors when controlling the correlation (shared variance) between the factors (Tabachnick & Fidell, 2007).

However, TCE6 (.341) obtained a higher loading on Factor 2, while TCE17 (.376) obtained a better on Factor 1. Consequently, in total, eight of the fourteen factors loaded on Factor 1, while six of the fourteen loaded on Factor 2. Based on the respective factor loadings, there was a strong indication that a second theme existed within this instrument. However, despite this, a majority of items loaded on to Factor 1, which may suggest that Factor 1 reflected a more general *time cognitively engaged* theme. With regards to Factor 2, none of the factors that loaded on the second factor reflect a specific theme. The reason for this is that this instrument was defined and constructed as a single, undifferentiated latent variable. Consequently, some of the items may possibly be worded in a way that may provide a hint of another theme that result in the participants responding differently. However, based on the fact that the proposed structural model treated *time cognitively engaged* as a single, undifferentiated latent variable, and the Burger (2012) results also provide support for this, the factor analysis was repeated, and this time the extraction of a single factor was forced. This assisted in determining whether the items of this scale reflect a single factor. The results of the repeated analysis are displayed in Table 4.26, which shows the single-factor factor structure.

Table 4.26
Factor matrix when forcing the extraction of a single factor (time cognitively engaged)

	Factor
	1
TCE1	.735
TCE2	.700
TCE3	.596
TCE4	.627
TCE5	.640
TCE6	.622
TCE7	.601
TCE8	.698
TCE10	.716
TCE12	.698
TCE13	.712
TCE15	.701
TCE16	.716
TCE17	.560

Table 4.26 indicates that all the items achieved loadings of greater than .50, which was acceptable. This provided a strong indication that even though traces of a second theme did exist within this instrument, a more general *time cognitively engaged* theme was strongly supported by the results.

The residual correlations[58] were computed for both the 1-factor and the 2-factor solutions. For the 2-factor solution, only 21% of non-redundant residuals had absolute values of greater than .05. This provided a strong indication that the rotated factor solution was a credible explanation for the observed inter-item correlation matrix. The 1-factor solution, however, failed to provide a credible explanation in that 53% of the residual correlations were greater than .05, which suggested that the hints of a second underlying theme should be investigated.

4.5.2 Academic Self-efficacy

Item ASE3 was labelled as a poor item, and was subsequently deleted from the *academic self-efficacy* scale. The dimensionality analysis was therefore conducted on the 11-item scale.

All the items in the correlation matrix obtained correlations exceeding the .30 cut-off value, except for ASE4 and ASE12 which correlated lower than the critical cut-off value. Regardless of this, all the correlations in the correlation matrix were statistically significant ($p < .05$). The *academic self-efficacy* scale obtained a KMO-value of .914, therefore signifying that this scale was factor analysable (> .60). The Bartlett test of sphericity ($p = .00$) showed that the null hypothesis that the correlation matrix was an identity matrix in the parameter could be rejected ($p < .05$), providing additional support that this matrix was factor analysable. The eigenvalue-greater-than-one rule and the scree plot suggested the extraction of two factors. The pattern matrix is presented in Table 4.27.

Table 4.27
Rotated factor structure for the academic self-efficacy scale

	Factor	
	1	2
ASE1	**.480**	.166
ASE2	-.008	**.722**
ASE4	**.798**	-.167
ASE5	**.808**	-.010
ASE6	.398	**.458**
ASE7	**.630**	.246
ASE8	**.709**	.095
ASE9	**.749**	.029
ASE10	**.779**	-.057
ASE11	**.572**	-.164
ASE12	.063	**.690**

[58] The residual correlations indicate the extent to which the factor structure provides a satisfactory explanation for the observed correlation matrix.

The *academic self-efficacy* latent variable was, conceptualised as a uni-dimensional construct in this study. However, the EFA finding in this study indicated that the *academic self-efficacy* scale measured two underlying dimensions. Consequently, the results produced in this study were in conflict with the original design intention of the measurement scale.

The results produced in Table 4.27 corroborate that eight of the eleven items loaded acceptable on Factor 1 (> .50), while three items (ASE2, ASE6 and ASE12) loaded onto the second factor. When considering the three items that loaded onto Factor 2; it became evident that these items were the only items containing the words 'if I tried hard enough' and 'if I put in enough effort'. In general it seemed that these items were slightly more positively worded in comparison with the other items; emphasising confidence in the possibility of success. The items that loaded onto Factor 1 contained words like 'overcoming obstacles', 'able to deal with the work, 'being able to cope' etc. Thus, suggesting that these items might reflect a theme of having confidence as a result of overcoming obstacle and problem. Despite this, it still seemed like the items loading on Factor 1 reflected a more general *academic self-efficacy* theme. Accordingly, the proposed structural model conceptualised *academic self-efficacy* as a single, undifferentiated latent variable. Therefore, in order to ensure that the items of this scale reflected a single factor, the factor analysis was re-run where the extraction of a single factor was forced. The results of the second EFA analysis are displayed in Table 4.28, which shows the single-factor factor structure.

Table 4.28
Factor matrix when forcing the extraction of a single factor (academic self-efficacy)

	Factor
	1
ASE1	.600
ASE2	.527
ASE4	.643
ASE5	.779
ASE6	.737
ASE7	.809
ASE8	.768
ASE9	.753
ASE10	.713
ASE11	.688
ASE12	.574

Table 4.28 indicates that all the items achieved loadings of greater than .50, which is acceptable. Therefore, no additional items were deleted from the 11-item *academic self-efficacy* scale.

The residual correlations were again computed for both the 1-factor and the 2-factor solutions. For the 2-factor solution, only 25% of non-redundant residuals had absolute values of greater than .05. This provided a strong suggestion that the rotated factor solution afforded a credible explanation for the observed inter-item correlation matrix. The 1-factor solution, to some degree, provided a permissible explanation in that 41% of the residual correlations were greater than .05. The 2-factor solution, however, clearly provided a more valid explanation for the observed inter-item correlation matrix.

4.5.3 Conscientiousness

Item CON3 was identified as a problematic item, and was therefore deleted from the *conscientiousness* scale after the item analysis was conducted. The dimensionality analysis was therefore performed on the 11-item *conscientiousness* scale.

Most of the items in the correlation matrix obtained correlations exceeding the .30 cut-off value; however, a few items achieved correlations below the cut-off value. These included the correlations of CON4 and CON10 (.250); CON4 and CON12 (.263); CON5 and CON10 (.268); CON5 and CON11 (.293); CON5 and CON12 (.263); CON7 and CON9 (.289); CON9 and CON10 (.211); CON9 and CON11 (.259); and CON9 and CON12 (.228). Regardless of this, all the correlations in the correlation matrix were statistically significant ($p < .05$).

The *conscientiousness* scale obtained a KMO-value of .891, thus indicating that this scale was factor analysable (> .60). The Bartlett test of sphericity ($p = .00$) showed that the null hypothesis stating that the population correlation matrix was an identity matrix could be rejected ($p < .05$). This provided further support that this matrix was indeed factor analysable. Both the eigenvalue-greater-than-one rule and the scree plot suggested the extraction of two factors. The pattern matrix is presented in Table 4.29.

Table 4.29
Rotated factor structure for the conscientiousness scale

	Factor	
	1	2
CON1	**.604**	-.167
CON2	**.695**	-.057
CON4	**.795**	.105
CON5	**.721**	.042
CON6	**.641**	-.123
CON7	.261	**-.629**
CON8	**.657**	-.172
CON9	**.678**	.089
CON10	-.072	**-.981**
CON11	.032	**-.885**
CON12	-.013	**-.890**

The results presented in Table 4.29 shows that four items (CON7, CON10, Con11, and CON12) loaded quite strongly onto the second factor. After considering the nature of these items, it was established that items CON10, CON11, and CON12 all refer to the use of a timetable to assist with the planning and scheduling of time, while CON7 referred to the learner's general tendency to plan their study time. Consequently, to some degree, the items loading on the second factor all appeared to refer to the planning, scheduling and managing of time. As emphasised by Burger (2012) and Van Heerden (2013), who obtained similar results, the factor fission obtained on this scale to some degree, does make substantial theoretical sense. So, despite the fact that these results were in accordance with two previous studies; it was more importantly in conflict with the original design intention of the measurement scale as presented by the authors.

The proposed structural model conceptualised *conscientiousness* as a single, undifferentiated latent variable. So, in order to determine how well the items of this scale reflected a single factor, the factor analysis was repeated, and the extraction of one factor was forced. The results of the single-factor factor structure are displayed in Table 4.30.

Table 4.30
Factor matrix when forcing the extraction of a single factor (conscientiousness)

	Factor
	1
CON1	.686
CON2	.667
CON4	.606
CON5	.601
CON6	.679
CON7	.767
CON8	.737
CON9	.524
CON10	.720
CON11	.747
CON12	.710

Table 4.30 indicates that all the items achieved loadings of greater than .50, which is satisfactory. Consequently, no additional items were deleted from the 11-item *Conscientiousness* scale.

The residual correlations were again computed for both the 1-factor and the 2-factor solutions. For the 2-factor solution, only 9 (16%) of non-redundant residuals had absolute values of greater than .05. This indicated that the rotated factor solution provided a credible explanation for the observed inter-item correlation matrix. The 1-factor solution completely failed to provide a plausible explanation in that 46 (83%) of the residual correlations were greater than .05.

4.5.4 Learning Motivation

None of the items present in the *learning motivation* scale were found to be problematic. So, the dimensionality analysis was conducted on the complete 6-item scale, seeing that no items were previously deleted.

All the items in the correlation matrix obtained correlations exceeding the .30 cut-off value and all the correlations in the correlation matrix were significant ($p < .05$). The *learning motivation* scale achieved a KMO-value of .840, therefore indicating that this scale was factor analysable (> .60). The Bartlett test of sphericity ($p = .00$) showed that the null hypothesis that the population correlation matrix was an identity matrix could be rejected ($p < .05$), providing additional support that this matrix was indeed factor analysable. The eigenvalue-greater-than-one rule and the scree plot suggested the extraction of one factor.

The pattern matrix is presented in Table 4.31. The *learning motivation* latent variable was conceptualised as a uni-dimensional construct in this study. The EFA results indicated that the *learning motivation* scale successfully measured a unidimensional construct. The results obtained by the Burger (2012) study also supported the unidimensionality of the *learning motivation* scale.

Table 4.31
Factor structure for the learning motivation scale

	Factor
	1
LM1	.592
LM2	.693
LM3	.785
LM4	.757
LM5	.735
LM6	.665

The results (Table 4.31) show that all the items loaded satisfactory on factor 1 (> .50). Therefore, *learning motivation* could be regarded as a single, undifferentiated latent variable. Despite the fact that the scale met the uni-dimensionality assumption; the 1-factor solution failed to provide a credible explanation for the observed inter-item correlation matrix in that 8 (53%) of the residual correlations were greater than .05. The corroboration of the unidimensionality of the *learning motivation* scale was, therefore, somewhat tenuous.

4.5.5 Academic Self-leadership

The item analysis conducted on the complete *academic self-leadership* scale didn't reveal any problematic items. Consequently, the complete 23-item scale underwent factor analysis. As was already explained; this scale is a multi-dimensional scale. It consists of nine factors that are measured by subscales consisting of 2, 3, and/or 4 items. Based on this small number of items per factor, it was not a fruitful option to conduct the item and factor analysis on each first-order factor separately. Consequently, the complete scale was subjected to the item analysis. No problematic items were identified. Subsequently, the complete 23-item scale was subjected to the factor analysis.

The correlation matrix results indicated a number of correlations smaller than .30. Regardless of this, all the correlations in the correlation matrix were statistically significant ($p < .05$).

The *academic self-leadership* scale obtained a KMO-value of .859, therefore signifying that this scale was factor analysable (> .60). The Bartlett test of sphericity (p = .00) showed that the null hypothesis claiming that the population correlation matrix was an identity matrix could be rejected (p < .05), providing further support that this matrix was factor analysable. The eigenvalue-greater-than-one rule and the scree plot suggested the extraction of six factors. The pattern matrix is presented in Table 4.32.

Table 4.32
Rotated factor structure for the academic self-leadership scale

	Factor					
	1	2	3	4	5	6
ASL1	-.051	.051	.007	**-.770**	.027	.033
ASL2	-.013	.024	-.034	**-.965**	.019	.040
ASL3	.100	-.016	.082	**-.521**	.014	-.199
ASL4	.059	.346	.084	-.207	.010	-.153
ASL5	.334	.120	-.039	-.236	-.011	-.235
ASL6	-.027	.002	-.007	.008	.009	**-.923**
ASL7	.000	.051	.062	.010	-.002	**-.783**
ASL8	-.021	.016	.057	-.010	**.858**	.005
ASL9	-.008	.039	-.042	-.025	**.916**	-.001
ASL10	.253	-.029	.102	-.151	.171	-.231
ASL11	.242	-.101	.073	-.191	.041	-.215
ASL12	.064	.023	**.802**	.005	.037	.006
ASL13	-.109	.057	**.941**	.063	.019	-.036
ASL14	.078	-.035	**.699**	-.062	-.033	-.010
ASL15	**.546**	.073	.152	-.041	.018	-.006
ASL16	**.679**	-.032	.029	-.124	-.043	.048
ASL17	**.795**	.074	.023	.028	-.089	-.012
ASL18	**.599**	.036	-.132	.079	.176	-.122
ASL19	**.517**	.066	.030	.066	.046	-.121
ASL20	.338	-.097	.125	-.017	.193	-.018
ASL21	.465	.058	.117	-.105	.193	.057
ASL22	-.013	**.905**	.055	.022	.036	.013
ASL23	.061	**.933**	-.036	-.032	.007	.003

This scale was originally conceptualised as measuring nine first-order factors that in turn load onto three second-order factors (Houghton & Neck, 2002). The factor analysis of this scale in the Burger (2012) study resulted in the extraction of five factors. In this study six factors had to be extracted to adequately explain the observed correlation matrix. The results produced in Table 4.32 shows that the factor loadings were spread over the six factors, and that there existed no evidence of a general *academic self-leadership* theme. As already mentioned, the *academic self-leadership* construct was constitutively defined in terms of a hierarchical factor structure consisting of nine first-order factors and three second-order factors.

Similar to the Burger (2012) study, it was therefore hypothesised that either a three factor structure or a nine factor structure will emerge from the dimensionality analysis and that the loading pattern of the items would correspond to the original design intention as shown in Table 4.12. Exploratory factor analysis was, due to its exploratory nature, not really the appropriate vehicle to empirically test this hypothesis. Consequently, it was realised that a more structured, confirmatory approach to the empirical testing of this measurement hypothesis should be followed. Therefore, it was decided to rather conduct confirmatory factor analysis[59] on the *academic self-leadership* scale, to identify whether the proposed structure exist.

4.5.6 Hope

Due to the limited number of items in this subscale (only 6-items), the decision with regards to the deletion of poor items was taken with much consideration. The item analysis revealed that items PC7 and PC9 were problematic. However, factor analysis was first conducted with all six items, to ensure that the deletion of those two items were really necessary. Factor analysis was consequently initially performed on the 6-item *hope* subscale. Items PC8, PC10, PC11, and PC12 obtained correlations exceeding .30, while items PC7 and PC9 correlated below the cut-off value with all the other items with correlations ranging from (.103 to .248). Regardless of this, all the correlations in the correlation matrix were statistically significant ($p < .05$). The *hope* subscale obtained a KMO-value of .800, thus indicating that this subscale was factor analysable (> .60). The Bartlett test of sphericity ($p = .00$) showed that the null hypothesis that the correlation matrix was an identity matrix in the parameter could be rejected ($p < .05$), providing additional support that this matrix was indeed factor analysable. Both the eigenvalue-greater-than-one rule and the scree plot suggested the extraction of two factors. The pattern matrix is presented in Table 4.33.

Table 4.33
Rotated factor structure for the hope subscale

	Factor	
	1	2
PC7	.059	.322
PC8	**.715**	.025
PC9	-.053	**.745**
PC10	**.726**	.096
PC11	**.637**	.245
PC12	**.898**	-.169

[59] The CFA results will be discussed in Section 4.6.

Table 4.33 shows that PC8, PC10, PC11, and PC12 loaded onto Factor 1 (> .50), while PC7 loaded low on both factors and only PC9 loaded on the second factor. Both items PC7 and PC9 refer to “getting around problems” whereas the remaining items (but for PC11) refer to the achievement of goals. It could therefore be argued that Factor 1 is the agency factor, whereas Factor 2 could possibly be seen as the pathway factor. The fact that PC11 loaded on Factor 1, however, tends to erode this interpretation. The explanation of these results corresponds with the constitutive definition of *hope* .The low loading of PC7 on Factor 2 taken in conjunction with the results of the item analysis led to the decision to delete PC7, and perform the factor analysis again, to see whether a one-factor structure would be obtained with the exclusion of this poor item. The results from the subsequent factor analysis are presented in Table 4.34.

Table 4.34
Factor matrix for the hope subscale (without PC7)

	Factor
	1
PC8	**.720**
PC9	.312
PC10	**.788**
PC11	**.774**
PC12	**.767**

The results produced in Table 4.34 shows that without PC7 only one factor was extracted. It also demonstrates that all the items load satisfactory onto this factor (> .50), except for PC9 (.312). Consequently, despite the fact that *hope* was conceptualised as a two-dimensional construct, it was decided to also delete PC9 and repeat the factor analysis again without PC9. The results are displayed in Table 4.35.

Table 4.35
Factor matrix for the hope subscale (without PC7 and PC9)

	Factor
	1
PC8	.731
PC10	.780
PC11	.741
PC12	.798

After the deletion of these two items, the KMO value increased to .822, which provides a stronger indication that this subscale was indeed factor analysable. All four remaining items loaded very well (>.50) onto this factor.

Given the constitutive definition of *hope*, the current outcome raised the concern that the reduced scale might suffer from scale deficiency in that it fails to adequately reflect the pathway dimension of *hope*. This concern becomes evident when considering the residual correlations computed for all the solutions. For the 2-factor solution, 9 (16%) of non-redundant residuals had absolute values of greater than .05. This indicated that the rotated 2-factor solution provided a credible explanation for the observed inter-item correlation matrix, which is in line with the two-dimensional nature of *hope*. The 1-factor solution provided a permissible, albeit a less plausible, explanation for the observed correlation matrix in that 33% of the residual correlations was greater than .05.

4.5.7 Resilience

The factor analysis procedure followed with the *hope* subscale was again followed for the analysis of the *resilience* subscale. Due to the limited length (6 items) of this subscale, any decision with regards to the deletion of poor items was taken with a great deal of deliberation and caution.

The item analysis revealed that item PC13 was problematic in nature, so this item was considered for deletion. However, factor analysis was first conducted on all six items, to ensure that the deletion of this item was really required. The results showed that PC13 did not correlate well with any of the other items ($< .30$), and most of PC13's correlations with the remaining items were not statistically significant ($p > .05$). The other correlations in the correlation matrix ranged between .185 and .421. Thus, not all of them are satisfactory ($> .30$), but all of them were at least significant ($p < .05$).

The *resilience* scale obtained a KMO-value of .746, thus indicating that this scale was factor analysable ($> .60$). The Bartlett test of sphericity ($p = .00$) showed that they identity matrix null hypothesis could be rejected ($p < .05$), providing added support that this matrix was certainly factor analysable. Both the eigenvalue-greater-than-one rule and the scree plot suggested the extraction of two factors. The pattern matrix is presented in Table 4.36.

Table 4.36
Rotated factor structure for the resilience subscale

	Factor	
	1	2
PC13	.127	**.559**
PC14	**.647**	.013
PC15	**.608**	-.066
PC16	**.416**	-.272
PC17	**.584**	.085
PC18	**.460**	.055

As is evident in Table 4.36**,** items PC14, PC15, and PC17 loaded on Factor 1 with factor loadings exceeding .50. Items PC16 and PC18 also loaded on Factor 1 but with loadings below the cut-off value, however, still with values greater than .40 and higher than the loadings obtained for Factor 2. PC13 was the only item that loaded on Factor 2 with a loading above the cut-off value of .50 (.559). This can be due to the fact that item PC13 is negatively worded, as already indicated in the item analysis. Despite this, no other distinction was apparent between the items that loaded strongly on Factor 1 and PC13 (Factor 2) when comparing the wording of the items. The identity of the two extracted factors could therefore not be inferred from the items. Neither did the constitutive definition of *resilience* point towards more than one dimension. With a single item loading on Factor 2 this factor is also under defined. Based on these results, and in accordance with the results of the item analysis, it was decided to delete PC13, and re-run the factor analysis.

Table 4.37 shows that without PC13, a single factor is extracted to account for the correlations between the remaining 5-items of the *resilience* subscale. PC16 (.408) and PC18 (.457), are two items that do not load acceptably on the single underlying factor. The low factor loadings provide an explanation for the low internal consistency of the subscale found in the item analysis even after the deletion of PC13.

Table 4.37
Factor matrix for the resilience subscale (without PC13)

	Factor
	1
PC14	.647
PC15	.617
PC16	.408
PC17	.575
PC18	.457

The loadings of these two items (PC16 and PC18) are not completely unacceptable but nonetheless fall below the stated cut-off value of .50. These two items were not identified as possible poor items during the item analysis. In the case of a longer scale these two items would have been deleted because of their relatively low loadings. The reduced *resilience* subscale, however, only consists of 5 items which inevitably lowers the standard in terms of which items are judged. The deletion of these items was therefore not regarded as a wise strategy. The factor analysis was repeated again on all 6-items, but this time the extraction of one factor was forced. The results are displayed in Table 4.38.

Table 4.38
Factor matrix when forcing the extraction of a single factor (resilience)

	Factor
	1
PC13	-.103
PC14	.651
PC15	.612
PC16	.395
PC17	.583
PC18	.461

The results of this analysis emphasise, yet again, that items PC13 should not form part of the *resilience* subscale, and should therefore be deleted. PC16 and PC18 are again flagged as marginal items that under ideal conditions should have been deleted, but that were retained because of the limited number of items in the subscale. The residual correlations were calculated for all the solutions.

For the 2-factor solution, 0% of non-redundant residuals had absolute values of greater than .05. The rotated factor solution therefore provided a highly credible explanation for the observed inter-item correlation matrix. In the 1-factor solution 13% of the non-redundant residual had absolute values greater than .05 thereby indicating that this solution provided a permissible, albeit somewhat less credible, explanation for the observed inter-item correlation matrix.

4.5.8 Optimism

Similar to the procedure followed with the factor analyses of the *hope* and *resilience* subscales, the decision with regards to the deletion of poor items from the *optimism* subscale was taken with much contemplation. The item analysis revealed that item PC23 was a problematic item as this item was also a negatively keyed item.

Consequently, this item was earmarked for deletion. However, factor analysis was first conducted on all six items, to ensure that the deletion of item PC23 was really necessary. Items PC20 and PC23 obtained poor correlations with all the remaining items (< .30), with values ranging from .022 to .151. The only acceptable correlation obtained for these two items, were their correlation with each other (.350). Additionally, all the correlations of these two items (except for the correlation with one another) were also not statistically significant ($p > .05$). The correlation matrix also revealed that the correlation between item PC19 and PC22 was also not acceptable (.094); however, it was at least significant ($p < .05$). The other correlations were regarded as satisfactory in magnitude (> .30), and statistically significant ($p < .05$).

The *optimism* subscale obtained a KMO-value of .595, thus indicating that this subscale was not factor analysable (< .60). The low KMO value indicated that the items share relatively little common variance. This tends to provide an explanation for the low Cronbach alpha obtained for this subscale. However, the Bartlett test of sphericity ($p = .00$) showed that the identity matrix null hypothesis could be rejected ($p < .05$), which did indicate that it was worth factor analysing the correlation matrix in search of one or more common factors. The Bartlett test is, however, known to be notoriously sensitive (Tabachnick & Fidell, 2001). Both the eigenvalue-greater-than-one rule and the scree plot suggested the extraction of two factors. The pattern matrix is presented in Table 4.39.

Table 4.39
Rotated factor structure for the optimism subscale

	Factor	
	1	2
PC19	**.435**	.109
PC20	.068	**.755**
PC21	**.681**	-.075
PC22	**.475**	.032
PC23	-.169	**.477**
PC24	**.595**	.029

The results presented in Table 4.39 demonstrate that 2 factors underlie the *optimism* subscale. Four items load onto Factor 1. Only two of these, however, display loadings that exceed the stated cut-off value of .50. PC19 and PC22 do not load acceptable (> .50) on Factor 1, but their loadings were at least higher than .40. PC20 and PC23 loaded on factor two, with loadings of .755 and a somewhat borderline .477. Items PC20 and PC23 are two negatively phrased items.

Factor 1 can therefore be interpreted as a positively keyed *optimism* factor whereas Factor 2 can be interpreted as a negatively keyed factor. Item analysis revealed that PC23 can be regarded as a poor item; consequently it was decided to earmark this item for deletion. The item was flagged in the item analysis because of its relatively low loading on Factor 2. The factor analysis on the other hand also indicated that PC20 could possibly be a poor item. This is especially true when considering the item's poor correlations and high loading on Factor 2. As a result, it was decided to delete both PC20 and PC23, and to repeat the factor analysis. The results from the subsequent factor analysis are presented in Table 4.40.

Table 4.40
Factor matrix of optimism subscale (without PC20 and PC23)

	Factor
	1
PC19	.422
PC21	.661
PC22	.478
PC24	.619

The results of the second factor analysis revealed that the KMO-value increased from .595 to .652, which provided a pleasing indication that this adapted subscale was indeed factor analysable. The results, (Table 4.40) show that one factor was extracted. It, however, also illustrates that only two items load satisfactory onto this factor (> .50). Again the same argument that applied in the case of the *resilience* subscale also applied here. If more items had existed, PC19 and PC22 would have been deleted. However, in the absence of this luxury these two items had to be retained even though the loadings for PC19 (.422) and PC22 (.478) were below the .50 cut-off value.

The factor analysis was repeated again on all 6-items while forcing the extraction of one factor. The results are displayed in Table 4.41.

Table 4.41
Factor matrix when forcing the extraction of a single factor (optimism)

	Factor
	1
PC19	**.428**
PC20	.045
PC21	**.677**
PC22	**.478**
PC23	-.144
PC24	**.602**

The results showed in Table 4.41 highlight, yet again, that items PC20 and PC23 with loadings of less than .50, should not form part of the *optimism* subscale, and should therefore be deleted. The borderline status of items PC19 and PC22 were also again highlighted.

The residual correlations were computed for all the solutions. For the 1-factor solution without PC20 and PC23, only 2 (33%) of non-redundant residuals had absolute values of greater than .05. The 2-factor solution therefore provided an acceptable and a credible explanation for the observed inter-item correlation matrix. The forced 1-factor solution provided a somewhat tenuous, but still plausible, explanation for the observed correlation matrix in that 6 (40%) of the residual correlations were greater than .05.

Consequently, it was decided to delete both PC20 and PC23 from the *optimism* subscale. In accordance with the research conducted by Luthans et al., (2007), the *optimism* subscale consistently shows the poorest reliability statistics of all the Psycap subscales.

4.5.9 Psychological Capital

After the range of item analyses and exploratory factor analyses conducted on the multi-dimensional *Psychological Capital* questionnaire, it was decided to delete items PC7, PC9, PC13, PC20 and PC23 from the Psycap scale. Confirmatory factor analysis was performed on the reduced Psycap scale to determine whether this instrument was psychometrically credible.

4.6 CONFIRMATORY FACTOR ANALYSIS (CFA) ON MULTI-DIMENSIONAL MEASUREMENT SCALES

The purpose for performing item- and dimensionality analyses was to provide insight into the functioning of the chosen scales of the latent variables included in the learning potential structural model as depicted in Figure 2.5. These analyses were performed to gain an understanding of the psychometric integrity of each of the instruments used to represent the latent variables of this study.

The final results for the *time cognitively engaged-, academic self-efficacy-, conscientiousness-,* and *learning motivation* scales were already obtained, and the analyses provided sound evidence of high levels of psychometric integrity for these measurement scales. However, the item- and dimensionality analyses performed on the *academic self-leadership-* and *psychological capital* scales emphasised that it was necessary to conduct Confirmatory Factor Analyses (CFA) on these two scales prior to drawing final conclusions on the psychometric integrity of these measures. Consequently, CFA analyses were conducted and the results will be discussed in detail in the next two subsections (4.6.1 and 4.6.2).

4.6.1 Academic Self-Leadership (ASL)

Prior to performing Confirmatory Factor Analysis with the fitting of the measurement model of the *academic self-leadership* scale, the data had to be screened. Screening of the data is necessary due to the fact that multivariate statistics in general and structural equation modelling in particular, are based on a range of critical assumptions (Burger, 2012).

Prior to proceeding with the analyses, it is crucial to assess the extent to which the data complies with these assumptions (Tabachnick & Fidell, 2007). If the data does not comply with these assumptions; the quality of the obtained solutions can be seriously compromised. Therefore, this section will firstly report on whether the data satisfied these assumptions. Secondly, the measurement model fit of the *academic self-leadership* scale will be evaluated.

4.6.1.1 Screening of the data

The most important assumption to consider, prior to fitting the measurement model, is the effect of non-normality (Du Toit & Du Toit, 2001; Mels, 2003). The default method of estimation when fitting the measurement model to continuous data (i.e. maximum likelihood) assumes that the distribution of the indicator variables follow a multivariate normal distribution (Mels, 2003). If this assumption is not satisfied, the standard errors and chi-square estimates will be incorrect (Du Toit & Du Toit, 2001; Mels, 2003).

The univariate and multivariate normality of the items comprising this scale was evaluated via PRELIS. The univariate test examines each variable individually for departures from normality. This is done through the evaluation of the standardised coefficients of skewness and kurtosis, and whether these are significantly different from zero. Departures from normality are indicated by significant skewness and/or kurtosis values.

The multivariate normality test is performed to substantiate the univariate findings. If any of the observed variables deviate substantially from univariate normality, then the multivariate distribution fails to be normal. The opposite is, however, not true. If all the univariate distributions are normal, it does not necessarily mean multivariate normality is achieved (Van Heerden, 2013). Therefore, it is crucial to examine multivariate values of skewness and kurtosis and not exclusively evaluate univariate normality.

The screening process started by evaluating the individual items of each scale in terms of their univariate and multivariate normality before a normalisation procedure was attempted. If the data did not display normality, the data were normalised using PRELIS. Then the items were again evaluated in terms of their univariate and multivariate normality. The results of test of univariate and multivariate normality of the *academic self-leadership* scale are presented in Table 4.42.

Table 4.42
Test of univariate normality for academic self-leadership scale before normalisation

Skewness		Kurtosis		Skewness and Kurtosis		
Variable	Z-score	p-value	Z-score	p-value	Chi-square	p-value
ASL1	-5.252	.000	1.361	0.174	29.433	**.000**
ASL2	-3.983	.000	0.257	0.797	15.927	**.000**
ASL3	-2.608	.009	0.114	0.909	6.812	**.033**
ASL4	-0.662	.508	-4.177	0.000	17.887	**.000**
ASL5	-3.141	.002	-1.843	0.065	13.262	**.001**
ASL6	-6.233	.000	2.108	0.035	43.298	**.000**
ASL7	-5.879	.000	1.853	0.064	38.001	**.000**
ASL8	-3.118	.002	-4.165	0.000	27.067	**.000**
ASL9	-3.-43	.002	-4.190	0.000	26.816	**.000**
ASL10	.562	.574	-.883	0.377	1.096	.578
ASL11	-.045	.964	-2.030	0.042	4.124	.127
ASL12	-5.332	.000	1.198	0.231	29.870	**.000**
ASL13	-3.295	.001	-1,714	0.087	13.795	**.001**
ASL14	-5.836	.000	1.264	0.206	35.650	**.000**
ASL15	-4.245	.000	1.233	0.218	19.543	**.000**
ASL16	-3.848	.000	.794	0.427	15.438	**.000**
ASL17	-2.721	.007	-0.633	0.527	7.803	**.020**
ASL18	-2.977	.003	-.468	0.639	9.079	**.011**
ASL19	-3.499	.000	-1.194	0.232	13.670	**.001**
ASL20	-3.888	.000	-0.466	0.641	15.331	**.000**
ASL21	-3.645	.000	.266	0.790	13.356	**.001**
ASL22	-2.530	.011	-7.155	0.000	57.596	**.000**
ASL23	-2.060	.039	-7.655	0.000	62.844	**.000**

ASL1 to ASL23 = Academic Self-leadership 23-items

Table 4.43
Test of multivariate normality for academic self-leadership scale before normalisation

Skewness			Kurtosis			Skewness and Kurtosis	
Value	Z-score	p-value	Value	Z-score	p-value	Chi-Square	p-value
97.113	25.818	0.000	705.757	16.125	0.000	**926.573**	**0.000**

The chi-square for skewness and kurtosis, presented in Table 4.43, shows that twenty-one of the twenty-three items failed the test for univariate normality ($p < .05$). Additionally, the null hypothesis that the data follows a multivariate normal distribution also had to be rejected ($X^2 = 926.573$; $p < .05$). Due to the fact that the quality of the solution obtained in the structural equation modelling depends largely on multivariate normality, it was decided to normalise the items with PRELIS. The subsequent results of the test of univariate normality are presented in Table 4.44, while the results of the test of multivariate normality are presented in Table 4.45.

Table 4.44

Test of univariate normality for academic self-leadership scale after normalisation

	Skewness		**Kurtosis**		**Skewness and Kurtosis**	
Variable	Z-score	p-value	Z-score	p-value	Chi-square	p-value
ASL1	-1.969	.049	-3.001	0.003	12.884	**.002**
ASL2	-1.296	.195	-2.092	.036	6.058	**.048**
ASL3	-0.644	.519	-1.529	0.126	2.752	.253
ASL4	-.263	.793	-2.900	0.004	8.479	**.014**
ASL5	-1.423	.155	-2.729	0.006	9.471	**.009**
ASL6	-3.108	.002	-3.337	.001	20.793	**.000**
ASL7	-1.936	.053	-3.091	.002	13.302	**.001**
ASL8	-1.312	.189	-4.624	.000	23.103	**.000**
ASL9	-1.020	.308	-4.183	.000	18.542	**.000**
ASL10	-0.212	.832	-1.090	.276	1.232	.540
ASL11	-.844	.399	-1.622	.105	3.343	.188
ASL12	-2.291	.022	-3.700	.000	18.935	**.000**
ASL13	-1.885	.059	-3.539	.000	16.077	**.000**
ASL14	-3.272	.001	-3.254	.001	21.297	**.000**
ASL15	-0.743	.458	-1.502	.133	2.807	.246
ASL16	-1.182	.237	-1.883	.060	4.943	.084
ASL17	-1.253	.210	-2.018	.044	5.644	.059
ASL18	-1.355	.175	-2.269	.023	6.986	**.030**
ASL19	-1.099	.272	-2.670	.008	8.337	**.015**
ASL20	-1.517	.129	-2.529	.011	8.699	**.013**
ASL21	-1.708	.088	-2.426	.015	8.803	**.012**
ASL22	-0.728	.467	-5.476	.000	30.517	**.000**
ASL23	-0.417	.677	-5.634	.000	31.913	**.000**

ASL1 to ASL23 = Academic Self-leadership 23-items

Table 4.45

Test of Multivariate normality for academic self-leadership scale after normalisation

Skewness			**Kurtosis**			**Skewness and Kurtosis**	
Value	Z-score	p-value	Value	Z-score	p-value	Chi-Square	p-value
83.752	19.678	0.000	679.259	14.320	0.000	**592.274**	**0.000**

The results presented in Table 4.44 and Table 4.45 shows that the normalisation procedure did not succeed in rectifying neither the univariate normality problem nor the multivariate problem.

Table 4.44 shows that the p-values on some of the items did increase, however seventeen of the twenty-three items still failed the test for univariate normality ($p < .05$). Therefore, even though normalisation tends to typically improve the symmetry and kurtosis of the data, in this case it wasn't completely successful. Additionally, Table 4.45 shows that the null hypothesis that the data follows a multivariate normal distribution still had to be rejected ($X^2 = 592.274$; $p < .05$).

To conclude, even though normalisation was attempted, neither univariate nor multivariate normality was achieved for this scale. The normalisation, however, has succeeded in reducing the deviation of the observed indicator distribution from the theoretical multivariate normal distribution as was evident in the decrease in chi-square statistic from 926.573 to 592.274.

Since normalisation did not result in the desired outcomes, and the data still did not meet the multivariate normality assumption even after the normalisation procedure, the use of an alternative estimation method, more suited to the data, was considered. There exist three estimation methods which are appropriate to use to fit structural equation models to non-normal data. These include; Weighted least Squares (WLS), Diagonally Weighted Least Squares (DWLS), and Robust Maximum Likelihood (RML) (Mels, 2003). Robust maximum likelihood estimation technique was chosen as the appropriate alternative method to employ in this study. This method is the suggested technique by Mels (2003) for the fitting of measurement models of continuous data, which do not fulfil the multivariate normality assumption. This method necessitates the computation of an asymptotic covariance matrix via PRELIS to enable the calculation of more appropriate fit indices in LISREL (Mels, 2003).

Since the normalisation had the effect of reducing the deviation of the observed indicator distribution from the theoretical multivariate normal distribution, the normalised data was used for the succeeding analyses.

4.6.1.2 Measurement model fit of the first-order academic self-leadership scale

The measurement model, in this instance, represents the relationship between the *academic self-leadership* latent variable and its manifest indicators. The aim of confirmatory factor analysis (CFA) was to determine whether the operationalisation of the *academic self-leadership* latent variable was successful. The operationalisation of the *academic self-leadership* scale can be regarded as successful if the measurement model can successfully reproduce the observed covariance matrix, i.e. if the model fits the data well, if the factor loadings were statistically significant ($p < .05$) and sufficiently large ($\lambda > .50$), and if the error variances are sufficiently small. The original *academic self-leadership* scale was conceptualised as a scale consisting of nine first-order factors, with three second-order-factors (Houghton & Neck, 2002).

The item analysis conducted in this study on the complete scale did not identify any poor items. The dimensionality analysis that was conducted on the complete 23-item scale[60] extracted 6 factors. This finding raised the question as to whether a 9 factor model would not also provide a valid (i.e., permissible) account of the observed correlation/covariance matrix. Consequently, a need existed to conduct CFA to further evaluate the integrity of this measurement scale. It was decided to fit the *academic self-leadership* measurement model on its conceptualised nine first-order factors. A visual representation of the fitted *academic self-leadership* measurement model is shown in Figure 4.1 and the overall fit statistics are presented in Table 4.46.

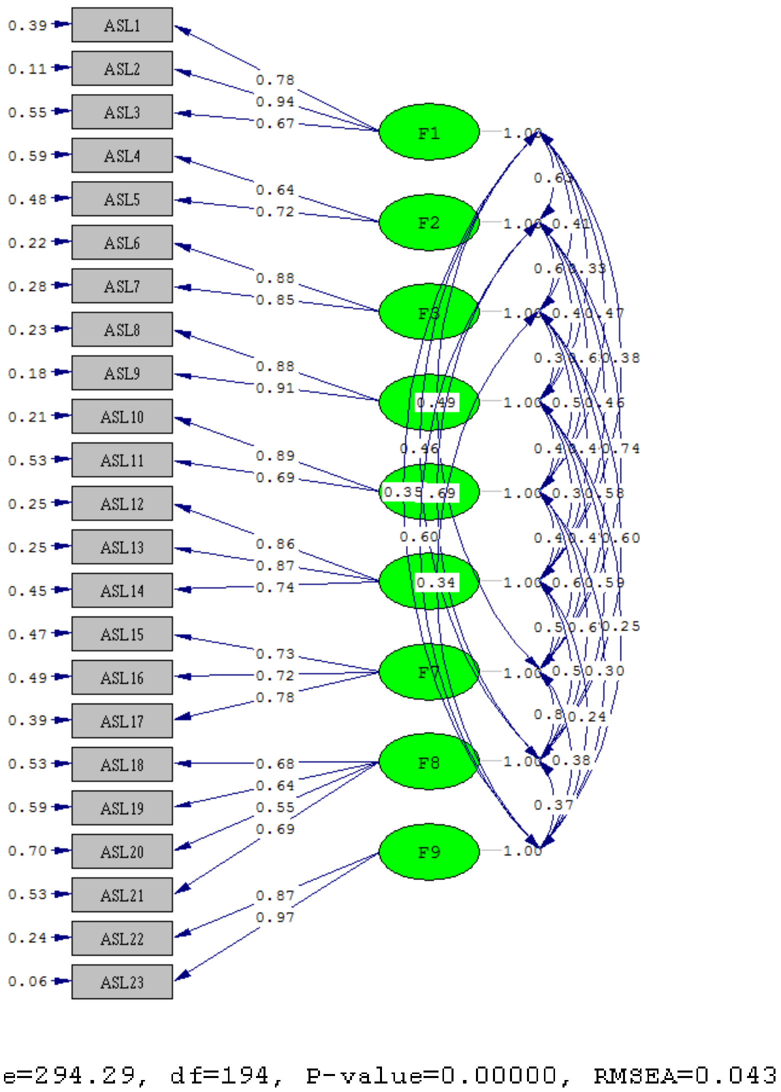

Figure 4.1 Representation of the fitted first-order academic self-leadership measurement model (completely standardised solution)

[60] To highlight again, item-and dimensionality analyses was conducted on the complete 23-item scale, seeing that the nine first-order factors consisted of 2,3, and 4 items respectively. Therefore, it was not feasible to conduct item- and dimensionality analyses on the separate nine factors.

The results of this analysis will be discussed by evaluating the overall fit statistics based on the array of model fit indices produced by LISREL. After which, a conclusion on the psychometric integrity of the *academic self-leadership* scale[61] will be drawn.

The purpose of assessing the overall fit of a model is to determine the degree to which the model as a whole is consistent with the empirical data at hand (Diamantopoulos & Siguaw, 2000). A wide range of goodness-of-fit indices have been developed that can be used as a summary of the model's overall fit. However, Diamantopoulos and Siguaw (2000) warn that none of these indices are unambiguously superior to the rest in all conditions, and that specific indices have been shown to operate fairly differently under a range of conditions. These authors assert that sample size, estimation procedure, model complexity, degree of multivariate normality and variable independence, or any combination thereof, may influence the statistical power of the resulted indices. Based on the existing controversy, a brief description of each index will follow[62], after which an interpretation of the reported value for the given data of the specific instrument will be provided. The results of the full range of fit indices (both comparative and absolute) for the ASL are reported in Table 4.46.

Table 4.46
Goodness of fit statistics for the first-order academic self-leadership measurement model

Degrees of Freedom	194
Minimum Fit Function Chi-Square	371.369 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	357.760 (p = 0.00)
Satorra-Bentler Scaled Chi-square	**294.292 (p = 0.00)**
Chi-square Corrected for NON-Normality	1016.834 (p = 0.00)
Estimated Non-centrality Parameter (NCP)	100.292
90 Percent Confidence Interval for NCP	(58.024 ; 150.525)
Minimum Fit Function Value	1.331
Population Discrepancy Function Value (FO)	.359
90 Percent Confidence Interval for FO	(0.208 ; 0.540)
Root Mean Square Error of Approximation (RMSEA)	**.0430**
90 Percent Confidence Interval for RMSEA	**(0.0327 ; 0.0527)**
P-value for test of Close Fit (RMSEA < .05)	**.877**
Expected Cross-Validation Index (ECVI)	**1.643**
90 Percent Confidence Interval for ECVI	(1.491 ; 1.823)

[61] In Section 4.6 Confirmatory Factor Analysis is used to ensure that the Academic Self-leadership- and Psychological Capital scale show acceptable psychometric integrity. As a result, the CFA results will not be discussed in that much detail as when CFA will be conducted on the Learning Potential measurement model. So, for now only the overall fit statistics will be discussed.
[62] A description of each of the fit indices will only be discussed in this section, after which the goodness-of-fit statistics will only be reported. This applies to the CFA results for the Psychological Capital measurement model, the Learning Potential measurement model and the Learning Potential Structural model.

ECVI for Saturated Model	**1.978**
ECVI for Independence model	**30.172**
Chi-square for Independence Model with 253 Degrees of Freedom	8371.988
Independence AIC	**8417.988**
Model AIC	**458.292**
Saturated AIC	**552.000**
Independence CAIC	**8524.589**
Model CAIC	**838.345**
Saturated CAIC	**1831.202**
Normed Fit Index (NFI)	**.965**
Non-Normed Fit Index (NNFI)	**.984**
Parsimony Normed Fit Index (PNFI)	.740
Comparative Fit Index (CFI)	**.988**
Incremental Fit Index (IFI)	**.988**
Relative Fit Index (RFI)	**.954**
Critical N (CN)	**231.128**
Root Mean Square Residual (RMR)	**.123**
Standardised RMR	**.0537**
Goodness of Fit Index (GFI)	**.900**
Adjusted Goodness of Fit Index (AGFI)	**.857**
Parsimony Goodness of Fit Index	.632

The Chi-square statistics (X^2) is the traditional evaluation for assessing the overall model fit in covariance structure models and provides a test of perfect fit for the hypothesis of exact model fit. The X^2 test statistic tests the null hypothesis that the model fits the population data perfectly. This hypothesis is displayed below:

H_0: RMSEA=0[63]

H_a: RMSEA>0

A statistically significant chi-square results in the rejection of the null hypothesis meaning imperfect model fit and possible rejection of the model. Although the chi-square seems an attractive measure of the model's fit, caution needs to be taken as it is sensitive to departures from multivariate normality, sample size, and also assumes that the model fits perfectly in the population. This represents a somewhat unrealistic position that a model is able to reproduce an observed covariance matrix to a degree of accuracy that could be explained in terms of sampling error only.

[63] Statistical hypotheses were not formulated in Chapter 3 for the tests of exact and close fit for the academic self-leadership and Psycap measurement models.

For these reasons, it has been suggested that it should be regarded as a goodness (or badness)-of-fit measure in the sense that large X^2 values correspond to bad fit and small X^2 values to good fit. Also, to corroborate whether a model achieves a good fit, and provides an approximate description of the processes that operate in reality (Davis, 2013), the substantive measurement hypothesis translates into the following close fit null hypothesis:

$$H_0\text{: RMSEA} \leq 0.05$$

$$H_a\text{: RMSEA} > 0.05$$

Table 4.46 shows that this model achieved a Satorra-Bentler scaled chi-square value of 294.292 ($p = .000$). Thus, implying that the null hypothesis of exact fit (H_0: RMSEA=0) should be rejected. Therefore, the model could not reproduce the observed covariance matrix in the sample, to a degree of accuracy that could be explained by sampling error alone (Kelloway, 1998). However, this assumption of exact fit is highly unlikely, and thus the rejection of the exact fit null hypothesis was not surprising. Therefore, it is more sensible to assess the degree of lack of fit of the model (Van Heerden, 2013).

To assess whether the model displayed an approximate of the processes that operate in reality, the p-value for the test of close fit (RMSEA < .05) had to be considered. For this model, the close fit null hypothesis should not be rejected seeing that $p > .05$ (.877). Thus, the position that this model displayed close fit in the parameter was a permissible position.

The root mean square of approximation (RMSEA) is a popular measure of fit that expresses the difference between the observed and estimated sample covariance matrices. The RMSEA-value shows how well the model, with unknown but optimally chosen parameter values, fit the population covariance matrix if it were available. Diamantopoulos and Siguaw (2000) suggest that this value is one of the most informative fit indices as it takes into consideration the complexity of the model. These authors further explained that values below .05 are generally regarded as indicative of a good model fit in the sample, values above .05 but less than .08 indicate reasonable fit, values greater than .08 but less than .10 show mediocre fit, and values exceeding .10 are generally regarded as indicative of poor fit.

This model achieved a RMSEA value of .0430 (Table 4.46), which indicated good close fit in the sample. The probability of obtaining this sample RMSA estimate value under the assumption that the model fits closely in the population (i.e., RMSEA = .05) was sufficiently high (.887) not to discard this assumption as a permissible position. The 90 percent confidence interval for RMSEA should be considered in collaboration with the RMSEA-value, as it assists in the evaluation of the precision of the fit statistic. Byrne (2001) explains that if this interval is small, it is indicative of a higher level of precision in the reflection of the model fit in the population.

Since the 90 percent confidence interval for RMSEA (0.0327; 0.0527) was small and fell relatively close to the target value of .05, it provided further support of good close model fit. Hence it was concluded that this model provided a plausible explanation and an approximate reproduction of the observed covariance matrix.

The expected cross-validation Index (ECVI) focuses on overall error. This value expresses the difference between the reproduced sample covariance matrix derived from fitting the model on the sample at hand, and the expected covariance that would be obtained in another sample of equivalent size, from the same population (Byrne, 1998; Diamantopoulos & Siguaw, 2000). It, therefore, focuses on the difference between Σ and Σ (θ). To assess the model's ECVI, it must be compared to the independence model and the saturated model. Table 4.46 shows that the model ECVI (1.643) is smaller than the value obtained for the independence model (30.172). The model ECVI (1.643) is also smaller than the saturated model (1.978). Therefore, a model more closely resembling the fitted model seems to have a better chance of being replicated in a cross-validation sample than the saturated or independence models.

Akaike's information criterion (AIC) and the consistent version of AIC (CAIC) comprises what are known as information criteria and are used to compare models (Van Heerden, 2013). Information criteria attempt to incorporate the issue of model parsimony in the assessment of model fit by taking the number of estimated parameters into consideration.

Similar to the EVCI, the model AIC and CAIC must be compared to those of the independence- and the saturated models. Table 4.46 shows that the model AIC (458.292) suggested that the fitted measurement model provided a more parsimonious fit than the independent model (8417.988) and the saturated model (552.00). Similarly, the CAIC (838.345) also achieved a value lower than both the independence model (8524.589) and the saturated model (1831.202). These results provide further support for the fitted model.

The *comparative fit* indices (CFI) contrast how much better the given model reproduce the observed covariance matrix than a baseline model which is usually an independence or null model (‘*a priori’*). The fit indices presented in Table 4.46, include the normed fit index (NFI = .965), the non-normed fit index (NNFI = .984), the comparative fit index (CFI = .988), the incremental fit index (IFI = .988), and relative fit index (RFI = .954).

The closer these values are to unity (1.00), the better the fit of the model. However, Diamantopoulos and Siguaw (2000) suggest that values above .90 provide a strong indication of a well-fitting model. The results reflected in Table 4.46, shows that all these values fell comfortably above the .90 level. This provided a strong indication of satisfactory comparative fit relative to the independent model.

The critical N (CN) shows the size that a sample must achieve in order to acknowledge the data fit of a given model on a statistical basis (Van Heerden, 2013). As a rule-of-thumb, a critical N greater than 200 is suggestive that a model is a sufficient representation of the data. The results presented in Table 4.46 shows that this model achieved a CN of 231.128, which was above the stated threshold.

The standardised root mean residual (SRMR) is considered as a summary measure of standardized residuals, which represent the average difference between the elements of the sample covariance matrix and the fitted covariance matrix. Lower SRMR values signify better fit and higher values represent worse fit. Therefore, if the model fit is good, the fitted residuals should be small in comparison to the magnitude of the elements (Diamantopoulos & Siguaw, 2000). SRMR-values that are smaller than .05 are indicative of an acceptable fit (Kelloway, 1998). The model produced a SRMR of .0537, which was regarded as acceptable, further emphasising the good model fit.

The goodness-of-fit index (GFI) and the adjusted goodness-of-fit index (AGFI) reflect how closely the model comes to perfectly reproducing the sample covariance matrix (Diamantopoulos & Siguaw, 2000). The AGFI (.857) adjusts the GFI (.900) for the degrees of freedom in the model and should be between zero and 1.0; with values exceeding .90. This would provide a strong indication that the data fits the model well (Jöreskog & Sörbom, 1993). The GFI and AGFI produced by this model can also be regarded as acceptable[64] and as further indications of good model fit.

The assessment of parsimonious fit acknowledges that model fit can always be improved by adding more paths to the model and estimating more parameters until perfect fit is achieved in the form of a saturated or just-identified model with no degrees of freedom (Kelloway, 1998).

The parsimonious normed fit index and the parsimonious goodness-of-fit index, according to Kelloway (1998) and Hair et al., (2006) are more meaningfully used when comparing two competing theoretical models and are not very useful indicators in this CFA analysis or any of the CFA analyses conducted in this study. Therefore, these indices were not considered when evaluating the fit of this or any of the other models.

All the factor loadings were statistically significant ($p < .05$), and the magnitude of all the factor loadings could be considered satisfactory in that all λ_{ij} in the completely standardised solution exceeded the critical cut-off value of .50.

In conclusion, with regards to the fit of the nine first-order factor *academic self-leadership* model, the results, seemed to suggest that good measurement model fit was achieved. However, this model, even though conceptualised as multi-dimensional, was included in the learning potential structural model as one construct. Therefore, a second-order measurement model had to be evaluated, to strengthen the psychometric integrity of the *academic self-leadership* scale and the *academic self-leadership* construct. Initially a second-order measurement model was fitted that allowed the 9 first-order factors to load onto three second-order factors (as defined in section 2.3.1b). This model, however, failed to fit the data, which eroded the confidence in the construct validity of the *academic self-leadership* scale.

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[64] Kelloway (1998) suggest that the GFI and AGFI should be used with some circumspection as guidelines, seeing that the interpretation is grounded in experience and therefore somewhat subjective.

It was subsequently decided to fit the second-order model shown in Figure 4.2, in which the 9 first-order factors load on a single second-order factor representing the construct of *academic self-leadership*. The fitting of this specific second-order model can be justified in that the current study utilises the measures of the *academic self-leadership* scale to represent *academic self-leadership* as an undifferentiated latent variable in the learning potential structural model.

4.6.1.3 Measurement model fit of a second-order academic self-leadership scale

A visual representation of the fitted *academic self-leadership* second-order measurement model is shown in Figure 4.2 and the overall fit statistics are presented in Table 4.47.

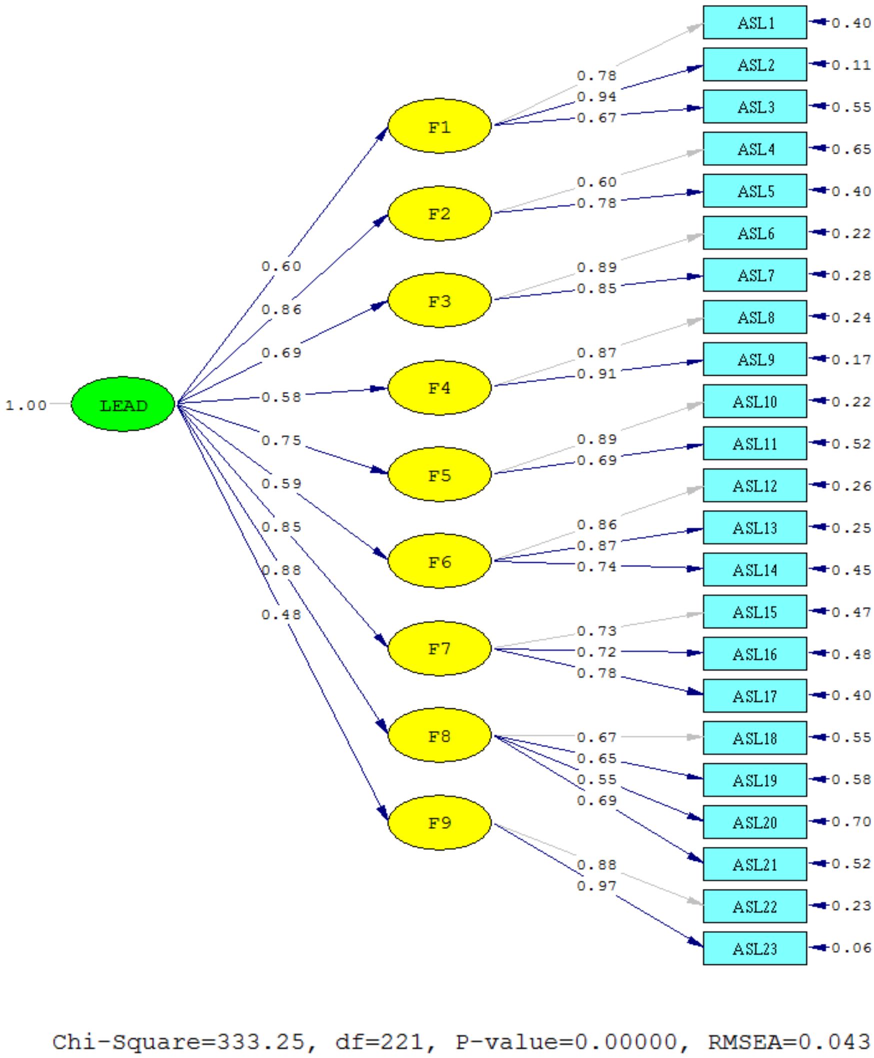

Figure 4.2 Representation of the fitted second-order academic self-leadership measurement model (completely standardised solution)

The results of this analysis will be discussed by evaluating the overall fit statistics based on the array of model fit indices produced by LISREL (as presented in Table 4.47)***.*** After which, a conclusion on the psychometric integrity of this scale will be drawn.

Table 4.47
Goodness of fit statistics for the second-order academic self-leadership measurement model

Degrees of Freedom	221
Minimum Fit Function Chi-Square	415.546 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	404.938 (p = 0.00)
Satorra-Bentler Scaled Chi-square	**333.245 (p = 0.00)**
Chi-square Corrected for NON-Normality	1838.910 (p = 0.00)
Estimated Non-centrality Parameter (NCP)	112.245
90 Percent Confidence Interval for NCP	(67.092 ; 165.368)
Minimum Fit Function Value	1.489
Population Discrepancy Function Value (FO)	0.402
90 Percent Confidence Interval for FO	(0.240 ; 0.593)
Root Mean Square Error of Approximation (RMSEA)	**0.0427**
90 Percent Confidence Interval for RMSEA	**(0.0330 ; 0.0518)**
P-value for test of Close Fit (RMSEA < .05)	**0.905**
Expected Cross-Validation Index (ECVI)	**1.589**
90 Percent Confidence Interval for ECVI	(1.427 ; 1.779)
ECVI for Saturated Model	**1.978**
ECVI for Independence model	**30.172**
Chi-square for Independence Model with 253 Degrees of Freedom	8371.988
Independence AIC	**8417.988**
Model AIC	**443.245**
Saturated AIC	**552.000**
Independence CAIC	**8524.589**
Model CAIC	**698.159**
Saturated CAIC	**1831.202**
Normed Fit Index (NFI)	**0.960**
Non-Normed Fit Index (NNFI)	**0.984**
Parsimony Normed Fit Index (PNFI)	0.839
Comparative Fit Index (CFI)	**0.986**
Incremental Fit Index (IFI)	**0.986**
Relative Fit Index (RFI)	**0.954**
Critical N (CN)	**229.418**
Root Mean Square Residual (RMR)	**0.148**
Standardised RMR	**0.0603**
Goodness of Fit Index (GFI)	0.888
Adjusted Goodness of Fit Index (AGFI)	**0.860**
Parsimony Goodness of Fit Index	0.711

This model achieved a Satorra-Bentler Scaled Chi-Square value of 333.245 (p = .000) (Table 4.47). Thus, implying that the null hypothesis of exact fit (H_0: RMSEA=0) should be rejected. This was not surprising; hence, the null hypothesis for close fit was tested. For this model, the close fit null hypothesis should not be rejected (p > .05; .905). Thus, this model displayed good fit (RMSEA = .0427) in the sample and the position of close fit in the parameter was permissible.

The 90 percent confidence interval for RMSEA (0.0330; 0.0518) was small and fell close to the target value of .05, it providing further support of good close model fit. It could, therefore be concluded that this model provided a plausible explanation and an approximate reproduction of the observed covariance matrix.

Table 4.47 further reveals that the model ECVI (1.589) was smaller than the value obtained for the independence model (30.172). The model ECVI (1.589) was also smaller than the saturated model (1.978). Therefore, a model more closely resembling the fitted model seems to have a better chance of being replicated in a cross-validation sample than the saturated or independence models.

The results of the CFA analysis additionally showed that the model AIC (443.245) suggested that the fitted measurement model provided a more parsimonious fit than the independent model (8411.988) and the saturated model (552.00). Similarly, the model CAIC (689.159) also achieved a value lower than both the independence (8524.589) and the saturated models (1831.202). These results provided further support for the fitted model.

The results for the normed fit index (NFI = .0.960), the non-Normed Fit Index (NNFI = .984), the comparative fit index (CFI = .986), the incremental fit index (IFI = .986), and relative fit index (RFI = .954) all fell comfortably above the .90 level. This provided a strong indication of satisfactory comparative fit relative to the independent model.

Additionally, this model achieved a CN of 229.418, which was well above the threshold (>200). The GFI (.888) and AGFI (.860) produced by this model could be regarded as acceptable and indications of good model fit. The model also produced a SRMR of .0603, which could, however, not be regarded as acceptable. The SRMR results were the first statistic that doesn’t fully support the fit of the second-order measurement model.

All the γ estimates in the second-order measurement model were statistically significant ($p < .05$). Figure 4.2 indicates that the magnitude of the loadings on the first-order factors on the single higher-order factor were satisfactory.

In conclusion, with regards to the fit of the fit of the second-order *academic self-leadership* model, the results seemed to suggest that good measurement model fit was achieved. The loadings of the items on the first-order factors and the loadings of the first-order factors on the higher-order *academic self-leadership* factor was satisfactory. Consequently, the conducted confirmatory factor analyses, in collaboration with the item and dimensionality analyses provided satisfactory reliability and validity results that emphasised relatively strong psychometric integrity for the *academic self-leadership* scale as a measure of the *academic self-leadership* construct.

4.6.2 Psychological Capital scale

The data was first screened prior to the fitting of the Psycap measurement model. Specifically the extent to which the data complied with the normality assumption first had to be evaluated, after which the measurement model fit of the three-subscale[65] *Psychological Capital* scale was assessed.

4.6.2.1 Screening of the data

The results of test of univariate and multivariate normality for the Psycap scale are presented in Table 4.48.

Table 4.48
Test of univariate normality for the psychological capital scale before normalisation

	Skewness		**Kurtosis**		**Skewness and Kurtosis**	
Variable	Z-score	p-value	Z-score	p-value	Chi-square	p-value
PC8	-3.664	.000	1.345	0.179	15.232	**.000**
PC10	-3.509	.000	-0.083	0.934	12.322	**.002**
PC11	-3.422	.001	1.454	0.143	13.852	**.001**
PC12	-2.971	.003	-0.129	0.897	8.844	**.012**
PC14	-54.777	.000	1.861	0.083	26.287	**.000**
PC15	-4.403	.000	-0.487	0.626	19.525	**.000**
PC16	-2.102	.036	-1.220	0.222	5.910	.052
PC17	-6.280	.000	1.925	0.054	43.146	**.000**
PC18	-4.264	.000	.735	0.462	18.726	**.000**
PC19	-2.574	.010	-.450	0.653	6.830	**.033**
PC21	-4.452	.000	.900	0.368	20.627	**.000**
PC22	-6.894	.000	3.283	0.001	58.302	**.000**
PC24	-3.321	.001	1.386	0.166	12.950	**.002**

ASL1 to ASL23 = Academic Self-leadership 23-items

[65] The Psychological Capital scale consists of four subscales, one for each construct, i.e. *self-efficacy, hope, resilience,* and *optimism*. The proposed learning potential structural model only used three of the four constructs. Consequently, the Psycap scale, for this study, is only a three dimensional scale. The three dimensional model was also fitted to the data, and these results will be reported on in Section 4.6.2.

Table 4.49
Test of multivariate normality for psychological capital scale before normalisation

Skewness			Kurtosis			Skewness and Kurtosis	
Value	Z-score	p-value	Value	Z-score	p-value	Chi-Square	p-value
100.944	23.708	0.000	731.030	14.274	0.000	**765.821**	**0.000**

The Chi-square for skewness and kurtosis, showed in Table 4.48, revealed that twelve of the thirteen items failed the test for univariate normality ($p < .05$). Additionally, the null hypothesis that the data followed a multivariate normal distribution (Table 4.49) also had to be rejected ($X^2 = 765.821$; $p < .05$). Therefore, it was decided to normalise the item distributions with PRELIS.

The results of the test of univariate normality after normalisation are presented in Table 4.50, while the results of the test of multivariate normality after normalisation are presented in Table 4.51.

Table 4.50
Test of univariate normality for psychological capital scale after normalisation

	Skewness		Kurtosis		Skewness and Kurtosis	
Variable	Z-score	p-value	Z-score	p-value	Chi-square	p-value
PC8	-O.965	.334	-1.022	.307	1.977	.372
PC10	-1.322	.186	-2.037	.042	5.897	.052
PC11	-1.235	.217	-1.429	.153	3.567	.168
PC12	-0.554	.580	-0.731	.465	0.841	.657
PC14	-1.063	.288	-0.845	.398	1.845	.398
PC15	-1.505	.132	-2.035	.042	6.407	**.041**
PC16	-0.490	.624	-0.990	.322	1.220	.543
PC17	-2.523	.012	-3.451	.001	18.271	**.000**
PC18	-0.962	.336	-1.077	.282	2.085	.353
PC19	-0.521	.602	-0.489	.625	0.510	.775
PC21	-1.628	.104	-2.040	.041	6.813	**.033**
PC22	-3.249	.001	-2.792	.005	18.349	**.000**
PC24	-0.877	.380	-1.173	.241	2.145	.342

ASL1 to ASL23 = Academic Self-leadership 23-items

Table 4.51
Test of multivariate normality for academic self-leadership scale after normalisation

Skewness			Kurtosis			Skewness and Kurtosis	
Value	Z-score	p-value	Value	Z-score	p-value	Chi-Square	p-value
83.433	15.504	0.000	701.493	11.868	0.000	**384.030**	**0.000**

The results presented in Tables 4.50 and 4.51 show that the normalisation procedure did not succeed in rectifying either the univariate- or the multivariate problem.

Table 4.50 shows that the normalisation succeeded in correcting the univariate problem on some items, but that four of the thirteen items still failed the test for univariate normality ($p < .05$). Additionally, Table 4.51 shows that the null hypothesis that the data follows a multivariate normal distribution still had to be rejected ($X^2 = 384.030$; $p < .05$). Therefore, even though normalisation was attempted, neither univariate nor multivariate normality was achieved for this scale. The normalisation, however, did succeed in reducing the deviation of the observed indicator distribution from the theoretical multivariate normal distribution as was evidenced by the decrease in chi-square statistic.

Since the normalisation procedure did not result in the desired outcomes, and the data still did not meet the multivariate normality assumption (even after the normalisation procedure), the use of an alternative estimation method more suited to the data was used (i.e. Robust maximum likelihood estimation). This process resulted in the normalisation of the data and the reduction of the deviation of the observed indicator distribution from the theoretical multivariate normal distribution. The normalised data was used for the succeeding analyses.

4.6.2.2 Measurement model fit of the psychological capital three dimensional scale

The *Psycap* scale was conceptualised as a scale consisting of four subscales, i.e. four dimensions. However, only three of these subscales were used in this study. Consequently this analysis focussed only on the *hope-, resilience-,* and *optimism* subscales. Item analysis identified PC7, PC9, PC13 and PC23, as poor items.

Dimensionality analysis further highlighted PC20 as a possible poor item. The *Psycap* measurement model was consequently fitted with only the three latent Psycap dimensions used in this study. The poor items identified earlier were excluded from the fitted measurement model. A visual representation of the fitted *psychological capital* measurement model is shown in Figure 4.3 and the overall fit statistics are presented in Table 4.52.

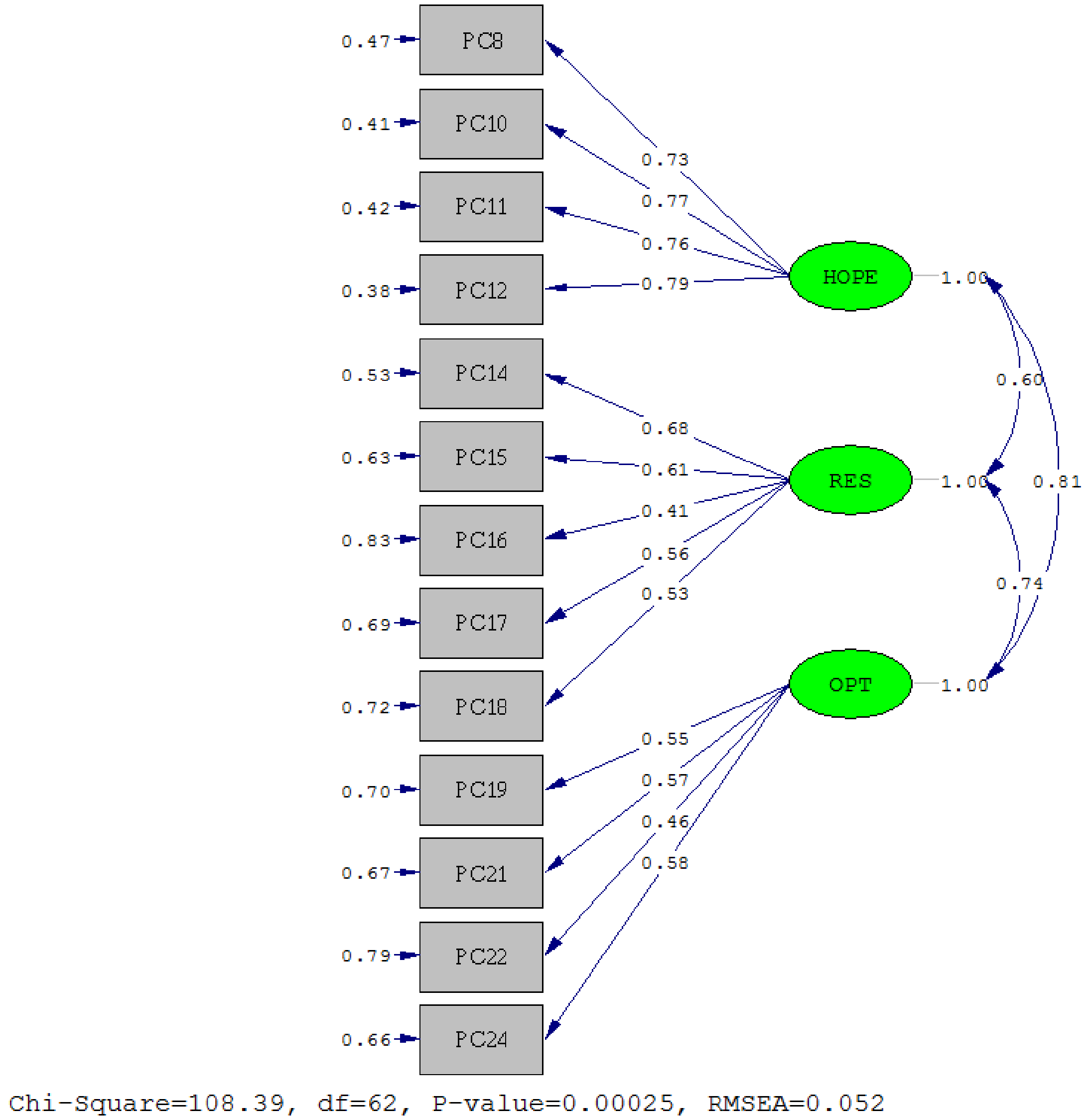

Figure 4.3 Representation of the fitted PsyCap measurement model (completely standardised solution)

The results of the full range of fit indices (both comparative and absolute) are reported in Table 4.52.

Table 4.52

Goodness of Fit Statistics for the psycap measurement model

Degrees of Freedom	62
Minimum Fit Function Chi-Square	130.286 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	127.902 (p = 0.00)
Satorra-Bentler Scaled Chi-square	**108.393 (p = 0.000245)**
Chi-square Corrected for NON-Normality	152.901 (p = 0.00)
Estimated Non-centrality Parameter (NCP)	46.393
90 Percent Confidence Interval for NCP	(21.309 ; 79.335)
Minimum Fit Function Value	0.467
Population Discrepancy Function Value (FO)	.166
90 Percent Confidence Interval for FO	(0.0764 ; 0.284)
Root Mean Square Error of Approximation	**.0518**

(RMSEA)	
90 Percent Confidence Interval for RMSEA	**(0.0351 ; 0.0677)**
P-value for test of Close Fit (RMSEA < .05)	**.409**
Expected Cross-Validation Index (ECVI)	**0.596**
90 Percent Confidence Interval for ECVI	(0.506; 0.714)
ECVI for Saturated Model	**0.652**
ECVI for Independence model	**8.125**
Chi-square for Independence Model with 253 Degrees of Freedom	2240.931
Independence AIC	**2266.931**
Model AIC	**166.393**
Saturated AIC	**182.000**
Independence CAIC	**2327.183**
Model CAIC	**300.802**
Saturated CAIC	**603.766**
Normed Fit Index (NFI)	**.952**
Non-Normed Fit Index (NNFI)	**.973**
Parsimony Normed Fit Index (PNFI)	.756
Comparative Fit Index (CFI)	**.979**
Incremental Fit Index (IFI)	**.979**
Relative Fit Index (RFI)	**.939**
Critical N (CN)	**234.724**
Root Mean Square Residual (RMR)	**.0714**
Standardised RMR	**.0531**
Goodness of Fit Index (GFI)	**.934**
Adjusted Goodness of Fit Index (AGFI)	**.903**
Parsimony Goodness of Fit Index	.636

Table 4.52 indicates that this model achieved a Satorra-Bentler scaled chi-square value of 108.393 (p = .000245), implying that the null hypothesis of exact fit (H_0: RMSEA=0) should be rejected. This assumption of exact fit is highly unlikely, and thus the rejection is not surprising. Therefore, the close fit null hypothesis was tested. To assess whether the model closely approximates the processes that operate in reality, the p-value for the test of close fit (RMSEA < .05) must be considered.

For this model, the close fit null hypothesis should not be rejected (p > .05; .409). Thus, the position that the model displayed close fit in the parameter was permissible. The root mean square of approximation (RMSEA) showed how well the model, with unknown but optimally chosen parameter values, fit the population covariance matrix if it were available. Table 4.52 shows that this model achieved a RMSEA value of .0518, which indicates that this model achieved reasonable close fit in the sample. Therefore it was concluded that this model provided a plausible explanation and a reasonable approximation of the reproduction of the observed covariance matrix.

Table 4.52 shows that the model ECVI (.596) was smaller than the value obtained for the independence model (8.125). The model ECVI (.596) was also smaller than the saturated model (.652). Therefore, a model more closely resembling the fitted model seemed to have a better chance of being replicated in a cross-validation sample than the saturated or independence models.

Table 4.52 further reveals that the model AIC (166.393) showed that the fitted measurement model provided a more parsimonious fit than the independent model (2266.931) and the saturated model (182.000). Likewise, the CAIC (300.802) also achieved a value lower than both the independence model (2327.183) and the saturated model (603.766). These results provided further support for the fitted model. The incremental fit indices all fell above the .90 cut-off value [the normed fit index (NFI = .952), the non-normed fit index (NNFI = .973), the comparative fit index (CFI = .979), the incremental fit index (IFI = .979), and relative fit index (RFI = .939)]. This provided a strong indication of satisfactory comparative fit relative to the independent model. The statistics presented in Table 4.52 further revealed that the model achieved a CN of 234.724, which is well above the threshold (>200).

With reference to the SRMR-value, Kelloway (1998) explains that a value smaller than .05 are indicative of an acceptable fit. The model produced a SRMR of .0714, which is indicative of reasonable to poor fit, which was a little bit in conflict with the other results. However, the GFI (.934) and AGFI (.903) produced by this model, exceeded .90, which can be regarded as acceptable and further indications of good model fit. All the factor loadings were statistically significant ($p < .05$). Figure 4.3, however, indicates that the factor loadings generally were at best moderately high with two of the loadings falling below the critical cut-off value of .50. The Psycap items therefore provided somewhat noisy measures of the three Psycap latent variables (*hope*, *optimism* and *resilience*). The relatively low Cronbach alpha values obtained in the item analyses reinforced this interpretation

In conclusion, with regards to the fit of the three dimensional Psycap model, the results seem to suggest that reasonable measurement model fit was achieved but that the items generally provided reasonably noisy measures with quite substantial measurement error. Subsequently, a conclusion can be drawn, with regards to the psychometric integrity of each of the measurement instruments included in this study.

4.7 CONCLUSION REGARDING PSYCHOMETRIC INTEGRITY OF INSTRUMENTS

The item analysis conducted on the range of scales and subscales used in this study achieved the results presented in Table 4.53. An in-depth analysis assisted in the identification of a number of problematic items, and after gaining sufficient evidence incriminating these items, nine items were deleted across the eight scales/subscales. The results depicted in Table 4.53 summarises the results after the deletion of poor items.

Table 4.53
A summary of the reliability results of the expanded learning potential questionnaire latent variable scales

SCALE	SAMPLE SIZE	NUMBER OF ITEMS	MEAN	VARIANCE	STANDARD DEVIATION	CRONBACH ALPHA
TCE	280	14	56.068	130.085	111.405	.916
ASE	280	11	48.007	94.867	9.739	.910
CON	280	11	38.604	141.495	11.895	.900
LM	280	6	32.171	38.315	6.189	.854
ASL	280	23	92.268	437.666	20.920	.913
PSYCAP	280	24	102.000	176.344	13.279	.836
HOPE	280	4	17.378	13.655	3.695	.846
RES	280	4	21.414	11.598	3.405	.670
OPT	280	5	21.718	15.988	3.998	.547

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The item analyses revealed that six scales and one subscale obtained Cronbach alpha values greater than .80; thus, showing satisfactory internal consistency on those scales/subscales. The *resilience* and *optimism* subscales, however, returned unsatisfactory levels of internal consistency. *Optimism* obtained the lowest level of internal consistency. This finding corresponded to the research findings obtained by Luthans et al., (2007), and Görgens-Ekermans and Herbert (2013).

Dimensionality analyses were performed to provide insight into the functioning of the scales of the latent variables included in the proposed model. Four of the eight scales passed the unidimensionality assumption, and four failed. In all instances of failure, the items were successfully forced onto a single factor and loaded successfully onto the extracted factor. Only one additional item was deleted, i.e. PC20, from the *optimism*-scale, based on the dimensionality analysis results. Therefore, the item- and dimensionality analysis resulted in the deletion of 10 items from the composite scale. The summary of the factor analyses results are displayed in Table 4.54.

Table 4.54
A summary of the factor analyses results for the expanded learning potential questionnaire scales

Scales/Subscales	KMO	Bartlett's Test	Maximum Loading	Minimum Loading	Number of factors extracted
TCE	.921	2016.703	.735	.560	2
ASE	.914	1606.660	.809	.527	2
CON	.891	1948.302	.524	.767	2
LM	.840	686.205	.592	.785	1
ASL	.859	3452.286	.011	.654	6
HOPE	.822	522.428	.731	.780	1
RES	.767	193.039	.408	.647	1
OPT	.652	191.548	.422	.661	1

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The item- and dimensionality results of all the scales, except for the *academic self-leadership* and the *psychological capital* scales indicated acceptable reliability and validity statistics.

To strengthen the psychometric support for the *academic self-leadership*- and the *psychological capital* scales, confirmatory factor analyses was conducted. The results revealed adequate support for the fit of these models. More importantly the completely standardised factor loadings and measurement error variances for the *academic self-leadership* scale proved to be quite satisfactory. For the *psychological capital* scale the completely standardised factor loadings and measurement error variances showed the *psychological capital* items to be somewhat more noisy measures. The majority of the factor loadings nonetheless exceeded the critical cut-off point set in this study. Although there is, no doubt, room for improvement with regards to the validity and reliability of the *psychological capital* measures the CFA results for the *psychological capital* scale sufficiently mitigated the rather bleak psychometric picture that emerged from the item analysis to retain the three *psychological capital* latent variables in the model. Consequently, the basket of evidence provided sufficient justification to use all of these scales in the subsequent analyses to represent the latent variables they were earmarked to reflect, without the deleted items.

4.8 ITEM PARCELS

When using LISREL to assess the structural model, the individual items comprising the scales/subscales used to operationalise the latent variables contained in the model, could have been used. This, however, would have led to extensively comprehensive models in which a very large number of parameters have to be estimated. To avoid this, at least two parcels of indicator variables consisting of the items of each scale/subscale, were formed; to operationalise the latent variables in the proposed model.

The results of the item-, dimensionality, and confirmatory factor analyses justified the formation of item parcels for each of the latent variables included in the structural model. Item parcels, otherwise known as composite variables, were computed by adding the means of the even and uneven numbered items of each scale or subscale in SPSS. *Learning performance during evaluation* was represented by three item parcels that were formed by taking the mean of the first and second term marks in Afrikaans, English and Mathematics. The item parcel data set was subsequently imported into PRELIS to evaluate the multivariate normality of the item parcel distribution. These parcels were treated as continuous variables.

4.9 LEARNING POTENTIAL MEASUREMET MODEL

The measurement model represents the relationship between the learning potential latent variables and its corresponding item parcel indicator variables. Before this model was fitted to the data, the data were screened to test the assumption of normality. Afterwards, the confirmatory factor analysis was conducted. Based on the results produced by the CFA, the overall model fit was evaluated based on the array of fit indices produced by LISREL. A decision was then derived based on the credibility of the measurement model parameter estimates. The parameter estimates of the fitted model will also be discussed, and will result in the interpretation of the measurement model. Lastly, an evaluation of the standardised residuals and an interpretation of the modification indices will be included in the next section.

4.9.1 Screening of the data

The most important assumption to consider, prior to fitting the measurement model, is the effect of non-normality (Du Toit & Du Toit, 2001). The default method of estimation when fitting the measurement model to continuous data (maximum likelihood) assumes that the distribution of the indicator variables follow a multivariate normal distribution (Mels, 2003). As a result, the univariate and multivariate normality of the item parcels comprising this model were evaluated via PRELIS.

The screening process started with the evaluation of the composite parcels for each latent variable in terms of their univariate and multivariate normality before a normalisation procedure was attempted. The results of the test of univariate and multivariate normality of the learning potential measurement model are presented in Table 4.55 and Table 4.56.

Table 4.55
Test of univariate normality for the measurement model before normalisation

	Skewness		**Kurtosis**		**Skewness and Kurtosis**	
Variable	Z-score	p-value	Z-score	p-value	Chi-square	p-value
TCE_1	-0.509	.611	-0.564	0.573	0.577	.749
TCE_2	0.900	.368	0.268	0.245	7.453	**.024**
ASL_1	-2.471	.013	1.161	0.245	7.453	**.024**
ASL_2	-2.722	.006	1.530	0.126	9.751	**.008**
ASE_1	-0.515	.607	-0.936	0.349	1.142	.565
ASE_2	-0.919	.358	-2.524	0.012	7.218	**.027**
CON_1	0.685	.494	-1.476	0.140	2.648	.266
CON_2	0.467	.640	-2.146	0.032	4.824	**.090**
LM_1	-4.626	.000	1.515	0.130	23.691	**.000**
LM_2	-5.065	.000	1.521	0.128	27.969	**.000**
HOPE_1	-3.895	.000	2.137	0.033	19.742	**.000**
HOPE_2	-2.960	.003	-0.380	0.704	8.903	**.012**
RES_1	-2.099	.036	-0,189	0.850	4.443	.108
RES_2	-3.942	.000	-0.380	0.704	15.683	**.000**
OPT_1	-2.795	.005	1.499	0.134	10.057	**.007**
OPT_2	-5.988	.000	3.559	0.000	48.514	**.000**
ENG	-0.657	.511	-2.667	0.008	7.542	**.023**
AFR	0.879	.379	-1.192	0.233	2.192	.334
MATH	2.759	.006	-3.013	0.003	16.693	**.000**

TCE_1 & TCE_2 = Time Cognitively Engaged; ASL_1 &ASL_2 = Academic Self-Leadership; ASE_1 & ASE_2 = Academic Self-efficacy; CON_1 & CON_2 = Conscientiousness; LM_1 & LM_2 = Learning Motivation; HOPE_1 & HOPE_2 = Hope; RES_1 & RES_2 = Resilience; OPT_1 & OPT_2 = Optimism; ENG = English First Additional Language; AFR = Afrikaans Home Language; MATH = Mathematics.

Table 4.56
Test of multivariate normality the measurement model before normalisation

	Skewness			**Kurtosis**		**Skewness and Kurtosis**	
Value	Z-score	p-value	Value	Z-score	p-value	Chi-Square	p-value
48.564	15.054	0.000	445.237	9.653	0.000	**319.794**	**0.000**

The Chi-square for skewness and kurtosis, presented in Table 4.55, showed that thirteen of the nineteen item parcels failed the test for univariate normality ($p < .05$). Additionally, the null hypothesis that the item parcel distribution follows a multivariate normal distribution (Table 4.56) also had to be rejected ($X^2 = 319.794$; $p < .05$). Due to the fact that the quality of the solution obtained in the structural equation modelling depends largely on multivariate normality, it was decided to normalise the items with PRELIS. Afterwards, the null hypothesis of univariate- and multivariate normality was tested again. The results of this test of univariate normality are presented in Table 4.57, while the results of the test of multivariate normality are presented in Table 4.58.

Table 4.57
Test of univariate normality for the measurement model after normalisation

	Skewness		Kurtosis		Skewness and Kurtosis	
Variable	Z-score	p-value	Z-score	p-value	Chi-square	p-value
TCE_1	-0.026	.980	0.026	0.979	0.001	**.998**
TCE_2	-0.009	.993	0.059	0.953	0.004	**.998**
ASL_1	-0.041	.967	-0.026	0.980	0.002	**.999**
ASL_2	-0.014	.989	0.060	0.952	0.004	**.998**
ASE_1	-0.336	.737	-0.624	0.533	0.502	**.778**
ASE_2	-0.215	.829	-0.368	0.713	0.182	**.913**
CON_1	-0.002	.998	-0.135	0.892	0.018	**.991**
CON_2	-0.059	.953	-0.073	0.942	0.009	**.996**
LM_1	-0.299	.765	-0.342	0.666	0.276	**.871**
LM_2	-0.619	.536	-0.933	0.351	1.253	**.534**
HOPE_1	-0.519	.604	-0.680	0.496	0.732	**.694**
HOPE_2	-0.430	.667	-0.664	0.507	0.626	**.731**
RES_1	-0.029	.977	-0.213	0.831	0.046	**.977**
RES_2	-1.009	.313	-1.448	0.148	3.114	**.211**
OPT_1	-0.283	.777	-0.347	0.728	0.201	**.905**
OPT_2	-0.677	.4989	-0.721	0.471	0.979	**.613**
ENG	-0.004	.997	0.078	0.938	0.006	**.997**
AFR	0.002	.999	0.086	0.931	0.007	**.996**
MATH	0.021	.984	0.034	0.973	0.002	**.999**

TCE_1 & TCE_2 = Time Cognitively Engaged; ASL_1 &ASL_2 = Academic Self-Leadership; ASE_1 & ASE_2 = Academic Self-efficacy; CON_1 & CON_2 = Conscientiousness; LM_1 & LM_2 = Learning Motivation; HOPE_1 & HOPE_2 = Hope; RES_1 & RES_2 = Resilience; OPT_1 & OPT_2 = Optimism; ENG = English First Additional Language; AFR = Afrikaans Home Language; MATH = Mathematics.

Table 4.58
Test of multivariate normality for academic self-leadership scale after normalisation

	Skewness			Kurtosis		Skewness and Kurtosis	
Value	Z-score	p-value	Value	Z-score	p-value	Chi-Square	p-value
40.863	9.886	0.000	431.744	7.695	0.000	**156.958**	**0.000**

The results presented in Table 4.57 shows that the normalisation procedure did succeed in rectifying the univariate normality problem. Table 4.57 shows that the p-values for each of the item parcels sufficiently increased, so as not to reject the null hypothesis of univariate normality ($p > .05$). It was evident that normalisation did improve the symmetry and kurtosis of the univariate item parcel distributions. However, the null hypothesis that the data followed a multivariate normal distribution still had to be rejected ($X^2 = 156.958$; $P < .05$) (Table 4.58). Even though normalisation did allow the attainment of univariate normality, multivariate normality, however, was still not achieved. The normalisation, however, did succeed in reducing the deviation of the observed item parcel indicator distribution from the theoretical multivariate normal distribution as was evidenced by the decrease in chi-square statistic.

Maximum likelihood estimation is the default method when fitting measurement models to continuous data, but requires a multivariate normal distribution (Mels, 2003). Since normalisation did not result in the desired outcomes, and the data still did not meet the multivariate normality assumption even after the normalisation procedure, robust maximum likelihood estimation technique was used. This method necessitates the computation of an asymptotic covariance matrix via PRELIS to enable the calculation of more appropriate fit indices in LISREL (Mels, 2003). Since the normalisation had the effect of reducing the deviation of the observed indicator distribution from the theoretical multivariate normal distribution, the normalised data was used to fit the learning potential measurement- and structural models.

The confirmatory factor analyses results will be discussed in the next sections. Firstly, the fit indices will be discussed; afterwards the measurement model will be interpreted by referring to the parameter estimates. Lastly, the measurement model residuals, and the modification indices will be evaluated.

4.9.2 Fit of the learning potential measurement model

The measurement model characterises the relationship between the item parcels/composites and the latent variables manifested in the model. The aim of confirmatory factor analysis (CFA) was to determine whether the operationalisation of the item parcels/composites in terms of its latent variables, was successful.

The operationalisation can be regarded as successful if the measurement model can successfully reproduce the observed covariance matrix, i.e. if the model fits the data well, the item parcels load statistically significantly on the latent variables they were earmarked to reflect, the completely standardised factor loadings exceeded .71 (Hair et al., 2006) and the completely standardised measurement error variances were statistically significant but small (i.e., $\Theta_\delta < .50$).

A visual representation of the fitted learning potential measurement model is shown in Figure 4.4 and the overall fit statistics are presented in Table 4.59.

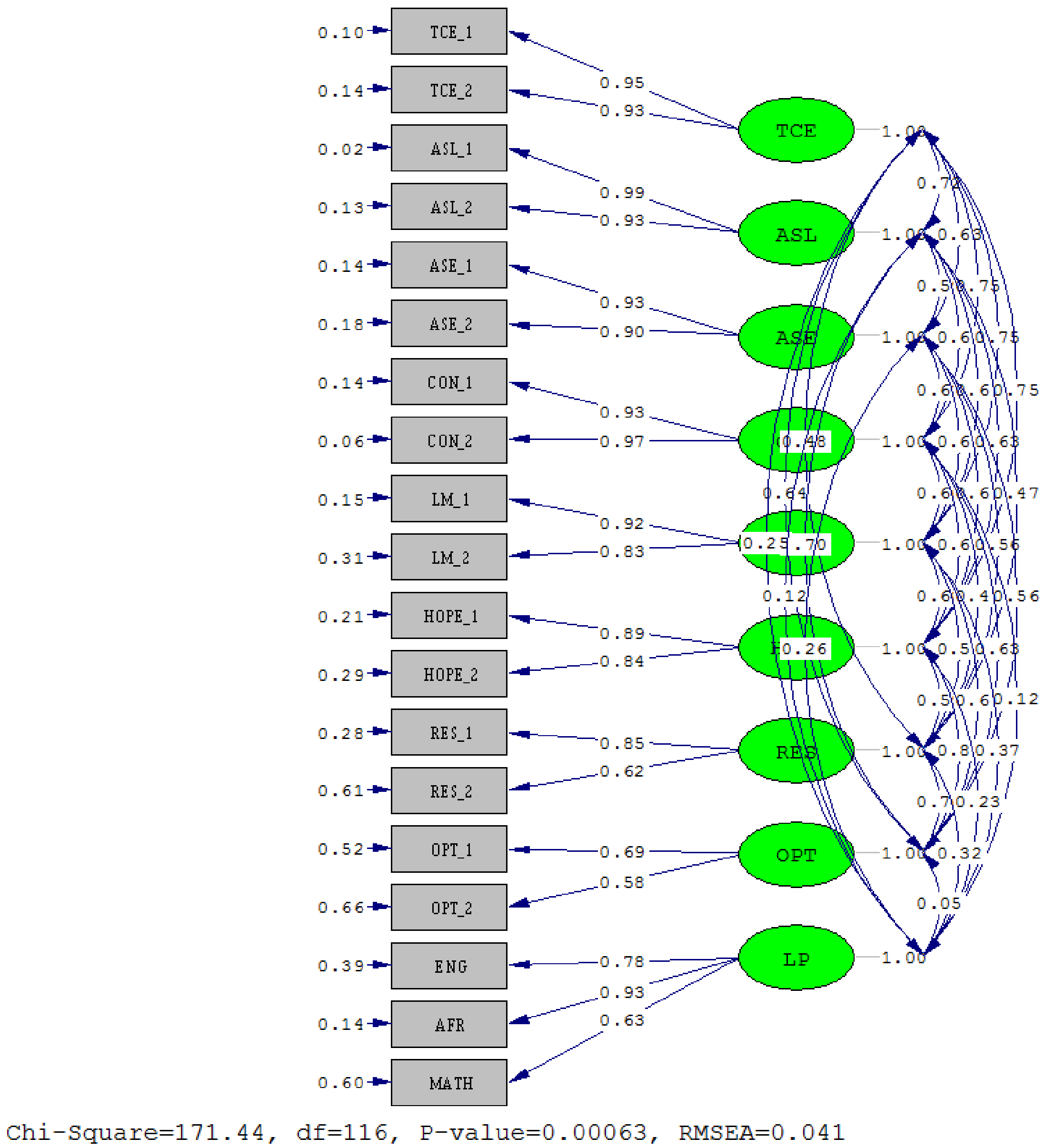

Figure 4.4 Representation of the fitted learning potential measurement model (completely standardised solution)

4.9.2.1 Measurement Model Fit Indices

Diamantopoulos and Siguaw (2000) explained that the purpose of assessing the overall fit of a model is to determine the degree to which the model as a whole is consistent with the empirical data at hand. This section will discuss, in detail, the results of the measurement model for each of the fit indices identified in Section 4.6.1.2. The full range of fit indices (both comparative and absolute) is reported in Table 4.59.

Table 4.59
Goodness of fit statistics for the learning potential measurement model

Degrees of Freedom	116
Minimum Fit Function Chi-Square	184.157 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	181.218 (p = 0.000103)
Satorra-Bentler Scaled Chi-square	**171.443 (p = 0.000631)**
Chi-square Corrected for NON-Normality	299.579 (p = 0.0)
Estimated Non-centrality Parameter (NCP)	55.443
90 Percent Confidence Interval for NCP	(24.343 ; 94.530)
Minimum Fit Function Value	0.660
Population Discrepancy Function Value (FO)	0.199
90 Percent Confidence Interval for FO	(0.0872 ; 0.339)
Root Mean Square Error of Approximation (RMSEA)	**0.0414**
90 Percent Confidence Interval for RMSEA	**(0.0274 ; 0.0540)**
P-value for test of Close Fit (RMSEA < .05)	**.862**
Expected Cross-Validation Index (ECVI)	**1.145**
90 Percent Confidence Interval for ECVI	(1.033 ; 1.285)
ECVI for Saturated Model	**1.362**
ECVI for Independence model	**34.517**
Chi-square for Independence Model with 253 Degrees of Freedom	9592.369
Independence AIC	**9630.362**
Model AIC	**319.443**
Saturated AIC	**380.000**
Independence CAIC	**9718.430**
Model CAIC	**662.418**
Saturated CAIC	**1260.610**
Normed Fit Index (NFI)	**.982**
Non-Normed Fit Index (NNFI)	**.991**
Parsimony Normed Fit Index (PNFI)	**.666**
Comparative Fit Index (CFI)	**.994**
Incremental Fit Index (IFI)	**.994**
Relative Fit Index (RFI)	**.974**
Critical N (CN)	**252.173**
Root Mean Square Residual (RMR)	**.807**
Standardised RMR	**.0485**
Goodness of Fit Index (GFI)	**.936**
Adjusted Goodness of Fit Index (AGFI)	**.895**
Parsimony Goodness of Fit Index	**.571**

The Chi-square statistics (X^2) is the traditional evaluation for assessing the overall model fit in covariance structure models and provides a test of perfect fit for the hypothesis of exact model fit. The X^2 test statistic tests the null hypothesis that the model fits the population data perfectly:

$$H_{01}: RMSEA=0$$

$$H_{a1}: RMSEA>0$$

Table 4.59 indicates that this model achieved a Satorra-Bentler Chi-square value of 171.443 (P = 0.000631). The null hypothesis of exact fit should therefore be rejected (H_{01}: RMSEA=0). A statistically significant chi-square results in the rejection of the null hypothesis meaning imperfect model fit and possible rejection of the model. Even though the Chi-square seems an attractive determinant of the model's fit, care needs to be taken as it is very susceptible to departures from multivariate normality, and sample size. This hypothesis also assumes that the model fits perfectly in the population, which represents a rather unrealistic position. Therefore the null hypothesis of close fit should be tested, that translates into the following hypothesis:

$$H_{02}: RMSEA \leq .05$$

$$H_{a2}: RMSEA > .05$$

To assess whether the model closely approximates the psychological processes that underlie *learning performance during evaluation*, the value for the test of close fit (RMSEA < .05) was considered. For this model, Table 4.59 shows that the close fit null hypothesis should not be rejected ($p > .05$; .862). It was therefore permissible to claim that this model displayed close fit in the parameter. The RMSEA value of .0414 indicated that this model achieved good close fit in the sample.

The 90 percent confidence interval for RMSEA should be considered in collaboration with the RMSEA-value, as it assists in the evaluation of the precision of the fit statistic. The 90 percent confidence interval for RMSEA (0.0274; 0.0540) was small and fell relatively close to the target value of .05. Therefore, it provided further support for this model's good close fit. Based on these results, it was concluded that the model provided a plausible explanation and a close reproduction of the observed covariance matrix.

The expected cross-validation index (ECVI) focuses on the overall error. This value expresses the difference between the reproduced sample covariance matrix derived from fitting the model on the sample at hand, and the expected covariance that would be obtained in another sample of equivalent size, from the same population (Byrne, 1998; Diamantopoulos & Siguaw, 2000). To assess the model's ECVI, it must be compared to the independence model and the saturated model. Table 4.59 shows that the model ECVI (1.145) was smaller than the value obtained for the independence model (34.517). The model ECVI (1.145) was also smaller than the saturated model (1.362). Based on these results it was evident that a model more closely resembling the fitted model seemed to have a better chance of being replicated in a cross-validation sample than the saturated or independence models.

The assessment of a parsimonious fit acknowledges that model fit can always be improved by adding more paths to the model, and estimating more parameters until perfect fit is achieved in the form of a saturated or just-identified model with no degrees of freedom (Kelloway, 1998). Throughout the process of defining and fitting of models, it would seem essential to find the most parsimonious model that achieves satisfactory fit with as few model parameters as possible (Jöreskog & Sörbom, 1993). The parsimonious normed fit index (PNFI = .666) and the parsimonious goodness-of-fit index (PGFI = .571) approach model fit from this perspective. These two values should range from 0 to 1.0, with higher values indicating a more parsimonious fit.

There is no standard for how high either index should be to indicate a more parsimonious fit (Kelloway, 1998). However, both the PNFI and PGFI were above .50, which was acceptable for this study, seeing that these indices are not very helpful indicators in CFA analysis. The parsimonious normed fit index and the parsimonious goodness-of-fit index, according to Kelloway (1998) and Hair et al., (2006) are more meaningfully used when comparing two competing theoretical models and are therefore not feasible for any of the CFA analyses in this study. Therefore, these two indices were noted but they did not play a superior role in the interpretation of the overall fit indices.

Akaike's information criterion (AIC) and the consistent version of AIC (CAIC) comprises what are known as information criteria and are used to compare models (Van Heerden, 2013). Similar to the EVCI, the AIC and CAIC must be compared to the independence- and the saturated model.

Table 4.59 shows that the model AIC (319.443) suggested that the fitted measurement model provided a more parsimonious fit than the independent model (9730.362) and the saturated model (380.00). Similarly, the CAIC (662.418) also achieved a value lower than both the independence model (9718.430) and the saturated model (1260.610). These results provided further support for the fitted measurement model.

The comparative fit indices (CFI) contrast how much better the given model fit reproduce the observed covariance matrix than a baseline model which is usually an independence or null model (‘*a priori’*). The fit indices presented in Table 4.59 reflects the normed fit index (NFI = .982), the non-normed fit index (NNFI = .991), the comparative fit index (CFI = .994), the incremental fit index (IFI = .994), and relative fit index (RFI = .974). The closer these values are to unity (1.00), the better the fit of the measurement model. However, Diamantopoulos and Siguaw (2000) recommend that .90 provides a strong suggestion of a well-fitting model. The results reflected in Table 4.59 shows that all these values fell comfortably above the .90 level. This was indicative of satisfactory comparative fit relative to the independent model. The critical N (CN) shows the size that a sample must achieve in order to acknowledge the data fit of a given model on a statistical basis (Van Heerden, 2013). As a rule-of-thumb, a critical N greater than 200 is evocative of sufficient representation of the data by a specific model. The CN of 252.173 was well above the 200 threshold.

The standardised root mean residual (SRMR) is considered as a summary measure of standardised residuals, which represent the average difference between the elements of the sample covariance matrix and the fitted covariance matrix. Lower SRMR values indicate better fit and higher values symbolise worse fit. So, if the model fit is good, the fitted residuals should be small in comparison to the enormity of the elements (Diamantopoulos & Siguaw, 2000). Kelloway (1998) suggested that SRMR-values that are smaller than .05 are indicative of an acceptable fit. The model produced a SRMR of .0485, which is lower than the .05 cut-off value, thus signalling acceptable model fit.

The goodness-of-fit index (GFI) and the adjusted goodness-of-fit index (AGFI) reflect how closely the model comes to perfectly reproducing the sample covariance matrix (Diamantopoulos & Siguaw, 2000).

The AGFI (.895) adjusts the GFI (.936) for the degrees of freedom in the model and should be between 0 and 1.0; with values exceeding .90. This would provide a strong indication that the data fits the model well (Jöreskog & Sörbom, 1993). The GFI and AGFI produced by this model could be regarded as satisfactory and indicative of good model fit.

In conclusion, with regards to the fit of the learning potential measurement model, the results seemed to suggest that good close fit was achieved. It is also suggested that the proposed measurement model clearly outperformed the independence and saturated models. However, the interpretation of the standardised residuals, the modification indices and the parameter estimates were first considered prior to the final conclusion, regarding model fit.

4.9.2.2 Examination of the measurement model residuals and modification indices

Diamantopoulos and Siguaw (2000) suggest that the examination of the standardised residuals and the modification indices provide relevant information that can be used for the modification of the model for the sole purpose of improving the model fit. At the same time, however, the standardised residuals and the modification indices calculated for the lambda-X and theta-delta, comment on the quality of the measurement model. If a limited number of ways exists to improve the model fit then this comments positively on the fit of the model. Therefore, in this section the standardised residuals will be firstly discussed, after which the modification indices of the learning potential structural model will be discussed. The aim of these discussions is primarily to comment on the fit of the model rather than on the identification of ways of improving the fit of the model.

a.) Standardised Residuals

Standardised residuals refer to the difference between corresponding cells in the observed and fitted covariance matrix (Jöreskog & Sörbom, 1993). A standardised residual is a residual that is divided by its estimated standard error. Kelloway (1998) explained that residuals and especially standardised residuals provide diagnostic information on sources of lack of fit in models.

Positive residuals indicate underestimation and therefore imply the need for additional explanatory paths. Negative residuals, on the other hand, are indicative of overestimation, and thus suggest the need to reduce the number of paths (Burger, 2012). Standardised residual values can be considered as positively large if they exceed +2.58 or negatively large if they are smaller than -2.58 (Diamantopoulos & Siguaw, 2000). Residuals should also be dispersed more or less symmetrical around zero. This is due to the fact that the standardised residual-values can be interpreted as standard normal deviates.

The shape and distribution of the standardised residuals for this study are shown in Figure 4.5.

```
-4 | 6
-4 |
-3 |
-3 | 441
-2 | 765555
-2 | 4221
-1 | 988776666655
-1 | 4421110000
-0 | 8888877665555
-0 | 44433333222111000000000000000000000000000000000000000000000000000000000
 0 | 11111222334
 0 | 5555555566666678888888999
 1 | 00111224
 1 | 556789
 2 | 01113
 2 | 56799
 3 | 799
 3 | 02
 4 | 5
 4 |
```

Figure 4.5 Stem-and-leaf plot of the standardised residuals

From the stem and leaf plot presented in Figure 4.5, the distribution of the standardised residuals appeared slightly more positively skewed. Thus providing evidence that, in terms of substantial estimation errors, the measurement model do tend to underestimate rather than overestimate the observed covariance matrix. There were, however, a number of both large negative and large positive standardised residuals. The large positive and negative residuals are shown in Table 4.60.

Table 4.60
Summary statistics for the learning potential measurement model standardised residuals

Description	Values
Smallest Standardised Residual	-4.588
Median Standardised Residual	0.000
Largest Standardised Residual	4.515
Largest Negative Standardised Residuals	
Residual for RES_1 and LM_2	-3.110
Residual for OPT_1 and HOPE_1	-3.356
Residual for OPT_2 and TCE_1	-2.613
Residual for ENG and TCE_1	-2.728
Residual for ENG and OPR_1	-4.588
Residual for AFR and OPT_1	-3.400
Largest Positive Standardised Residuals	
Residual for RES_2 and ASL_1	2.731
Residual for ENG and OPR_2	2.957
Residual for AFR and OPT_2	3.208
Residual for MATH and TCE_1	3.665
Residual for MATH and TCE_2	3.869
Residual for MATH and ASE_1	4.515
Residual for MATH and ASE_2	4.247
Residual for MATH and CON_1	2.926
Residual for MATH and CON_2	2.863
Residual for MATH and LM_1	3.972
Residual for MATH and LM_2	3.057
Residual for MATH and HOPE_1	2.585
Residual for MATH and HOPE_2	3.890
Residual for MATH and RES_1	3.203

TCE_1 & TCE_2 = Time Cognitively Engaged; ASL_1 &ASL_2 = Academic Self-Leadership; ASE_1 & ASE_2 = Academic Self-efficacy; CON_1 & CON_2 = Conscientiousness; LM_1 & LM_2 = Learning Motivation; HOPE_1 & HOPE_2 = Hope; RES_1 & RES_2 = Resilience; OPT_1 & OPT_2 = Optimism; ENG = English First Additional Language; AFR = Afrikaans Home Language; MATH = Mathematics.

Table 4.60 provides a summary of the standardised residuals and shows that fourteen standardised residuals obtained values greater than 2.58, and six standardised residuals obtained values smaller than -2.58. The twenty large residuals constitute 10.53% of the total number of unique variance and covariance terms in the observed variance-covariance matrix. Therefore, only approximately 11% of the observed variances and covariances were inaccurately estimated from the measurement model parameter estimates. This can be regarded as acceptable, and relatively small. However it should be taken cognisance of the fact that in general the prevalence of large positive residuals is more than the number of large negative residuals. This suggested that the observed variance and covariance terms in the observed covariance matrix were typically underestimated by the derived model parameter estimates. Adding paths to the model might rectify this problem. This suggests complex items parcels and/or correlated measurement error terms.

The Q-plot, presented in Figure 4.6, serves as an additional graphical display of residuals. This graph plotted the standardised residuals (horizontal axis) against the quintiles of the normal distribution (Diamantopoulos & Siguaw, 2000). When interpreting the Q-plot, it is crucial to note the extent to which the data points fall on a 45 degrees reference line. Good model fit would be indicated if the points fall on the 45-degrees reference line (Jöreskog & Sörbom, 1993).

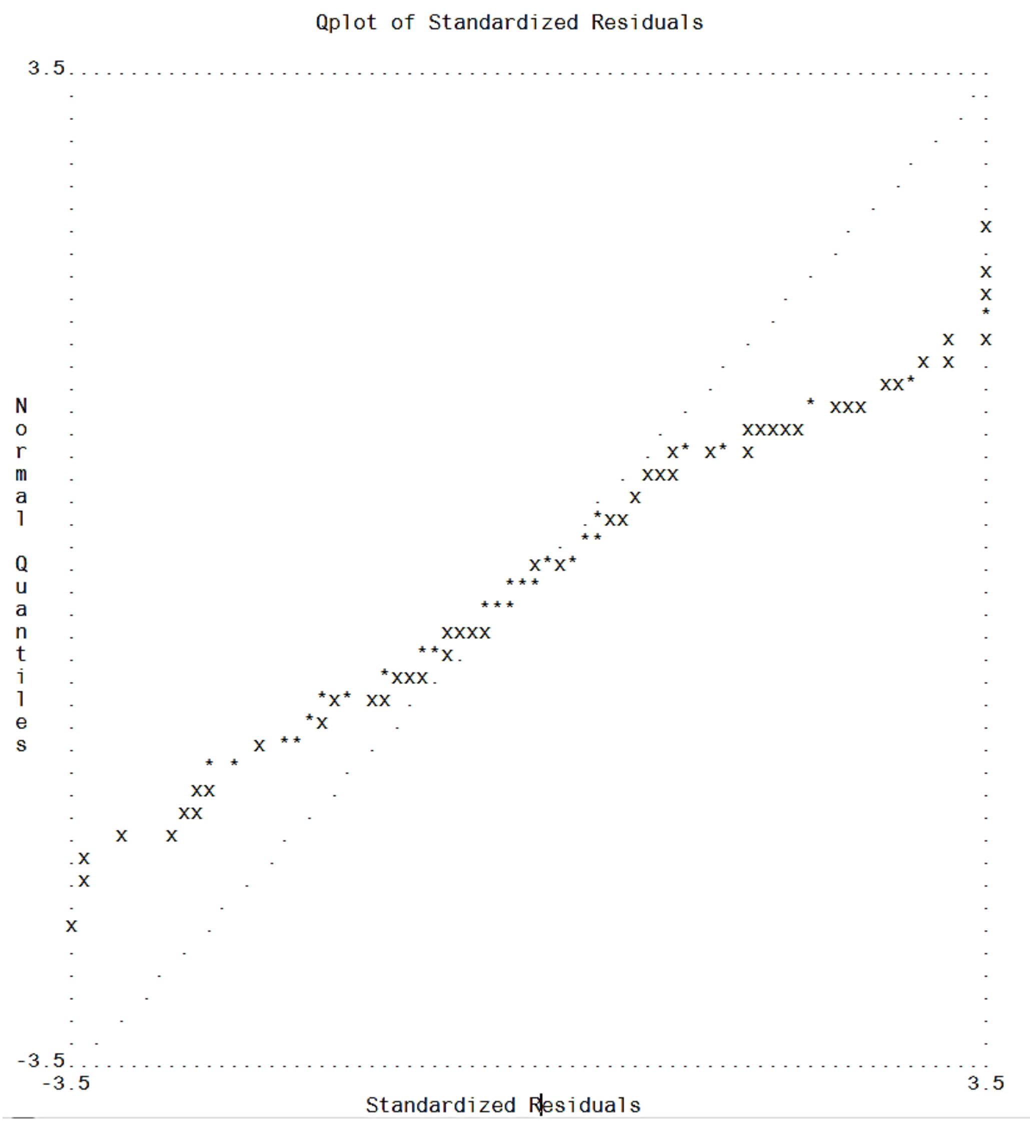

Figure 4.6 Q-plot for the learning potential standardised residuals

The data points do swivel away from the Q-plot presented in Figure 4.6. The Q-plot, however, clearly indicates good to reasonable measurement model fit as the standardised residuals tend to deviate from the 45-degree line; however only really in the upper and lower regions on the X-axis.

These findings are in line with the results reported in Figure 4.6 and Table 4.60 where there were both large positive and large negative standardised residuals, but where the large positive standardised residuals dominated. Subsequently, given the evaluation of the standardised residuals of the measurement model, it is also important to evaluate the measurement model modification indices.

b.) Modification Indices

The intention when operationalising the latent variables in the structural model was that each item parcel would reflect only a single latent variable. The intention was not that specific item parcels should serve to reflect respondent's standing on more than one latent variable. Although it was acknowledged that no item parcel will be a perfectly valid measure of the latent variable it was earmarked to reflect, the item parcels were created with the conviction that the systematic measurement error component of each item parcel does not have a common source. The intention was therefore that the measurement error terms should be uncorrelated.

The learning potential measurement model reflected these intentions. In Λ_X each item parcel was allowed to load on only one latent variable. The other loadings were fixed to zero. In Θ_δ all off-diagonal elements were fixed to zero. Model modification indices are aimed at answering the question whether any of the currently fixed parameters, when freed in the model, would significantly improve the fit of the model. Modification indices (MI) shows the extent to which the X^2 fit statistic will decrease if a currently fixed parameter in the model is freed and the model re-estimated (Jöreskog & Sörbom, 1993). Large modification index values (>6.64) is indicative of parameters that, if set free, would improve the fit of the model significantly ($p < .01$) (Theron. 2010). However, if these indices suggest any modification of the model, it should only be implemented if they can be theoretical/substantially justified (Kelloway, 1998). The purpose of the evaluation of the modification indices for this measurement model was however not so much on possible ways of actually modifying the measurement model. The purpose was therefore not to free paths; it was to evaluate the fit of this measurement model. If only a limited number of ways exist to improve the fit of the model, it comments favourably on the fit of the current model. The modification indices calculated for the lambda-X and theta-delta matrices are presented in Table 4.61 and Table 4.62.

Table 4.61
Learning potential measurement model modification indices calculated for lambda-X

	TCE	ASL	ASE	CON	LM	HOPE	RES	OPT	LP
TCE_1	-	0.878	0.004	0.187	1.131	0.275	0.153	0.167	0.081
TCE_2	-	0.859	0.004	0.172	0.913	0.244	0.135	0.136	0,081
ASL_1	0.000	-	0.354	1.115	0.094	2.743	0.008	0.335	0.004
ASL_2	0.000	-	0.392	3.092	0.082	4.864	0.009	0.781	0.004
ASE_1	0.000	**46.945**	-	2.783	0.000	0.000	0.037	0.000	0.063
ASE_2	0.000	**36.727**	-	6.557	0.000	0.000	0.030	0.000	0.065
CON_1	0.000	2.377	0.004	-	4.393	1.167	0.628	0.540	1.579
CON_2	0.000	3.107	0.006	-	**10.469**	2.563	0.731	0.808	1.697
LM_1	1.254	5.574	0.041	3.608	-	1.052	1.708	0.188	0.092
LM_2	1.307	5.468	0.016	3.339	-	1.989	1.691	0.242	0.101
HOPE_1	1.237	1.319	0.409	0.258	6.219	-	1.194	**8.472**	2.316
HOPE_2	0.992	1.006	0.346	0.214	4.784	-	0.889	3.832	2.197
RES_1	0.000	0.000	4.849	**27.202**	0.000	0.000	-	5.481	0.376
RES_2	4.624	5.711	1.464	5.782	1.458	0.002	**-**	1.342	0.417
OPT_1	6.263	0.161	0.000	3.066	0.000	0.000	**7.554**	**-**	**16.007**
OPT_2	1.324	0.030	0.986	0.655	0.578	1.616	3.141	**-**	**12.838**
ENG	**8.452**	3.407	1.241	3.056	4.524	**6.644**	1.667	4.559	-
AFR	0.100	0.386	2.934	0.140	0.589	0.004	0.916	0.021	-
MATH	**12.505**	2.656	**18.427**	**9.517**	**15.831**	**12.430**	**10.600**	**10.339**	**-**

TCE= Time Cognitively Engaged (TCE_1/2); ASL= Academic Self-leadership (ASL_1/2; ASE= Academic Self-efficacy (ASE_1/2); CON= Conscientiousness (CON_1/2); LM= Learning Motivation (LM_1/2l; RES= Resilience (RES_1/2); OPT= Optimism (OPT_1/2).

When examining the modification indices presented in Table 4.61, it is evident that seventeen parameters that, if set free, would improve the fit of the model significantly (p > .01). The matrix shows that *English* marks and *Mathematics* marks (Learning Performance), also loaded onto the *time cognitively engaged* construct. *Academic self-efficacy* also loaded onto *academic self-leadership*. The matrix revealed that the *Mathematics* marks (learning performance) also loaded onto a range of other constructs, including; *academic self-efficacy, conscientiousness, learning motivation, hope, resilience,* and *optimism*. The matrix further revealed that *conscientiousness* also loaded onto *learning motivation*, while *hope* also loaded on *optimism*. The matrix also showed that *resilience* loaded onto *conscientiousness*, and that *English* (*learning performance*) loaded onto *hope*. *Optimism* is said to load onto *resilience*, while *optimism* is said to load onto *learning performance*. The lambda-X modification results suggest that these additional paths would significantly improve the fit of the model. However, the matrix suggested that only 17 out of the 152 possible ways of modifying the model (11.2%) would result in significant improvements to the model fit. This small percentage commented favourably on the fit of the learning potential measurement model.

Table 4.62

Learning potential measurement model modification indices calculated for theta-delta

	TCE_1	TCE_2	ASL_1	ASL_2	ASE_1	ASE_2	CON_1	CON_2	LM_1	LM_2
TCE_1										
TCE_2										
ASL_1	0.630	0.210								
ASL_2	0.108	0.004								
ASE_1	0.763	0.538	0.197	2.509						
ASE_2	0.605	0.816	0.010	4.222						
CON_1	0.187	0.000	2.848	0.513	0.164	0.604				
CON_2	0.467	0.083	0.864	0.005	0.001	0.087				
LM_1	0.883	0.073	0.066	0.765	1.226	1.805	1.643	0.000		
LM_2	0.007	0.526	0.276	0.691	1.836	2.704	0.110	3.003		
HOPE_1	0.000	3.043	0.289	0.000	0.000	0.035	1.274	1.067	**8.074**	0.079
HOPE_2	0.142	5.268	0.038	0.745	0.243	0.083	2.967	2.426	2.195	2.311
RES_1	3.142	1.603	1.658	0.902	1.611	1.351	0.157	0.034	3.596	2.679
RES_2	6.868	3.866	4.176	2.824	2.464	2.050	0.025	0.913	0.262	0.004
OPT_1	0.499	0.455	0.001	0.115	1.190	0.040	0.887	3.205	1.465	1.964
OPT_2	2.107	0.071	0.285	1.114	2.010	0.092	0.405	0.230	0.336	0.276
ENG	0.595	0.331	0.051	0.052	0.581	2.137	0.007	0.033	0.097	0.194
AFR	0.517	0.051	1.758	0.606	0.521	0.527	0.334	0.552	1.435	0.878
MATH	0.010	1.281	5.700	2.110	2.159	0.070	0.012	0.011	0.704	0.007

Table 4.62 (Continue)

Learning potential measurement model modification indices calculated for theta-delta

	HOPE_1	HOPE_2	RES_1	RES_2	OPT_1	OPT_2	ENG	AFR	MATH
RES_1	1.216	0.061							
RES_2	0.568	1.329							
OPT_1	4.249	1.839	1.275	1.335					
OPT_2	1.585	0.197	1.801	2.099					
ENG	0.012	0.930	0.055	0.064	3.132	**7.246**			
AFR	1.014	2.497	0.221	0.011	0.388	0.327			
MATH	0.178	1.260	1.925	0.900	0.019	0.184	**8.141**	**6.128**	

TCE= Time Cognitively Engaged (TCE_1/2); ASL= Academic Self-leadership (ASL_1/2; ASE= Academic Self-efficacy (ASE_1/2); CON= Conscientiousness (CON_1/2); LM= Learning Motivation (LM_1/2l; RES= Resilience (RES_1/2); OPT= Optimism (OPT_1/2).

Upon inspection of Table 4.62, the modification indices reveal that 4 covariance terms out of the possible 162 (2.64%) terms in the matrix were significant (>6.640). Thus, 2.64% of the values, if set free, should result in a significant decrease in the X^2 measure. However, the resultant completely standardised expected changes did not warrant setting these parameters free. Also, no persuasive argument existed to justify correlated measurement error terms. Therefore, this very small percentage of large significant modification index values that were obtained for Θ_δ commented very favourably on the fit of the measurement model.

The small percentage of large standardised residuals along with the small percentage of large modification index values obtained for Λ_X and $\Theta\delta$ generally indicated good model fit.

This study, as was the case in the Burger (2012) study, argued that a possibility exists that the lack of exact fit of the measurement model could be accounted for by the fact that the measurement model does not model the structural relations existing between the learning competency potential latent variables, the learning competency latent variables, and the learning performance latent variable.

4.9.2.3 Interpretation of the measurement model

Taking the spectrum of fit indices, the distribution of standardised residuals, the percentage large standardised residuals and the percentage large modification indices calculated for Λ_X and Θ_δ into consideration, good to reasonable measurement model fit can be concluded. This warrants the interpretation of the measurement model parameter estimates since they allowed the close reproduction of the observed covariance matrix. The examination of the magnitude and the statistical significance of the slope of the regression of the observed variables on their respective latent variables provided an indication of the validity of the measures. In other words, if a measure is designed to provide a valid reflection of a specific latent variable, then the slope of the regression of X_i, the observed variable, on ξ_j, the respective latent variable in the fitted measurement model has to be substantial and significant (Diamantopoulos & Siguaw, 2000).

Table 4.63 contains the unstandardised regression coefficients of the regression of the item parcels on the latent variables they were connected to. The unstandardised $\boldsymbol{\Lambda}_x$ (lambda-X) matrix provides an indication of the average change expressed in the original scale units in the manifest variable associated with one unit change in the latent variable. The regression coefficients/loadings of the manifest variables on the latent variables are significant ($p < .05$) if the absolute value of the t-values exceed |1.96|. Significant indicator loadings provide validity evidence in favour of the item parcel indicators (Diamantopoulos & Siguaw, 2000). Table 4.63 shows the unstandardised factor loading matrix $\boldsymbol{\Lambda}_x$.

Table 4.63

Learning potential measurement model unstandardised lambda-X matrix

	TCE	ASL	ASE	CON	LM	HOPE	RES	OPT	LP
TCE_1	0.799 (0.037) **21.607**								
TCE_2	0,778 (0.039) **18.845**								
ASL_1		0.932 (0.040) **23.159**							
ASL_2		0.849 (0.043) **19.775**							
ASE_1			0.900 (0.045) **20.054**						
ASE_2			0.793 (0.042) **18.869**						
CON_1				1.043 (0.048) **21.573**					
CON_2				1.063 (0.048) **22.013**					
LM_1					0.988 (0.049) **20.186**				
LM_2					0.934 (0.054) **17.384**				
HOPE_1						0.807 (0.043) **18.939**			
HOPE_2						0.901 (0.051) **17.666**			
RES_1							0.695 (0.054) **12.762**		
RES_2							0.662 (0.070) **9.482**		
OPT_1								0.643 (0.060) **10.696**	
OPT_2								0.529 (0.060) **8.805**	
ENG									8.990 (0.616) **14.601**
AFR									8.398 90.507) **16.551**
MATH									12.306 (1.077) **11.427**

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism. TCE_1 & TCE_2 = Time Cognitively Engaged; ASL_1 &ASL_2 = Academic Self-Leadership; ASE_1 & ASE_2 = Academic Self-efficacy; CON_1 & CON_2 = Conscientiousness; LM_1 & LM_2 = Learning Motivation; HOPE_1 & HOPE_2 = Hope; RES_1 & RES_2 = Resilience; OPT_1 & OPT_2 = Optimism; ENG = English First Additional Language; AFR = Afrikaans Home Language; MATH = Mathematics.

All the indicator variables loaded significantly on the latent variables that they were designed to reflect. Diamantopoulos and Siguaw (2000) suggest that there exist a problem when relying solely on unstandardised loadings and associated t-values in that it may be difficult to compare the validity of different indicators measuring a particular construct. Consequently, it is recommended to also consider the completely standardised factor loading matrix.

The completely standardised estimates indicate the average change in standard deviation units in the indicator variable associated with one standard deviation change in the latent variable to which it has been linked,. The factor loading estimates were considered to be satisfactory if the completely standardised factor loading estimates exceeded a stringent cut-off of .71 (Hair et al., 2006). Interpreted from this perspective, Table 4.64 reveals that all loadings were greater than .71 except for the loadings of the second *resilience* item parcel on the *resilience* latent variable, the first *optimism* item parcel on the *optimism* latent variable, the second *optimism* item parcel on the *optimism* latent variable and the average Mathematics mark on the *learning performance during evaluation* latent variable. Based on these results, the identified item parcels could be regarded as to some degree problematic. The factor loadings of these three item parcels on their designated latent variables were, however, not that excessively low to warrant serious concern.

Table 4.64

Learning Potential measurement model completely standardised solution for lambda

	TCE	ASL	ASE	CON	LM	HOPE	RES	OPT	LP
TCE_1	0.951								
TCE_2	0,928								
ASL_1		0.991							
ASL_2		0.931							
ASE_1			0.926						
ASE_2			0.903						
CON_1				0.928					
CON_2				0.970					
LM_1					0.923				
LM_2					0.833				
HOPE_1						0.886			
HOPE_2						0.841			
RES_1							0.847		
RES_2							**0.624**		
OPT_1								**0.695**	
OPT_2								**0.584**	
ENG									0.779
AFR									0.928
MATH									**0.634**

TCE_1 & TCE_2 = Time Cognitively Engaged; ASL_1 &ASL_2 = Academic Self-Leadership; ASE_1 & ASE_2 = Academic Self-efficacy; CON_1 & CON_2 = Conscientiousness; LM_1 & LM_2 = Learning Motivation; HOPE_1 & HOPE_2 = Hope; RES_1 & RES_2 = Resilience; OPT_1 & OPT_2 = Optimism; ENG = English First Additional Language; AFR = Afrikaans Home Language; MATH = Mathematics.

Spangenberg and Theron (2005) explained that the total variance in the i^{th} item parcel (X_i) could be the result of the following:

1. Variance in the latent variable the item set was meant to reflect (ξ_j).
2. Variance due to variance in the other systematic latent effects the item parcel was designed to reflect, or
3. Variance due to random measurement error.

The R^2 values presented in Table 6.65 represents the squared multiple correlations for the regression of the item parcels on their designated latent variables. These reflect the proportion of variance in the item parcel/composite that can be explained by the variance in the latent variable it was tasked to reflect (Myburgh, 2013). Table 6.65 will therefore assist in determining the reliability of the item parcels/composites, which serves as the indicators. This is due to the fact that reliability refers to the extent to which variance in indicator variables can be attributed to systematic sources, irrespective of whether the source of variance is relevant to the measurement intention or not. The values in Table 4.65 could simultaneously be interpreted as lower-bound item reliabilities (Diamantopoulos & Siguaw, 2000).

Table 4.65
Learning potential measurement model squared multiple correlations for X-variables

TCE_1	0.904
TCE_2	0,861
ASL_1	0.983
ASL_2	0.867
ASE_1	0.857
ASE_2	0.816
CON_1	0.861
CON_2	0.940
LM_1	0.852
LM_2	0.694
HOPE_1	0.786
HOPE_2	0.708
RES_1	0.718
RES_2	**0.390**
OPT_1	**0.482**
OPT_2	**0.341**
ENG	0.607
AFR	0.862
MATH	**0.401**

TCE_1 & TCE_2 = Time Cognitively Engaged; ASL_1 &ASL_2 = Academic Self-Leadership; ASE_1 & ASE_2 = Academic Self-efficacy; CON_1 & CON_2 = Conscientiousness; LM_1 & LM_2 = Learning Motivation; HOPE_1 & HOPE_2 = Hope; RES_1 & RES_2 = Resilience; OPT_1 & OPT_2 = Optimism; ENG = English First Additional Language; AFR = Afrikaans Home Language; MATH = Mathematics.

Hair et al.'s (2006) critical factor loading of .71 implies a critical R^2 value of .50. A high R^2 value (> .50) would indicate a high reliability of the indicator, as it shows that a satisfactory proportion of variance in each indicator variable is explained by its underlying latent variable. All the indicators, except for the second *resilience* item parcel (.390), the first *optimism* item parcel (.482), the second *optimism* item parcel (.341) and the average Mathematics mark (.401) obtained reliabilities higher than .50. All of the item parcels, explained more than 61% of variance in the latent variables they were meant to reflect. These were the same problematic item parcels that were identified in Table 4.66. These item parcels were problematic because an unambiguous test of the structural relations hypothesised in the Burger – Prinsloo learning potential structural model would only be possible if sufficient confidence exists in the validity and reliability of the measures used to operationalise the latent variables. Table 4.65 indicates that the reliability and validity of these four indicators have been compromised. A substantial amount of item parcel variance can be attributed to systematic and random measurement error. This is illustrated in Table 4.66 that displays the completely standardised measurement error variances. These values can be interpreted as the proportion of item parcel variance that is due to systematic non-relevant variance and random error variance. Table 4.66 shows the percentage of variance in the indicator variable that cannot be explained in terms of the latent variable. The same four problematic indicators are yet again identified.

Table 4.66
Learning potential measurement model completely standardised theta-delta matrix

TCE_1	0.096
TCE_2	0,139
ASL_1	0.017
ASL_2	0.133
ASE_1	0.143
ASE_2	0.184
CON_1	0.139
CON_2	0.060
LM_1	0.148
LM_2	0.306
HOPE_1	0.214
HOPE_2	0.292
RES_1	0.282
RES_2	**0.610**
OPT_1	**0.518**
OPT_2	**0.659**
ENG	0.393
AFR	0.138
MATH	**0.599**

TCE_1 & TCE_2 = Time Cognitively Engaged; ASL_1 &ASL_2 = Academic Self-Leadership; ASE_1 & ASE_2 = Academic Self-efficacy; CON_1 & CON_2 = Conscientiousness; LM_1 & LM_2 = Learning Motivation; HOPE_1 & HOPE_2 = Hope; RES_1 & RES_2 = Resilience; OPT_1 & OPT_2 = Optimism; ENG = English First Additional Language; AFR = Afrikaans Home Language; MATH = Mathematics.

In the four problematic indicators presented in Table 4.66, more variance is explained by measurement error than is explained by the latent variable these indicators were meant to reflect. The unstandardised theta-delta matrix is presented in Table 4.67. This table revealed that all indicators were statistically significantly ($p < .05$) plagued by measurement error as is evident in the fact that all indicators report t-values greater than 1.96. Statistically significant measurement error variances are welcomed since perfectly reliable and valid measures of latent variables represent an unattainable ideal.

Table 4.67
Learning potential measurement model unstandardised solution for theta-delta

TCE_1	**TCE_2**	**ASL_1**	**ASL_2**	**ASE_1**
0.068	0,098	0.015	0.110	0.135
(0.014)	(0.015)	(0.020)	(0.019)	(0.031)
4.674	**6.360**	**6.360**	**5.795**	**4.393**
ASE_2	**CON_1**	**CON_2**	**LM_1**	**LM_2**
0.142	0.176	0.071	0.170	0.385
(0.029)	(0.031)	(0.026)	(0.038)	(0.044)
4.877	**5.590**	**2.711**	**4.439**	**8.745**
HOPE_1	**HOPE_2**	**RES_1**	**RES_2**	**OPT_1**
0.177	0.335	0.190	0.686	0.443
(0.028)	(0.042)	(0.050)	(0.090)	(0.062)
6.388	**8.016**	**3.813**	**7.607**	**7.109**
OPT_2	**ENG**	**AFR**	**MATH**	
0.540	52.340	11.307	225.777	
(0.063)	(7.995)	95.037)	(19.695)	
8.545	**6.546**	**2.245**	**11.463**	

TCE_1 & TCE_2 = Time Cognitively Engaged; ASL_1 &ASL_2 = Academic Self-Leadership; ASE_1 & ASE_2 = Academic Self-efficacy; CON_1 & CON_2 = Conscientiousness; LM_1 & LM_2 = Learning Motivation; HOPE_1 & HOPE_2 = Hope; RES_1 & RES_2 = Resilience; OPT_1 & OPT_2 = Optimism; ENG = English First Additional Language; AFR = Afrikaans Home Language; MATH = Mathematics.

If the measurement error variances were insignificant suspicion with regards to the measurement model would have been raised (Van Heerden, 2013).

4.9.3 Discriminant Validity

Discriminant validity refers to the degree of uniqueness achieved from item measures/indicators in defining a latent variable (Gefen, 2003). This form of validity implies that the measurement items of each latent variable load with a large coefficient together on that factor, while loading with small coefficients on the other latent variables in the model each measured by their own sets of items that load high on them (Churchill.1979). The nine latent variables comprising the Burger - Prinsloo learning potential structural model were expected to correlate to some degree. This was due to the fact that these nine latent variables were conceptualised as nine qualitatively distinct, although related constructs.

However, despite this, these nine latent variables should not correlate excessively high with each other. Consequently, it is crucial to consider the latent variable inter-correlations which are presented in the phi matrix depicted in Table 4.68.

Table 4.68
Phi matrix

	TCE	ASL	ASE	CON	LM	HOPE	RES	OPT	LP
TCE	1.000								
ASL	0.716	1.000							
	(0.037)								
	19.167								
ASE	0.630	0.587	1.00						
	(0.060)	(0.059)							
	10.431	9.971							
CON	0.743	0.652	0.631	1.000					
	(0.033)	(0.038)	(0.050)						
	22.716	17.070	12.627						
LM	0.748	0.599	0.678	0.662	1.000				
	(0.036)	(0.043)	(0.053)	(0.042)					
	20.554	13.942	12.741	15.733					
HOPE	0.754	0.635	0.611	0.665	0.682	1.000			
	(0.031)	(0.044)	(0.066)	(0.045)	(0.048)				
	24.140	14.350	9.208	14.645	14.166				
RES	0.476	0.469	0.561	0.446	0.590	0.587	1.000		
	(0.062)	(0.060)	(0.059)	(0.062)	(0.056)	(0.065)			
	7.651	7.783	9.455	7.175	10.531	9.002			
OPT	0.644	0.696	0.564	0.627	0.682	0.838	0.764	1.000	
	(0.063)	(0.059)	(0.086)	(0.071)	(0.072)	(0.061)	(0.070)		
	10.198	11.813	6.545	8.821	9.411	13.702	10.919		
LP	0.254	0.116	0.257	0.119	0.374	0.232	0.320	0.048	1.000
	(0.059)	(0.061)	(0.056)	(0.064)	(0.053)	(0.066)	(0.065)	(0.078)	
	4.305	1.918	4.613	1.850	7.125	3.495	4.911	0.618	

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

In Table 4.68, the top value represents the unstandardised φ_{ij} estimate, while the second value reflects the standard error of $\varphi_{ij,}$ and the third value shows the test statistic z. So, the results presented in Table 4.68 suggested that all the inter-latent variables correlations are statistically significant ($p < .05$). Correlations are considered excessively high if they exceed a value of .90. Judged by the results presented, none of the correlations in the phi matrix are excessively high; only one of the latent variables correlated with a value exceeding .80 (.838), but still lower than .88.

The absence of excessively high correlations between the latent variables in the phi matrix presented in Table 4.68 is however, not a very strong indication of discriminant validity (Myburgh, 2013). This is due to the fact that a possibility exists that the latent performance dimensions might correlate unity in the parameter but correlate less than unity in the statistic because of sampling errors.

Consequently, it was decided to evaluate this possibility by calculating a 95% confidence interval for each sample estimate in Φ utilizing an Excel macro developed by Scientific Software International (Mels, 2009). If any confidence interval includes the value of 1, it would imply that the null hypothesis H_0: p=1 cannot be rejected. Confidence in the claim that the two latent performance dimensions are unique, qualitatively distinct dimensions of the learning performance construct would thereby be seriously eroded. The 95% confidence intervals for the 36 inter-latent variable correlations are shown in Table 4.69. None of the 36 confidence intervals included unity. The discriminant validity of this measure was thereby indicated.

Table 4.69
95% confidence interval for sample phi estimates

	95% Confidence Interval		
Estimate	**Standard Error Estimate**	**Lower Limit of 95% Confidence Interval**	**Upper Limit of 95% Confidence Interval**
0.716	0.037	0.635	0.781
0.630	0.060	0.498	0.734
0.747	0.033	0.675	0.805
0.748	0.036	0.669	0.811
0.754	0.031	0.687	0.809
0.476	0.062	0.346	0.588
0.644	0.063	0.504	0.751
0.254	0.059	0.135	0.360
0.587	0.059	0.459	0.691
0.652	0.038	0.571	0.720
0.599	0.043	0.508	0.677
0.635	0.044	0.541	0.713
0.469	0.060	0.343	0.578
0.696	0.059	0.562	0.795
0.116	0.061	-0.005	0.233
0.631	0.050	0.523	0.719
0.678	0.053	0.560	0.769
0.611	0.066	0.465	0.724
0.561	0.059	0.435	0.666
0.564	0.086	0.373	0.709
0.257	0.056	0.144	0.363
0.662	0.042	0.572	0.737
0.665	0.045	0.567	0.744
0.446	0.062	0.317	0.559
0.627	0.071	0.468	0.747
0.119	0.064	-0.008	0.242
0.682	0.048	0.5767	0.765
0.590	0.056	0.469	0.689
0.682	0.072	0.515	0.799
0.374	0.053	0.266	0.473
0.587	0.065	0.445	0.700
0.838	0.061	0.671	0.924
0.232	0.066	0.099	0.357
0.764	0.070	0.589	0.871
0.320	0.065	0.187	0.441
0.048	0.078	-0.105	0.199

The latent variables did correlate to some degree, but none of the correlations were excessively large. Neither did any of the 36 confidence include unity. It can therefore, with 95% confidence, be concluded that none of the inter-latent variable correlations in the parameter are equal to 1. This means that each of the latent variables has unique aspects, although they share variance. Therefore the latent variables included in this study are qualitatively distinct. These findings therefore indicate that the discriminant validity of the Burger - Prinsloo Learning Potential model latent variables is satisfactory.

4.9.4 Summary of the Learning Potential Measurement Model

This section focussed on evaluating the way in which the measurement model represents the relationship between the learning potential latent variables and its matching indicator variables. The evaluations were based on the results presented by the CFA analyses conducted with LISREL.

The results showed that overall good close model fit was achieved. The null hypothesis of exact fit was rejected; subsequently, the null hypothesis for close fit was tested and not rejected. The interpretation of the measurement model, the standardised residuals and the modification indices all indicated good model fit. All the results obtained seemed to validate the claim that the specific indicator variables reflected the specific latent variables they were meant to reflect. Moreover, all but four of the composite indicator variables reflected in excess of 60% of the latent variable variance they were designed to represent. These four indicator variables included RES_2, OPT_1 and OPT_2 (i.e. *resilience* and *optimism*), as well as MATH (*learning performance during evaluation*). Measurement error variances, although significant ($p < .05$), were generally small.

Based on the results presented in this section, it was concluded that sufficient merit for the measurement model existed, and that the operationalisation of this model was successful. It would therefore be possible to derive an unambiguous verdict on the fit of the structural model from the fit of the comprehensive LISREL model.

4.10 EVALUATING THE FIT OF THE STRUCTURAL MODEL

The structural relations between the variables hypothesised by the proposed model displayed in Figure 2.5 were tested with the help of structural equation modelling. LISREL 8.8 was used to evaluate the fit of the comprehensive learning potential structural model. Robust maximum likelihood estimation method was used to produce the estimates. An admissible final solution of the parameter estimates for the revised learning potential structural model was obtained after 19 iterations. The next section consists of the fit- and the modification indices of the structural model for each of the revised forms leading to the final learning potential structural model. The full range of fit- and other statistics for the final learning potential structural model will be discussed in detail at the end of the next section.

4.10.1 Fit of the learning potential structural model (original model)

A visual representation of the fitted learning potential structural model is shown in Figure 4.7 and the overall fit statistics are presented in Table 4.70.

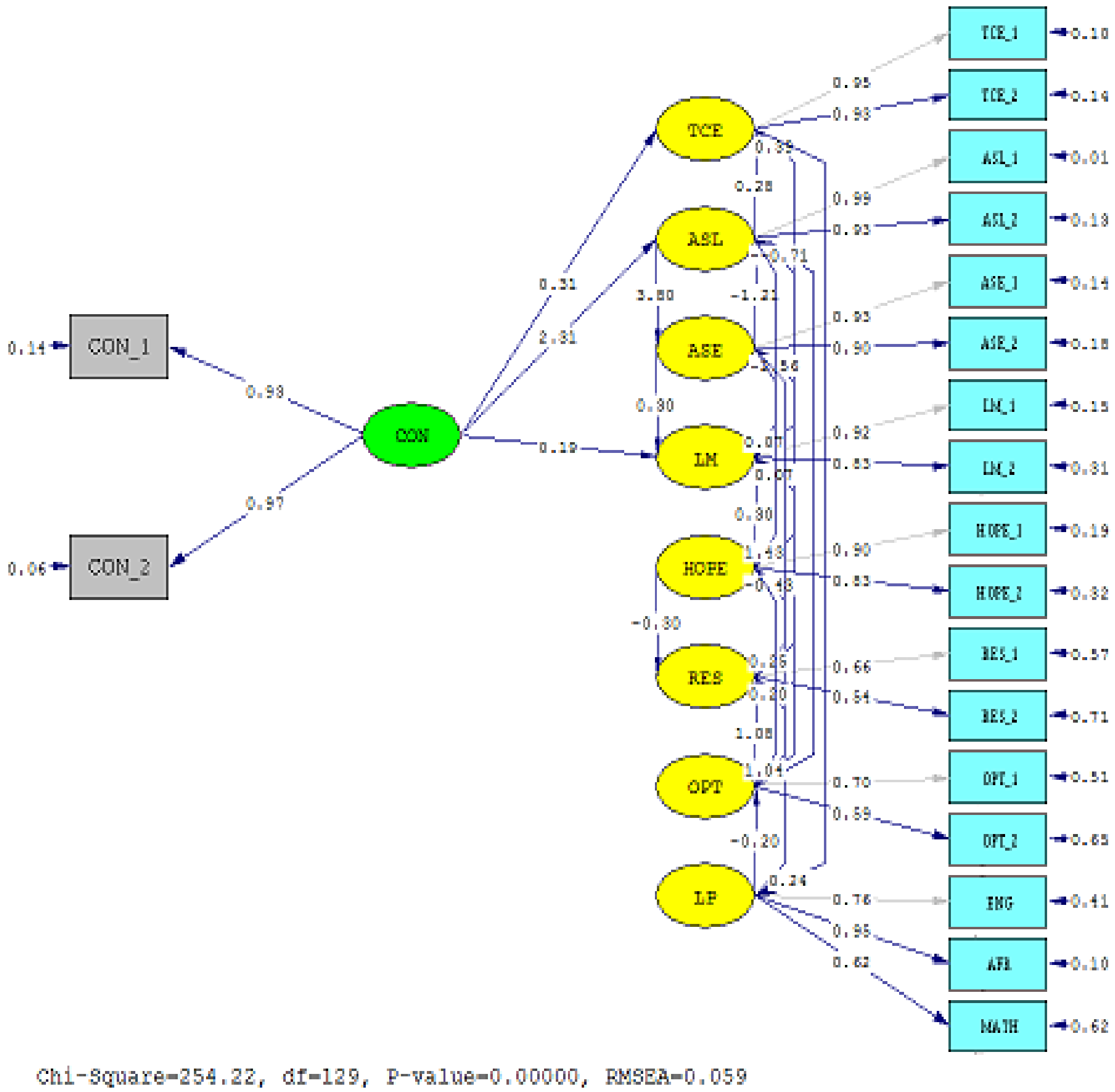

Figure 4.7 Representation of the fitted learning potential structural model (completely standardised solution)

The purpose of assessing the overall fit of a model is to determine the degree to which the model as a whole is consistent with the empirical data gathered (Diamantopoulos & Siguaw, 2000). They also explained that a wide range of goodness-of-fit indices have been developed that can be used as a summary of the model's overall fit, and these will be discussed with reference to the output results of this model. The full range of fit indices (both comparative and absolute) is reported in Table 4.70.

Table 4.70
Goodness of fit statistics for the learning potential structural model

Degrees of Freedom	129
Minimum Fit Function Chi-Square	279.977 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	272.961 (p = 0.000103)
Satorra-Bentler Scaled Chi-square	**254.217 (p = 0.0)**
Chi-square Corrected for NON-Normality	419.838 (p = 0.0)
Estimated Non-centrality Parameter (NCP)	125.217
90 Percent Confidence Interval for NCP	(83.752 ; 174.474)
Minimum Fit Function Value	1.004
Population Discrepancy Function Value (FO)	0.449
90 Percent Confidence Interval for FO	(0.300 ; 0.625)
Root Mean Square Error of Approximation (RMSEA)	**0.0590**
90 Percent Confidence Interval for RMSEA	**(0.0482 ; 0.0696)**
P-value for test of Close Fit (RMSEA < .05)	**0.0826**
Expected Cross-Validation Index (ECVI)	**1.348**
90 Percent Confidence Interval for ECVI	(1.200 ; 1.525)
ECVI for Saturated Model	**1.362**
ECVI for Independence model	**34.517**
Chi-square for Independence Model with 253 Degrees of Freedom	9592.369
Independence AIC	**9630.369**
Model AIC	**376.217**
Saturated AIC	**380.000**
Independence CAIC	**9718.430**
Model CAIC	**658.939**
Saturated CAIC	**1260.610**
Normed Fit Index (NFI)	**.973**
Non-Normed Fit Index (NNFI)	**.982**
Parsimony Normed Fit Index (PNFI)	**.734**
Comparative Fit Index (CFI)	**.987**
Incremental Fit Index (IFI)	**.987**
Relative Fit Index (RFI)	**.965**
Critical N (CN)	**186.781**
Root Mean Square Residual (RMR)	**.950**
Standardised RMR	**.0662**
Goodness of Fit Index (GFI)	**.907**
Adjusted Goodness of Fit Index (AGFI)	**.862**
Parsimony Goodness of Fit Index	**.616**

Table 4.70 indicates that the structural model achieved a Satorra-Bentler Chi-square value of 254.217 (P = 0.0). The p-value associated with the Satorra-Bentler X^2 clearly showed a significant test statistic. If this X^2-value was non-significant, it would have been indicative that the model can reproduce the observed covariance matrix to a degree of accuracy that can only be explained in terms of sampling error (Kelloway, 1998). However, in this case, the model is not able to achieve this, and therefore this model cannot reproduce the observed covariance matrix with the amount of accuracy to allow the discrepancy to be attributed to sampling error only.

Based on this, the exact fit null hypothesis was rejected, and the p-value for close fit (RMSEA < .05) presented in Table 4.70 was considered. It showed that the close fit null hypothesis should not be rejected (p > .05; .0826). Also, Table 4.70 shows that this model achieved a RMSEA value of .0590, which indicated that this model achieved reasonable close fit in the sample. The upper bound of the 90 percent confidence interval for RMSEA (0.0482; 0.0696) fell substantially above the target value of .05. Therefore, although close fit in the parameter was a permissible position to hold also is the position that the model only fits reasonably in the parameter.

Table 4.70 shows that the model ECVI (1.348) was smaller than the value obtained for the independence model (34.517). Also, the model ECVI (1.362) was also slightly smaller than the saturated model (1.362). Based on these results it is evident that a model more closely resembling the fitted model seemed to have a better chance of being replicated in a cross-validation sample than the independence models. However, it only has a slightly better chance than the saturated model.

The parsimonious normed fit index (PNFI = .734) and the parsimonious goodness-of-fit index (PGFI = .616) approach model fit from this perspective. These two values should range from 0 to 1.0, with higher values indicating a more parsimonious fit, as is evident in this case. According to Kelloway (1998) and Hair et al., (2006), the PNFI and the PGFI are more meaningfully used when comparing two competing theoretical models and are therefore not feasible for any of the CFA analyses in this study. So, again, this study did take cognisance of these two indices, but they did not play a superior role in the decision regarding the interpretation of the overall fit indices.

Table 4.70 shows that the model AIC (376.217) suggested that the fitted structural model provided a more parsimonious fit than the independent model (9630.369) and the saturated model (380.00). Similarly, the CAIC (658.939) also achieved a value lower than both the independence (9718.430) and the saturated models (1260.610). The fit indices presented in Table 4.70 reflect the normed fit index (NFI = .973 the non-normed fit index (NNFI = .982), the comparative fit index (CFI = .987), the incremental fit index (IFI = .987), and relative fit index (RFI = .965). The results reflected in Table 4.70, shows that all these values fell comfortably above the .90 level. This showed that satisfactory comparative fit relative to the independent model, existed.

The critical N (CN) shows the size that a sample must achieve in order to acknowledge the data fit of a given model on a statistical basis (Van Heerden, 2013). As a rule-of-thumb, a critical N greater than 200 is indicative of sufficient representation of the data by a specific model. Table 4.70 reveals that a CN of 186.781 was achieved, which was not above the threshold, and therefore not acceptable. Kelloway (1998) suggested that SRMR-values that are smaller than .05, presented in the goodness-of-fit indices, are indicative of an acceptable fit. This model produced a SRMR-value of .0662, which is above the .05 cut-off value, and will therefore not be regarded as adequate or acceptable.

The AGFI (.862) adjusts the GFI (.907) for the degrees of freedom in the model and should be between 0 and 1.0; with values exceeding .90. The GFI and AGFI produced by this model can be regarded as satisfactory and indicative of good model fit.

Determining and evaluating the fit of the structural model indicates to what extent the model can reproduce the observed covariance matrix (Diamantopoulos & Siguaw, 2000). The evidence presented up to this point showed that the proposed structural model was able to reproduce the observed covariance matrix to a degree of accuracy that warranted sufficient faith in the structural model and the derived parameter estimates to warrant the interpretation of these estimates. Consequently, the parameter estimates for Γ and $\mathbf{B}$ was interpreted. It is thereby not denied that the very real possibility exists that the fit of the model could be improved by freeing specific elements in Γ and $\mathbf{B}$ that are currently fixed to zero.

4.10.2 Interpretation of structural model parameter estimates

The investigation of the unstandardised beta matrix depicted in Table 4.71**,** showed that H_{09}, H_{012}, H_{015}, H_{017}, H_{019}, H_{020}, H_{021}, H_{024}, H_{025}, H_{027} could be rejected in favour of the formulated Ha hypothesis. The path specific hypotheses formulated as Hypotheses H_{05}, H_{06}, H_{07}, H_{08}, H_{10}, H_{011}, H_{013}, H_{014}, H_{016}, H_{018}, H_{022}, H_{023}, and H_{026} were therefore corroborated. Although the test statistic values associated with the estimates for β_{23} and β_{78} exceeded the critical value of |1.96|, it was nonetheless not permissible to reject H_{01} and $H_{016.}$ This was because the range of values hypothesised and H_{a10} and H_{a16} disagreed with the sign of the sample β estimates.

Consequently, even though the two hypothesised paths were significant; the output suggested that there existed a negative relationship between the latent variables at hand, and therefore resulting in the two null hypotheses in question were not rejected. These two paths included the hypothesis that *academic self-efficacy* positively influences *academic self-leadership*, and the hypothesis that *learning performance* positively influences *optimism*. The relationship between *academic self-efficacy* and *academic self-leadership* was hypothesised, in both this and the Burger (2012) study, to be positive. It was based on the argument that an increase in an individual's *academic self-efficacy*, the belief in their academic ability, would result in an increase in their *academic self-leadership*. The results produced in the Burger (2012) study indicated that the relationship should actually be negative. After theorising conducted by Burger (2012), it was discovered that the negative structural relationship between these latent variables to some degree, does make substantive theoretical sense. This is based on the argument that if an individual believes that s/he is capable of succeeding in an academic or learning task, that individual may not see the need to implement *academic self-leadership* strategies as this person may feel that they are capable of performing successfully without the implementation of such strategies. However, Burger (2012) suggested that cross-validation research should be conducted to resolve this debate. This is based on the idea that the mere fact that one research study yields certain results is no guarantee that the measure will work as well the next time; indeed, often it does not (Kendzierski & Morganstein, 2009). However, this study cannot be regarded as cross-validation[66], it can rather be seen as a way to 're-test' the paths hypothesised by Burger (2012). It therefore could be argued that this study serves as a way to confirm the paths supported by the Burger (2012) research.

The relationship between *learning performance during evaluation* and *optimism* was also hypothesised to be positive. However, despite the fact that the path was significant, the sign associated with this relationship did not agree as it was negative.

[66] Cross-Validation is the process of fitting a multi-group structural (or measurement) model on two or more samples from the same population. Seeing that this study elaborated on the Burger (2012) model, this study does not classify as a cross-validation study. The research can however, to some degree, be regarded as confirmation of the already established paths. However, it is important to take note of the fact that the Beta's and Gamma's in the proposed model are partial regression co-efficients, seeing that they are indeed affected by the other latent variables in the model. Nevertheless, this study to come degree can be regarded as a re-test of the paths confirmed by the Burger (2012) study.

The theorised relationship was based on the argument that if an individual achieved success in their learning opportunity and their *learning performance during evaluation* increased, their explanatory style will become more positive and attribute this positive event to personal, permanent, and pervasive cases, and therefore take credit for this positive occurrence. This relationship was hypothesised as a reinforcing circle, denoting that the success achieved by the individual will result in a more positive attributional style. However, when considering the argument for the negative relationship between *academic self-efficacy* and *academic self-leadership*, this line of thinking also makes substantive theoretical sense for this particular relationship. Because, if an individual achieves success in their learning opportunity, and achieves a high level of *learning performance during evaluation*, they don't necessarily see the need to implement a positive attribution style, as the 'boost' generated by the achievement/success related to a successful performance will be enough. *Optimism* is not viewed as necessary when achievement and success are high.

Table 4.71
Learning potential structural model unstandardised beta matrix

	TCE	ASL	ASE	LM	HOPE	RES	OPT	LP
TCE		0.279 (0.056) 5.016		0.387 (0.067) 5.800				
ASL			-1.210 (0.0530) **-2.284**		0.0683 (0.508) **-1.345**		-0.708 (0.575) **-1.231**	
ASE		3.799 (2.051) **1.852**				-2.557 (1.877) **-1.362**		
LM		0.069 (0.077) **0.900**	0.299 (0.096) 3.098		0.297 (0.156) **1.908**		0.072 (0.156) **0.462**	
HOPE			1.427 (0.481) 2.968				-0.432 (0.464) **-0.930**	
RES			0.249 (0.116) 2.154		-0.301 (0.369) **-0.818**		1.085 (0.411) 2.642	0.196 (0.110) **1.781**
OPT					1.041 (0.114) 9.125			-0.200 (0.078) **-2.548**
LP	0.241 (0.067) 3.617							

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The other 10 paths that were non-significant, where the null hypotheses were consequently not rejected and where the path-specific hypotheses were not corroborated included; the hypothesis that *academic self-leadership* positively influences *academic self-efficacy* (H_{012}); that *academic self-leadership* positively influences *learning motivation* (H_{09}); that *hope* positively influences *academic self-leadership* (H_{021}); that *hope* positively influences *learning motivation* (H_{020}); that *hope* positively influence *resilience* (H_{025}); that *resilience* positively influences *academic self-efficacy* (H_{024}); that *optimism* positively influences *academic self-leadership* (H_{017}); that *optimism* positively influences *learning motivation* (H_{015}); that *optimism* positively influences *hope* (H_{019}); and that *learning performance during evaluation* positively influences *resilience* (H_{027}). The other paths (thirteen) were supported, and therefore not rejected. These include the hypothesis that *time cognitively engaged* positively influences *learning performance during evaluation* (H_{05}); that *conscientiousness* positively influences *time cognitively engaged* (H_{06}); that *learning motivation* positively influences *time cognitively engaged* (H_{04}); that *conscientiousness* positively influences *learning motivation* (H_{08}); that ac*ademic self-efficacy* positively influences *academic self-leadership* (H_{010}); that ac*ademic self-leadership* positively influences *time cognitively engaged* (H_{011}); that *conscientiousness* positively influences *academic self-leadership* (H_{013}); that *academic self-efficacy* positively influences *learning motivation* (H_{014}); that *learning performance during evaluation* positively influences *optimism* (H_{078}); that *hope* positively influences *optimism* (H_{018}); that *academic self-efficacy* positively influences *hope* (H_{022}); that *optimism* positively influences *resilience* (H_{023}); and that *resilience* positively influences *academic self-efficacy* (H_{026}).

The beta matrix reflecting the statistically significance of the β_{ij} estimates revealed that 12 of the 20 hypothesised paths between the endogenous latent variables were not supported while 8 of the 20 hypothesised paths between the endogenous latent variables were supported. Table 4.72 shows the unstandardised gamma matrix. From an inspection of Table 4.72 it can be seen that all the hypothesised relationships were found to be statistically significant ($p < .05$). H_{06}, H_{013} and H_{08} were therefore all three rejected. Support was therefore obtained for Hypotheses H_{a6}, H_{a13} and H_{a8} that *conscientiousness* positively influences *time cognitively engaged* (H_{a6}), that c*onscientiousness* positively influences *academic self-leadership* (H_{a13}) and that *conscientiousness* positively affects *learning motivation* (H_{a8}).

Table 4.72
Learning potential structural model unstandardised gamma matrix

	CON
TCE	0.312 (0.065) 4.777
ASL	2.305 (0.624) 3.697
ASE	-
LM	0.191 (0.083) 2.297
HOPE	-
RES	-
OPT	-
LP	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The gamma matrix reflecting the statistically significance of the γ_{ij} estimates revealed that all 3 of the hypothesised paths between the single exogenous latent variable in the model and three endogenous latent variables were supported. In total therefore 13 of the 23 hypothesised paths in the model were supported while 10 were not supported.

4.10.3 Modification of structural model (model A)

Based on these results, it was decided to first delete the ten paths that were not statistically significant. It was further decided to retain the two paths were the β estimates were statistically significant but were an inappropriate formulation of the alternative hypothesis prevented the rejection of the null hypotheses. Although it cannot be claimed that these path-specific hypotheses were corroborated the post hoc theorising presented in this study and in Burger (2012) provides sufficient ground to retain these paths in the model, but now under revised path-specific substantive hypotheses that postulate negative relationships. The modified model (model A) was subsequently fitted again. A visual representation of the model, as well as the fit indices is presented in section 4.10.4.

4.10.4 Assessing the overall fit statistics of the modified structural model (model A)

A visual representation of the first modified structural model is presented in Figure 4.8. The full range of fit indices (both comparative and absolute) for the first modified model (model A) is reported in Table 4.73.

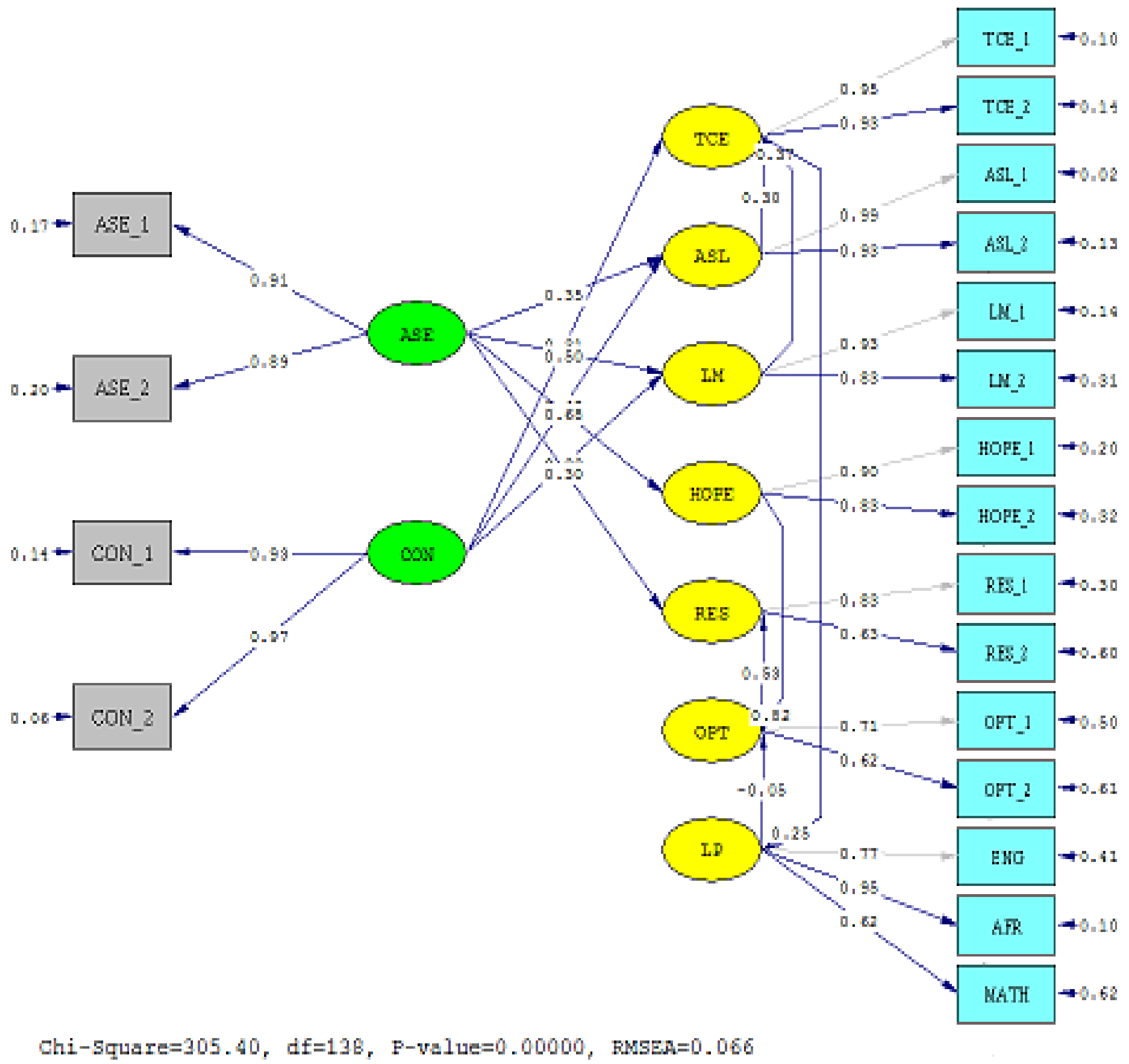

Figure 4.8 Representation of the first modified (model A) fitted learning potential structural model (completely standardised solution)

Table 4.73
Goodness of fit statistics for the modified learning potential model (model A)

Degrees of Freedom	138
Minimum Fit Function Chi-Square	355.921 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	339.311 (p = 0.00)
Satorra-Bentler Scaled Chi-square	**305.401 (p = 0.00)**
Chi-square Corrected for NON-Normality	500.522 (p = 0.0)
Estimated Non-centrality Parameter (NCP)	167.401
90 Percent Confidence Interval for NCP	(120.643 ; 221.896)
Minimum Fit Function Value	1.276
Population Discrepancy Function Value (FO)	0.600
90 Percent Confidence Interval for FO	(0.432 ; 0.795)
Root Mean Square Error of Approximation (RMSEA)	**0.0659**
90 Percent Confidence Interval for RMSEA	**(0.0560 ; 0.0759)**
P-value for test of Close Fit (RMSEA < .05)	**0.00495**
Expected Cross-Validation Index (ECVI)	**1.467**
90 Percent Confidence Interval for ECVI	(1.300 ; 1.525467
ECVI for Saturated Model	**1.362**
ECVI for Independence model	**34.517**
Chi-square for Independence Model with 253 Degrees of Freedom	9592.369
Independence AIC	**9630.369**
Model AIC	**409.401**
Saturated AIC	**380.000**
Independence CAIC	**9718.430**
Model CAIC	**650.410**
Saturated CAIC	**1260.610**
Normed Fit Index (NFI)	**.968**
Non-Normed Fit Index (NNFI)	**.978**
Parsimony Normed Fit Index (PNFI)	**.781**
Comparative Fit Index (CFI)	**.982**
Incremental Fit Index (IFI)	**.982**
Relative Fit Index (RFI)	**.961**
Critical N (CN)	**165.039**
Root Mean Square Residual (RMR)	**1.030**
Standardised RMR	**.104**
Goodness of Fit Index (GFI)	**.887**
Adjusted Goodness of Fit Index (AGFI)	**.844**
Parsimony Goodness of Fit Index	**.644**

The Satorra-Bentler Chi-square was 305.401 (p = 0.00), which showed that the null hypothesis of exact fit was again rejected. The p-value of close fit was 0.00495. Therefore indicating that the close fit null hypothesis should also be rejected (p < .05). The RMSEA value of .0659 indicates a reasonable fit in the sample. The upper and lower bounds of the 90 percent confidence interval for RMSEA (0.0560; 0.0759) fell above the .05 cut-off value. The upper bound, however still fell below the critical RMSEA value representing mediocre model fit. Reasonable, but not close model fit, in the parameter may therefore be concluded.

A CN of 165.039 (<200) was achieved, which was not above the 200 threshold, and therefore not acceptable. Kelloway (1998) suggested that SRMR-values that are smaller than .05, presented in the goodness-of-fit indices, are indicative of an acceptable fit. This model produced a SRMR-value of .104, which fell substantially above the .05 cut-off value, and will therefore not be regarded as adequate or acceptable. The evidence presented up to this point showed that the modified originally hypothesised structural model was able to reproduce the observed covariance matrix to a reasonable degree of accuracy that warranted some faith in the structural model and the derived parameter estimates. The model fit, however, deteriorated due to the deletion of the insignificant paths in the model. Consequently, the parameter estimates for gamma and beta, as well as the modification indices calculated by LISREL were explored to investigate possible ways in which the reduced model (model A) could be modified to improve the fit.

4.10.5 Modification of structural model (model B)

Tables 4.74 and 4.75 revealed that only one of the paths retained in the original model were no longer supported. The hypothesis that *learning performance* negatively influences *optimism* (H_{025}) was no longer significant, and the hypothesis was therefore rejected and the path subsequently deleted. All the remaining path-specific hypotheses that were retained in the original learning potential structural model were again supported.

Table 4.74
Learning potential structural modified model (model A) unstandardised beta matrix

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE		0.302 (0.056) 5.407	0.370 (0.066) 5.593				
ASL							
LM							
HOPE							
RES						0.526 (0.106) 4.944	
OPT				0.819 (0.093) 8.840			-0.049 (0.063) **-0.778**
LP	0.253 (0.063) 4.027						

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

Table 4.75 depicts the unstandardised gamma matrix for model A. Table 4.75 shows that all the hypothesised relationships that were retained in the original learning potential structural model were again found to be statistically significant (p < .05).

Table 4.75
Learning potential structural modified model (model A) unstandardised gamma matrix

	ASE	CON
TCE	-	0.308 (0.070) 4.381
ASL	0.352 (0.081) 4.330	0.422 (0.086) 4.878
LM	0.500 (0.086) 5.817	0.333 (0.088) 3.796
HOPE	0.682 (0.060) 11.316	-
RES	0.303 (0.083) 3.651	-
OPT	-	-
LP	-	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

Despite these results, it is important to not only consider whether to delete any of the existing paths, but also to determine whether any additional paths should be added. It was consequently decided to inspect the modification indices calculated for the beta and gamma matrices, to see whether the addition of theoretically justifiable new paths could possibly improve the fit of the model.

The modification indices (MI) assist in identifying fixed parameters that if freed, would statistically significantly improve the fit of the model. This is determined by calculating the extent to which the X^2 fit statistic decreases when each of the currently fixed parameters in the model is freed and the model re-estimated (Jöreskog & Sörbom, 1993). Structural parameters currently fixed to zero with large modification index values (> 6.64), are classified as parameters, that if set free, would improve the fit of the model significantly (p < .01) (Van Heerden, 2013). Parameters that are identified with high MI-values, should, however, only be freed if it makes substantive theoretical sense to do so (Kelloway, 1998).

Consequently, a very convincing theoretical argument should be set forward in support of the proposed linkage between the latent variables in question. The completely standardised expected change for the parameters should also be considered, as these suggest the extent to which it would change from its currently fixed value of zero in the completely standardised solution, if freed.

The magnitude of the completely standardised expected change should be substantial enough to warrant freeing the parameter, and the sign of the completely expected change should in addition make sense in terms of the theoretical argument proposed in support of the suggested path (Jöreskog & Sörbom, 1993). These authors further suggest that the modification indices calculated for the various matrices defining the structural model, i.e. **Γ, B** and **Ψ**, should be considered to identify the parameter with the highest MI-value. This value is then identified, and freed if a convincing theoretical argument exist, and the magnitude and sign (+ or -) of the completely standardised expected change is substantial and makes theoretical sense. If no convincing theoretical argument exists, nor the magnitude or sign is appropriate, then the parameter with the second highest MI-value should be considered.

In this study, and for the purpose of modifying the proposed structural model depicted in Figure 2.5*,* only the **Γ** and **B** matrix were evaluated. The possibility of freeing the fixed off-diagonal elements of the variance-covariance matrix **Ψ** was not considered. Suggesting an argument for the theoretical rational for freeing currently fixed covariance's terms in **Ψ** in a study with a chosen research design similar to this one, would require additional latent variables to be introduced and included in the model.

The modification indices calculated for the beta matrix are presented in Table 4.76, and modification indices calculated for the gamma matrix are presented in Table 4.77. In accordance with the process suggested by Jöreskog and Sörbom (1993), the parameter with the highest MI-value was located and found in the beta matrix.

Table 4.76
Modified (model A) learning potential structural model modification indices for the beta matrix

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE	-	-	-	11.101	0.175	2.933	0.251
ASL	-	-	3.482	15.620	6.585	22.400	2.336
LM	0.831	3,674	-	21.182	16.415	21.072	14.390
HOPE	**97.467**	49.524	60.490	-	1.280	**-**	1.524
RES	0.187	0.037	4.047	-	-	-	12.237
OPT	2.649	13.397	10.781	-	7.085	-	-
LP	-	2.227	13.713	0.674	10.874	0.421	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

When examining the modification indices presented in Table 4.76, it is evident that the parameter with the highest MI-value was β_{41} (97.467). This suggested that if a path was added to the proposed structural model hypothesising the relationship between *time cognitively engaged* and *hope*, the fit of the model would improve significantly. The completely standardised expected change for the beta coefficient is of sufficient magnitude (.848), and obtained a positive sign. However, despite this, a critical question to ask is whether a positive relationship between *time cognitively engaged* and *hope*, makes theoretical sense.

Following the process of theorising, an argument was developed that explained the positive influence of *time cognitively engaged* on *hope*. As mentioned in Chapter 2, *hope* consists of two components; a willpower and waypower segment. The first component forms the basis of this argument. A person's willpower assists them in setting their goals and determining the way in which they are going to achieve these goals. This part of the *hope* definition is supported by another definition of *hope* provided by Snyder (2002); *hope* is a person's generalised expectancy to achieve their goals. *Time cognitively engaged*, according to Burger (2012), refers to the extent to which an individual attend to and extend mental effort in a learning task. So, an increase in *time cognitively engaged* will lead to an increase in classroom learning performance, which will ultimately lead to more successful *learning performance during evaluation*[67].

[67] Success in terms of a learning opportunity is a very subjective goal. This is because what success means for one person, does not necessarily apply to another individual. For example, success to one learner may be 80%, while to another learner it may be just to pass the subject (50%). Success, and the goal of success depends on a range of factors, i.e. ability, interest, perceptions etc. However, despite the differences in the meaning of success for different people, an increase in *Time Cognitively Engaged* will very likely lead to an greater likelihood in the person's expectancy to achieve their goal of 'success', i.e. *hope*.

Therefore, if an individual is more cognitively engaged in a learning opportunity, their expectancy to achieve their goals will most probably increase. This is due to the fact that an increase in cognitive engagement will result in probable success; which are very likely to serve as a person's primary goal throughout a developmental opportunity. Therefore, based on this argument it made theoretical sense to include the positive relationship of *time cognitively engaged* and *hope* into the modified (model B) structural model.

The modification indices for gamma did not reveal a MI-value greater than those that were obtained for beta. The results of the modification indices for gamma are presented in Table 4.77.

Table 4.77
Modified (model A) learning potential structural model modification indices for gamma matrix

	ASE	**CON**
TCE	1.045	-
ASL	-	-
LM	-	-
HOPE	-	56.261
RES	-	0.656
OPT	4.306	3.847
LP	3.636	2.696

Based on the results presented in this section, it was decided to first delete the path that hypothesised the positive influence of *learning performance* on *optimism*, as it was not significant ($p > .05$). It was additionally decided to also include the hypothesised path that portray a positive relationship between *time cognitively engaged* and *hope*, seeing that it made theoretical sense, the magnitude of the expected change was satisfactory, and the sign of the expected change was in line with the theorised argument. The modified model (model B) was subsequently fitted; a visual representation of the model, as well as the fit indices will be discussed next.

4.10.6 Assessing the overall fit statistics of the modified structural model (model B)

A visual representation of the second modified, better fitting, structural model is presented in Figure 4.9. The full range of fit indices (both comparative and absolute) for the second modified model (model B) is presented in Table 4.78, and explained thereafter.

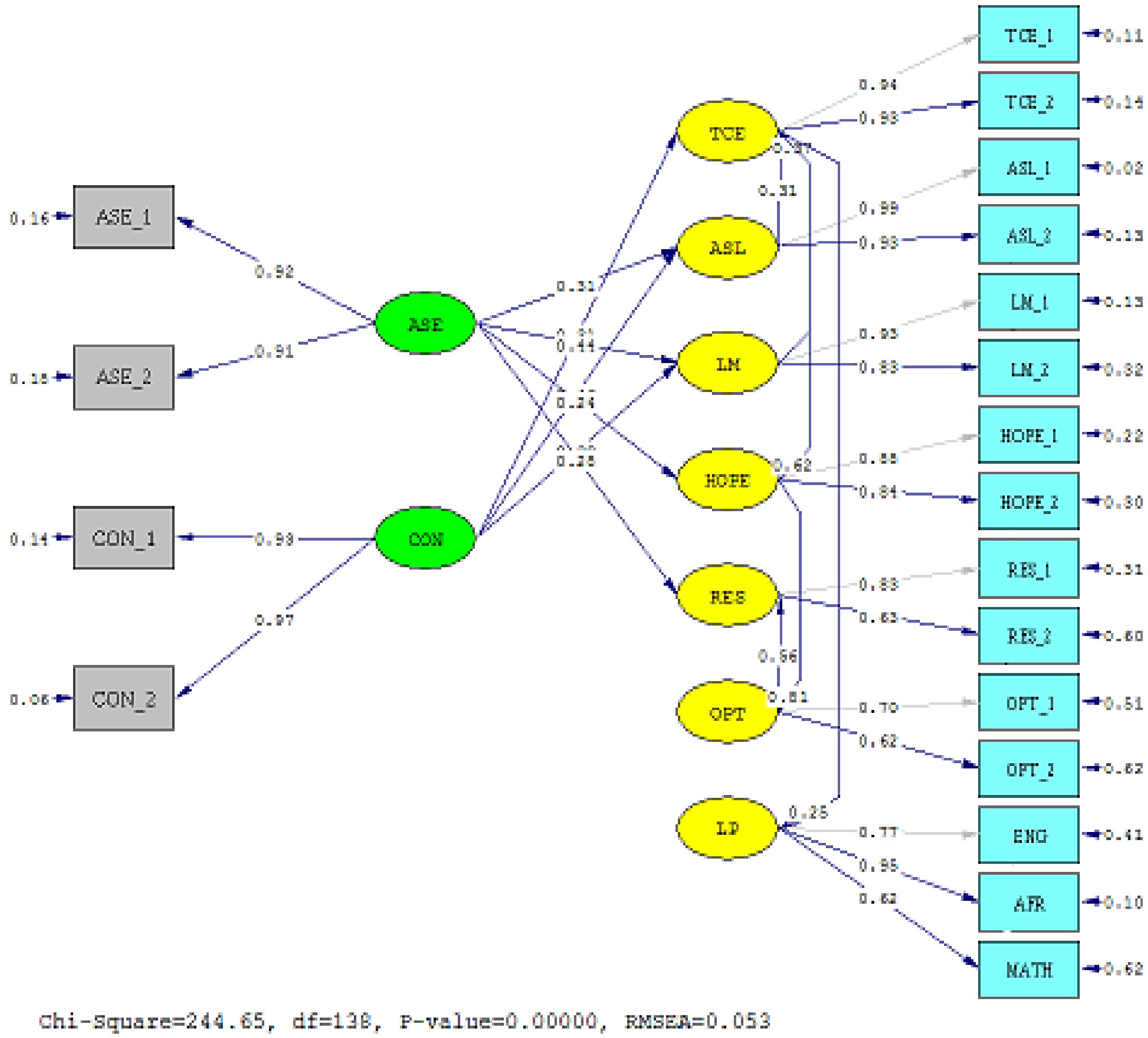

Figure 4.9 Representation of the modified fitted learning potential structural model (model B)

Table 4.78

Goodness of fit statistics for the modified learning potential model (model B)

Degrees of Freedom	138
Minimum Fit Function Chi-Square	273.920 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	262.978 (p = 0.00)
Satorra-Bentler Scaled Chi-square	**244.652 (p = 0.00)**
Chi-square Corrected for NON-Normality	488.842 (p = 0.0)
Estimated Non-centrality Parameter (NCP)	106.652
90 Percent Confidence Interval for NCP	(66.929 ; 154.226)
Minimum Fit Function Value	0.982
Population Discrepancy Function Value (FO)	0.382
90 Percent Confidence Interval for FO	(0.240 ; 0.553)
Root Mean Square Error of Approximation (RMSEA)	**0.0526**
90 Percent Confidence Interval for RMSEA	**(0.0417 ; 0.0633)**
P-value for test of Close Fit (RMSEA < .05)	**0.333**
Expected Cross-Validation Index (ECVI)	**1.250**
90 Percent Confidence Interval for ECVI	(1.107 ; 1.420)
ECVI for Saturated Model	**1.362**

ECVI for Independence model	**34.517**
Chi-square for Independence Model with 253 Degrees of Freedom	9592.369
Independence AIC	**9630.369**
Model AIC	**348.652**
Saturated AIC	**380.000**
Independence CAIC	**9718.430**
Model CAIC	**589.661**
Saturated CAIC	**1260.610**
Normed Fit Index (NFI)	**.974**
Non-Normed Fit Index (NNFI)	**.986**
Parsimony Normed Fit Index (PNFI)	**.786**
Comparative Fit Index (CFI)	**.989**
Incremental Fit Index (IFI)	**.989**
Relative Fit Index (RFI)	**.968**
Critical N (CN)	**205.771**
Root Mean Square Residual (RMR)	**0.964**
Standardised RMR	**.0712**
Goodness of Fit Index (GFI)	**.910**
Adjusted Goodness of Fit Index (AGFI)	**.876**
Parsimony Goodness of Fit Index	**.661**

The Satorra-Bentler Chi-square presented in Table 4.78 revealed a value of 244.652 (p = 0.00), which justified the rejection of the null hypothesis of exact fit. The close fit null hypothesis was not rejected (p > .05). The RMSEA value of .0526 indicated a good to reasonable fit in the sample. The upper bound of the 90 percent confidence interval for RMSEA (0.0417; 0.0633) was still above the .05 cut-off value, however, much closer than the previous fit-statistics revealed. The critical N (CN) also improved, Table 4.78 reveals a CN of 205.771 (>200), which is above the threshold, and therefor regarded as acceptable. Kelloway (1998) suggested that SRMR-values that are smaller than .05, are indicative of an acceptable fit. This model produced a SRMR-value of .0712, which emphasised that even though the fit has improved, acceptable fit was still not achieved.

Therefore, the evidence suggested that the proposed model was able to reproduce the observed covariance matrix to a degree of accuracy that warranted faith in the structural model and the derived parameter estimates. The question nonetheless remained whether there still existed theoretically justifiable ways of modifying the model that would improve the fit of the model and with that the plausibility of the parameter estimates. Consequently, the parameter estimates for beta and gamma, as well as the modification indices calculated by LISREL were explored, yet again, to investigate possible ways in which this model could be modified which would result in more acceptable fit.

4.10.7 Modification of structural model (model C)

Table 4.79 depicts the unstandardised **B** matrix for model B. Table 4.79 revealed that all the relationships hypothesised between endogenous latent variables in the model were found to be statistically significant ($p < .05$). All the retained original paths were still statistically significant ($p < .05$) and the newly added path between *time cognitively engaged* and *hope* was statistically significant as well ($p < .05$).

Table 4.79
Learning potential structural modified model (model B) unstandardised beta matrix

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE		0.309 (0.055) 5.586	0.371 (0.065) 5.673				
ASL							
LM							
HOPE	0.619 (0.086) **7.209**						
RES						0.560 (0.105) 5.339	
OPT				0.811 (0.092) 8.856			
LP	0.255 (0.063) 4.046						

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The results depicted in Table 4.80 for the unstandardised gamma matrices; revealed similar results where all the hypothesised relationships were statistically significant ($p < .05$). Consequently, no paths needed to be deleted from model B.

Table 4.80

Learning potential structural modified model (model B) unstandardised gamma matrix

	ASE	CON
TCE	-	0.311 (0.071) 4.391
ASL	0.310 (0.081) 3.812	0.459 (0.086) 5.326
LM	0.442 (0.088) 5.039	0.385 (0.089) 4.249
HOPE	0.238 (0.081) 2.951	-
RES	0.282 (0.078) 3.618	-
OPT	-	-
LP	-	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The modification indices for the beta matrix are presented in Table 4.81, and the MI-values for the fixed parameter in the gamma matrix are presented in Table 4.82. In accordance with the process introduced by Jöreskog and Sörbom (1993), the parameter with the highest MI-value was found in the beta matrix. The highest MI-value was between *hope* and *time cognitively engaged* (122.139). This suggested that if this path is added to the structural model hypothesising the relationship between these two constructs, the fit of this model would improve significantly. However, even though the completely standardised expected change for the beta coefficient is of sufficient magnitude (-3.131), it was a negative value. Therefore, it suggested that the path that should be added is the hypothesis that *hope* negatively influence time cognitively engaged. A critical question that therefore needed to be considered was whether a negative relationship between these variables made theoretical sense.

Table 4.81
Modified learning potential structural model (model B) modification indices for beta matrix

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE	-	-	-	**122.139**	10.742	33.027	0.179
ASL	-	-	4.801	4.408	2.113	9.165	1.862
LM	2.833	5.007	-	2.842	6.339	5.075	15.454
HOPE	**-**	4.430	3.810	-	0.290	0.622	0.015
RES	1.523	0.128	3.325	-	-	-	9.251
OPT	0.222	12.165	8.833	-	5.342	-	0.766
LP	-	2.405	13.518	0.464	7.031	0.001	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

Following the process of theorising, an argument was developed that explained the negative influence of *hope on time cognitively engaged*. Section 4.10.6 explained that an increase in the time a person cognitively engages in a developmental opportunity will result in an increase in the *hope* this person displays. This is because, if an individual is more cognitively engaged in a learning opportunity, their expectancy to achieve their goals will increase. This is based on the fact that *hope* arises when a concrete positive goal is expected (success in the developmental opportunity) (Van Ryzin, Gravely & Roseth, 2009). Staats and Stassen (1985) further explains that *hope* consists of the cognitive elements of visualising and expecting, as well as of the affective elements of feeling good about the expected events and outcomes. *Hope* requires setting goals, planning how to achieve them, using mental imagery, creativity, risk-taking and mental exploration (Breznitz, 1986; Fromm, 1994; Isen, 1990; Lazarus, 1991; & Snyder, 1994).

Averill, Catlin, and Chon (1990) argued that *hope* refer to an aspiration for achieving a concrete, aspired goal of vital interest, that has a strong likelihood of attainment. The argument up to this point may suggest that if an individual is high on *hope*, they will be more cognitively engaged, than individuals low on *hope* (Jarymowicz & Bar-tal, 2006). However, an equally plausible counter argument suggests that as individuals increase their *time cognitively engaged*, it will result in them being more hopeful (as explained in Section 4.10.6), and as soon as their levels of *hope* are heightened, and they are expecting positive goals with a strong likelihood of achievement, they will then because of the high expectancy decrease the time they cognitively engage, as they will not see the need for it. Also, individuals high on *hope*, have a greater tendency to solve problems using a rational problem solving style (Chang, 1998; Snyder, Cheavens & Michael, 1999).

It therefore makes sense to argue that individuals high on *hope* may tend to decrease the time they cognitively engage in the developmental opportunity in contrast to individuals low on *hope*. A negative relationship between these two latent variables does appear as unreasonable as it seemed at first glance. Based on the latter argument it makes theoretical sense that a person's *time cognitively engaged* will decrease as their level of *hope* increases. The negative relationship between *hope* and *time cognitively engaged* was therefore included in the modified structural model (model C).

The modification indices for the gamma matrix did not reveal any MI-value greater than the values that were obtained for the beta matrix. The modification indices calculated for the gamma matrix are revealed in Table 4.82.

Table 4.82
Modified learning potential structural model (model B) modification indices for gamma matrix

	ASE	CON
TCE	0.003	-
ASL	-	-
LM	-	-
HOPE	-	4.004
RES	-	1.032
OPT	2.474	2.573
LP	3.530	2.931

Based on the results shown in this section, it was decided to add the hypothesised path, that a negative relationship exists between *hope* and *time cognitively engaged*, seeing that it made theoretical sense, the magnitude of the expected change was satisfactory (-3.131), and the sign of the expected change was in line with the theorised argument. The modified model (model C) was subsequently fitted again; a visual representation of the model, as well as the fit indices will be presented in the next section.

4.10.8 Assessing the overall fit statistics of the modified structural model (model C)

A visual representation of the third modified structural model (model C) is presented in Figure 4.10. The full range of fit indices (both comparative and absolute) for the third modified model (model C) is shown in Table 4.83, and explained thereafter.

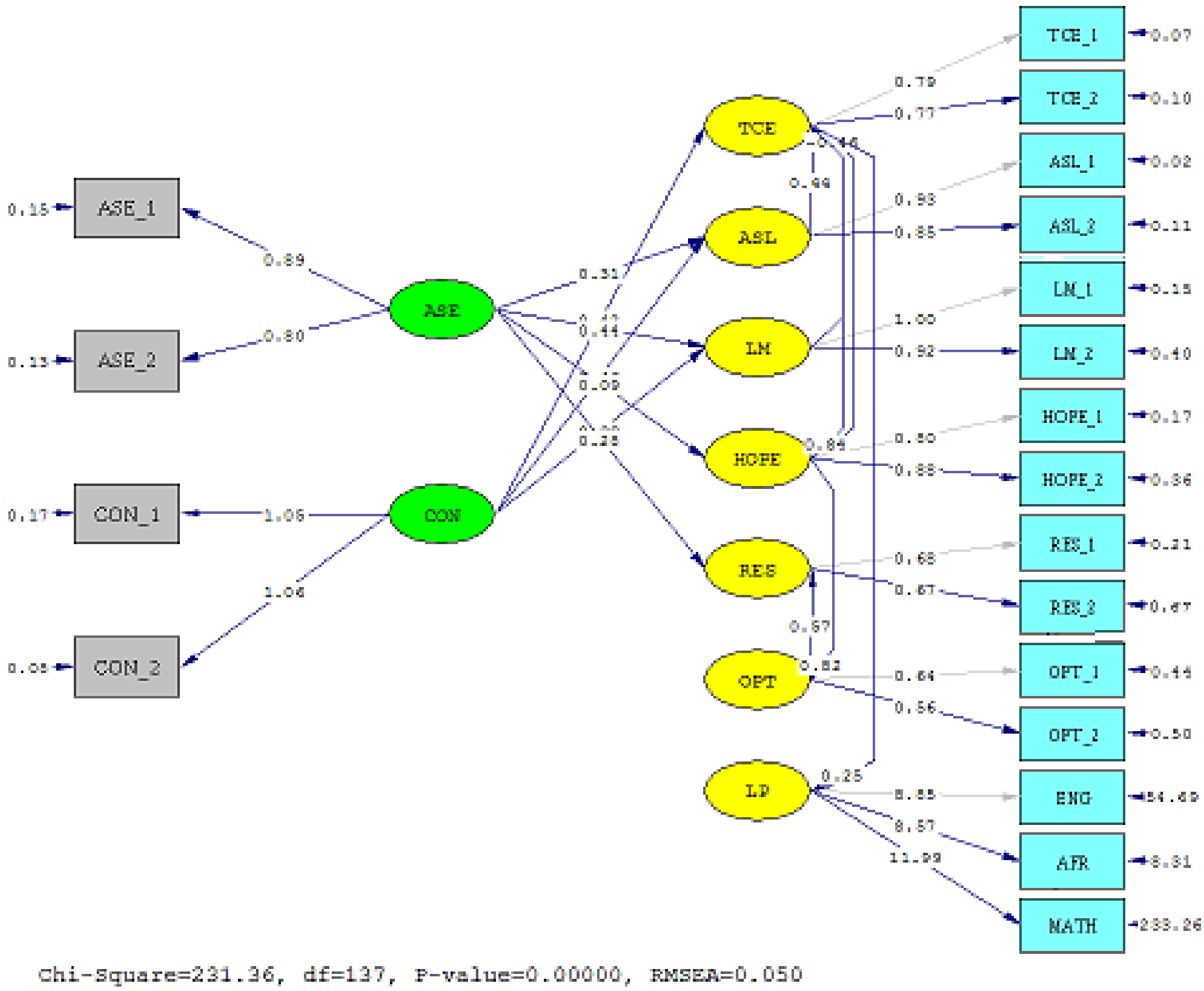

Figure 4.10 Representation of the modified fitted learning potential structural model (model C)

Table 4.83

Goodness of fit statistics for the modified learning potential model (model C)

Degrees of Freedom	137
Minimum Fit Function Chi-Square	259.546 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	249.318 (p = 0.00)
Satorra-Bentler Scaled Chi-square	**231.362 (p = 0.00)**
Chi-square Corrected for NON-Normality	453.225 (p = 0.0)
Estimated Non-centrality Parameter (NCP)	94.362
90 Percent Confidence Interval for NCP	(56.273 ; 140.336)
Minimum Fit Function Value	0.930
Population Discrepancy Function Value (FO)	0.338
90 Percent Confidence Interval for FO	(0.202 ; 0.503)
Root Mean Square Error of Approximation (RMSEA)	**0.0497**
90 Percent Confidence Interval for RMSEA	**(0.0384 ; 0.0497)**
P-value for test of Close Fit (RMSEA < .05)	**0.505**
Expected Cross-Validation Index (ECVI)	**1.209**
90 Percent Confidence Interval for ECVI	(1.073 ; 1.374)
ECVI for Saturated Model	**1.362**
ECVI for Independence model	**34.517**
Chi-square for Independence Model with 253	9592.369

Degrees of Freedom	
Independence AIC	**9630.369**
Model AIC	**337.362**
Saturated AIC	**380.000**
Independence CAIC	**9718.430**
Model CAIC	**583.006**
Saturated CAIC	**1260.610**
Normed Fit Index (NFI)	**.976**
Non-Normed Fit Index (NNFI)	**.987**
Parsimony Normed Fit Index (PNFI)	**.782**
Comparative Fit Index (CFI)	**.990**
Incremental Fit Index (IFI)	**.990**
Relative Fit Index (RFI)	**.970**
Critical N (CN)	**216.158**
Root Mean Square Residual (RMR)	**0.970**
Standardised RMR	**.0677**
Goodness of Fit Index (GFI)	**.914**
Adjusted Goodness of Fit Index (AGFI)	**.881**
Parsimony Goodness of Fit Index	**.659**

The Satorra-Bentler Chi-square presented in Table 4.83 revealed a value of 231.362 (p = 0.00), which sanctioned the rejection of the null hypothesis of exact fit. The exceedence probability associated with the test of close fit was 0.505. The close fit null hypothesis was therefore not rejected (p > .05). The RMSEA value of .0497 indicated a good fit in the sample, which was satisfactory. Supporting these results was the fact that the upper bound of the 90 percent confidence interval for the RMSEA (0.0384; 0.0497), fell below the .05 cut-off value, and therefore supported the good close fit achieved by this model. The critical N (CN) improved even more, as CN of 216.158 (>200) was achieved, which is above the threshold, and therefor regarded as acceptable. Kelloway (1998) suggested that SRMR-values that are smaller than .05, are indicative of acceptable fit. This model produced a SRMR-value of .0677, which emphasised that even though the fit has improved and can be regarded as acceptable, the output produced by LISREL still need to be investigated to determine if any way existed to improve the fit, and the other fit indices even more.

Therefore, to improve the evidence suggesting that the proposed model was to a degree able to reproduce the observed covariance matrix to a degree of accuracy that warranted faith in the structural model and the derived parameter estimates, the parameter estimates for beta and gamma, as well as the modification indices calculated by LISREL were explored, yet again, to investigate possible ways in which this model could be modified which would result in more acceptable fit.

4.10.9 Modification of structural model (model D)

The unstandardised beta matrix presented in Table 4.84**,** emphasised that no paths should be deleted from this model. All the paths were significant (p < .05) and therefore supported. This included the path between *hope* and *time cognitively engaged* that was added in the previous modification.

Table 4.84
Learning potential structural modified model (model C) unstandardised beta matrix

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE		0.435 (0.082) 5.301	0.538 (0.106) 5.066	-0.459 (0.168) **-2.725**			
ASL							
LM							
HOPE	0.841 (0.096) 8.729						
RES						0.565 (0.103) 5.514	
OPT				0.823 (0.093) 8.898			
LP	0.254 (0.063) 4.037						

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The unstandardised gamma matrix is depicted in Table 4.85. Table 4.85 revealed that one of the paths between an exogenous and an endogenous latent variable were no longer significant (p > .05). The hypothesis portraying the positive relationship between *academic self-efficacy* and *hope* were no longer supported. Consequently, this path was deleted from the structural model.

Table 4.85

Learning potential structural modified model (model C) unstandardised gamma matrix

	ASE	CON
TCE	-	0.423 (0.107) 3.946
ASL	0.306 (0.081) 3.763	0.463 (0.086) 5.380
LM	0.439 (0.088) 4.975	0.385 (0.089) 4.249
HOPE	0.089 (0.079) **1.127**	-
RES	0.278 (0.076) 3.675	-
OPT	-	-
LP	-	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The modification indices for the beta matrix are presented in Table 4.86, and the MI-values for the currently fixed gamma parameters are shown in Table 4.87. The parameter with the highest MI-value was β_{48} found in the beta matrix (15.100). This suggested that if the path between *learning performance* during evaluation and *learning motivation* was included in the structural model, the fit of the model would improve significantly. The completely standardised expected change for the beta coefficient was of sufficient magnitude (0.202), and the sign was positive. Therefore, it suggested that the path that should be added is the hypothesis that *learning performance during evaluation* positively influence *learning motivation*. Therefore, a critical question that had to be asked was whether a positive relationship between these two latent variables made substantive theoretical sense. If this does not make sense, it should not be considered as a possible modification.

Table 4.86

Modified learning potential structural model modification indices for beta matrix (model C)

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE	-	-	-	**-**	3.417	7.271	0.099
ASL	-	-	4.792	2.133	0.968	6.470	1.878
LM	0.501	4.970	-	0.924	4.343	2.421	**15.100**
HOPE	**-**	0.008	0.162	-	0.004	0.010	0.236
RES	1.653	0.335	3.299	-	-	-	9.152
OPT	0.002	10.710	7.389	-	5.235	-	0.659
LP	-	2.239	**13.734**	0.433	7.206	0.004	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The hypothesis suggesting a positive relationship between *learning performance during evaluation* and *learning motivation* was also suggested in the Burger (2012) study. This pathway made theoretical sense, based on the following argument presented by Burger (2012). If a learner performs well on a learning task she/he may be more motivated to learn, assuming that high *learning performance during evaluation* is intrinsically rewarding. Achieving success in the learning task should increase the expectancy that effort translate to performance (i.e. P (E to P)) and thereby increase motivation (Vroom, 1964). Therefore, Burger (2012) included this pathway as it made constructive sense. Burger (2012) found empirical support for this path in her study (2012).

This study acknowledged this feedback hypothesis but argued that it would operate through the positive mediating effect of *optimism*. This study therefore hypothesised that *learning performance* positively influences *optimism*, and *optimism* positively influences *learning motivation*. The argument was presented in Chapter 2. However, the results produced by LISREL did not provide support for any of these two hypothesised paths (i.e. *learning performance* on *optimism*, and *optimism* on *learning motivation*), and these paths were consequently deleted in the subsequent models. However, the results obtained for model C suggested that the pathway between *learning performance* and *learning motivation* should be included, and based on the argument presented by Burger (2012); this made substantive theoretical sense, and was therefore included in model D.

It is important to take note of the fact that the second highest MI-value (13.734) was also presented in the beta matrix, proposed the inclusion of a positive direct influence of *learning motivation* on *learning performance during evaluation*. This direct effect was also proposed by the LISREL output in the Burger (2012) study. In the Burger (2012) study, and in this study, the theoretical sense of this pathway is supported; however, both authors hold the opinion that this relationship is more complex and should be mediated by *time cognitively engaged* as depicted in the proposed structural model. It is argued that this is because a person’s behaviour is put into motion via *time cognitively engaged* and it is this construct that then ultimately positively influences *learning performance during evaluation*.

Also, Jöreskog and Sörbom (1993), suggest that one parameter should be freed at a time, as any change to the existing structural model will affect all the existing parameter estimates, and also all modification indices. Paths that would potentially improve the fit of the model will not necessarily do so in the revised model. Consequently, it was decided to only include the pathway hypothesising the structural linkage between *learning performance during evaluation* and *learning motivation in the revised model.*

The modification indices for gamma did not reveal a MI-value greater than what was obtained in the modification indices for beta. The results of the modification indices for gamma are shown in Table 4.87.

Table 4.87
Modified learning potential structural model modification indices for gamma matrix (model C)

	ASE	CON
TCE	1.285	-
ASL	-	-
LM	-	-
HOPE	-	0.156
RES	-	1.939
OPT	1.775	1.320
LP	3.478	2.619

Based on the presented results, it was decided to delete the statistically insignificant path between *academic self-efficacy* and *hope*, and to add the hypothesised positive relationship between *learning performance* and *learning motivation*, seeing that it made theoretical sense, the magnitude of the expected change was satisfactory (0.202), and the sign of the expected change was in line with the theorised argument. The modified model (D) was fitted again; and a visual representation of this fitted model, as well as the fit indices is presented next.

4.10.10 Assessing the overall fit statistics of the modified structural model (model D)

A visual representation of the fourth modified, structural model (model D) is presented in Figure 4.11. The full range of fit indices (both comparative and absolute) for the fourth modified model is shown in Table 4.90, and explained thereafter.

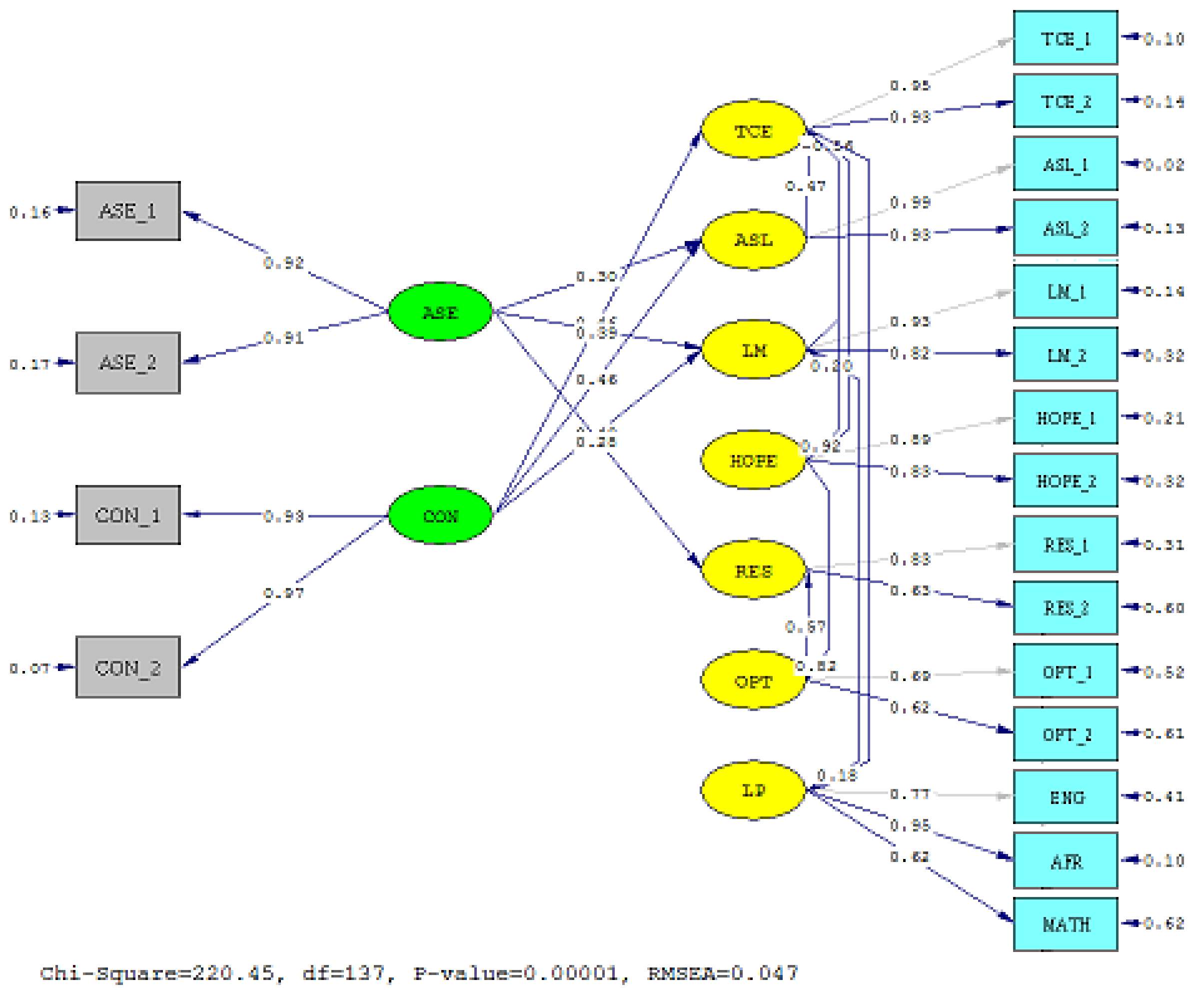

Figure 4.11 **Representation of the modified fitted learning potential structural model (model D)**

Table 4.88

Goodness of fit statistics for the modified learning potential model (D)

Degrees of Freedom	137
Minimum Fit Function Chi-Square	244.767 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	237.487 (p = 0.00)
Satorra-Bentler Scaled Chi-square	**220.449 (p = 0.00)**
Chi-square Corrected for NON-Normality	429.015 (p = 0.0)
Estimated Non-centrality Parameter (NCP)	83.449
90 Percent Confidence Interval for NCP	(46.806 ; 128.009)
Minimum Fit Function Value	0.877
Population Discrepancy Function Value (FO)	0.299
90 Percent Confidence Interval for FO	(0.168 ; 0.459)
Root Mean Square Error of Approximation (RMSEA)	**0.0467**
90 Percent Confidence Interval for RMSEA	**(0.0350 ; 0.0579)**
P-value for test of Close Fit (RMSEA < .05)	**0.672**
Expected Cross-Validation Index (ECVI)	**1.170**
90 Percent Confidence Interval for ECVI	(1.039 ; 1.330)
ECVI for Saturated Model	**1.362**
ECVI for Independence model	**34.517**
Chi-square for Independence Model with 253	9592.369

Degrees of Freedom	
Independence AIC	**9630.369**
Model AIC	**326.449**
Saturated AIC	**380.000**
Independence CAIC	**9718.430**
Model CAIC	**572.093**
Saturated CAIC	**1260.610**
Normed Fit Index (NFI)	**.977**
Non-Normed Fit Index (NNFI)	**.989**
Parsimony Normed Fit Index (PNFI)	**.783**
Comparative Fit Index (CFI)	**.991**
Incremental Fit Index (IFI)	**.991**
Relative Fit Index (RFI)	**.971**
Critical N (CN)	**226.810**
Root Mean Square Residual (RMR)	**0.908**
Standardised RMR	**.0649**
Goodness of Fit Index (GFI)	**.918**
Adjusted Goodness of Fit Index (AGFI)	**.886**
Parsimony Goodness of Fit Index	**.662**

The Satorra-Bentler Chi-square ($p = 0.00$) presented in Table 4.88 (220.449), justified the rejection of the exact fit null hypothesis. The close fit null hypothesis was rejected ($p > .05$). The RMSEA value of .0467 indicated a good fit in the sample. Supporting these results is the fact that the upper bound of the 90 percent confidence interval for the RMSEA (0.0350; 0.0579), fell slightly above the .05 cut-off value. This provided additional support for the good close fit achieved by this model. The critical N (CN) improved even more from the previous modification, and the results presented in Table 4.88 revealed a CN of 226.810, which is above the threshold of 200, and therefore regarded as satisfactory. This model produced a SRMR-value of .0649, which shows that even though the model fit did improve, the remaining results produced by LISREL need to be investigated to determine whether other ways to improve the fit of the model, exist. Therefore, the parameter estimates for beta and gamma, as well as the modification indices calculated by LISREL were explored, to investigate additional possible ways in which this model could be modified through either the deletion or addition of additional paths that may result in an improved fit.

4.10.11 Modification of structural model (model E)

From the unstandardised beta matrix presented in Table 4.89, it was evident that none of the current paths between the endogenous latent variables included in the model should be deleted. All the paths were supported. All the hypothesised pathways were found to be statistically significant ($p < .05$).

The results also revealed that empirical support was found for the theoretically sound positive relationship hypothesised to exist between *learning performance during evaluation* and *learning motivation*, which was added in the previous modification.

Table 4.89
Learning potential structural modified model unstandardised beta matrix (model D)

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE		0.472 (0.083) 5.705	0.540 (0.110) 4.928	-0.557 (0.165) -3.374			
ASL							
LM							0.203 (0.048) 4.277
HOPE	0.925 (0.065) 14.140						
RES						0.570 (0.099) 5.761	
OPT				0.824 (0.093) 8.889			
LP	0.185 (0.066) 2.803						

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The unstandardised gamma matrix is depicted in Table 4.90. The results depicted in Table 4.90 revealed that all of the paths between the exogenous and endogenous latent variables were statistically significant (p < .05). Consequently, no pathways were deleted from the structural model.

Table 4.90
Learning potential structural modified model unstandardised gamma matrix (model D)

	ASE	CON
TCE	-	0.463 (0.116) 4.001
ASL	0.304 (0.082) 3.728	0.464 (0.086) 5.385
LM	0.387 (0.083) 4.641	0.403 (0.083) 4.852
HOPE	-	-
RES	0.278 (0.076072 3.848	-
OPT	-	-
LP	-	-

The modification indices for the beta matrix are presented in Table 4.91, and the MI-values for the currently fixed gamma parameters are shown in Table 4.92.

Table 4.91
Modified learning potential structural model modification indices for beta matrix (model D)

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE	-	-	-	-	3.190	7.130	0.001
ASL	-	-	3.766	0.623	0.633	4.323	0.766
LM	0.496	5.789	-	0.703	2.719	2.613	-
HOPE	-	0.036	0.509	-	0.277	0.005	0.157
RES	2.075	0.403	4.409	-	-	-	9.710
OPT	0.012	**10.770**	7.088	-	5.448	-	0.537
LP	-	0.087	1.365	0.142	8.223	0.010	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

In line with the process suggested by Jöreskog and Sörbom (1993); the currently fixed parameter with the highest MI-value should be considered first. The parameter β_{62} found in the beta matrix was fixed to zero in model E but when freed would allow for a structural linkage between *academic self-leadership* and *optimism* (10.770).

This revealed that if a path was included that hypothesised the relationship between these two latent variables; the fit of this model would improve statistically significantly. The completely standardised expected change for the beta coefficient was of sufficient magnitude (0.305), and the sign was positive. Consequently, the modification would imply the addition of the hypothesis that depicts the positive influence of *academic self-leadership* on *optimism.* Prior to that, an important question that needed to be asked was whether a positive relationship between these latent variables made substantial theoretical sense. If this was not the case, then this possible modification would not be considered.

However, this relationship does make sense, and is based on the following argument. An individual high on *academic self-leadership* will most probably display the key components of this construct, which include constructive thought-pattern strategies and behavioural-focussed strategies. Constructive thought-pattern strategies will be displayed in the form of creating and maintaining functional patterns of habitual thinking. Such an individual will consequently tend to engage in, for example, self-management of beliefs and assumptions by implementing self-talk- and mental imagery strategies. The individual will also display behavioural-focussed strategies in the form of repeated practice and self-goal setting (Manz, 1992).

An optimist, on the other hand, attribute positive events to personal, permanent and pervasive causes, and as a result take credit for the positive events in their lives. They tend to attribute the causes of negative events to external, temporary, and specific situations. Optimistic individuals therefore engage in self-management of beliefs and assumptions. These individuals also tend to expect to encounter continuous success in the future, as they tend to experience positive emotional states and continual constructive (i.e. positive) patterns of habitual thinking (Roux, 2010). Roux (2010) further argued that individuals high on this construct enjoy a host of positive outcomes, including; higher levels of motivation, perseverance, and achievement resulting in academic, and/or occupational success, as well as mental health. These can be the result of successful self-goal setting, self-talk and mental imagery. To summarise, *optimism* is associated with a positive outcome, outlook or attribution of events, which includes positive emotions and motivation (Luthans, 2002a). The foregoing argument seems to suggest that the key components of *academic self-leadership* will encourage an optimistic approach to life. It therefore seems safe to argue that individuals that show high levels of *academic self-leadership* are more prone to show high levels of *optimism*. Consequently, it seemed safe to include this theoretically sound path in the modified structural model (model E).

The modification indices for gamma did not reveal a MI-value that was greater than those that were obtained for beta. The modification indices for gamma are shown in Table 4.92.

Table 4.92

Modified learning potential structural model modification indices for gamma matrix (model D)

	ASE	**CON**
TCE	1.777	-
ASL	-	-
LM	-	-
HOPE	0.884	0.464
RES	-	2.469
OPT	1.966	1.302
LP	6.944	0.204

The results presented and explained in this section warrant the inclusion of the positive hypothesised path between *academic self-leadership* and *optimism* in the modified structural model (model E). This path made substantive theoretical sense, the magnitude of the expected change was satisfactory (0.305), and the sign of the expected change was in line with the theorised argument. The results for model E further revealed that no existing paths should be deleted from this model. The modified model (model E) was fitted again; and a visual representation of this fitted model, as well as the fit indices is presented in Section 4.10.12.

4.10.12 Assessing the overall fit statistics of the modified structural model (model E)

A visual representation of the modified model is presented in Figure 4.12. The full range of fit indices for the fifth modified model (model E) is illustrated in Table 4.93, followed by a discussion on the results.

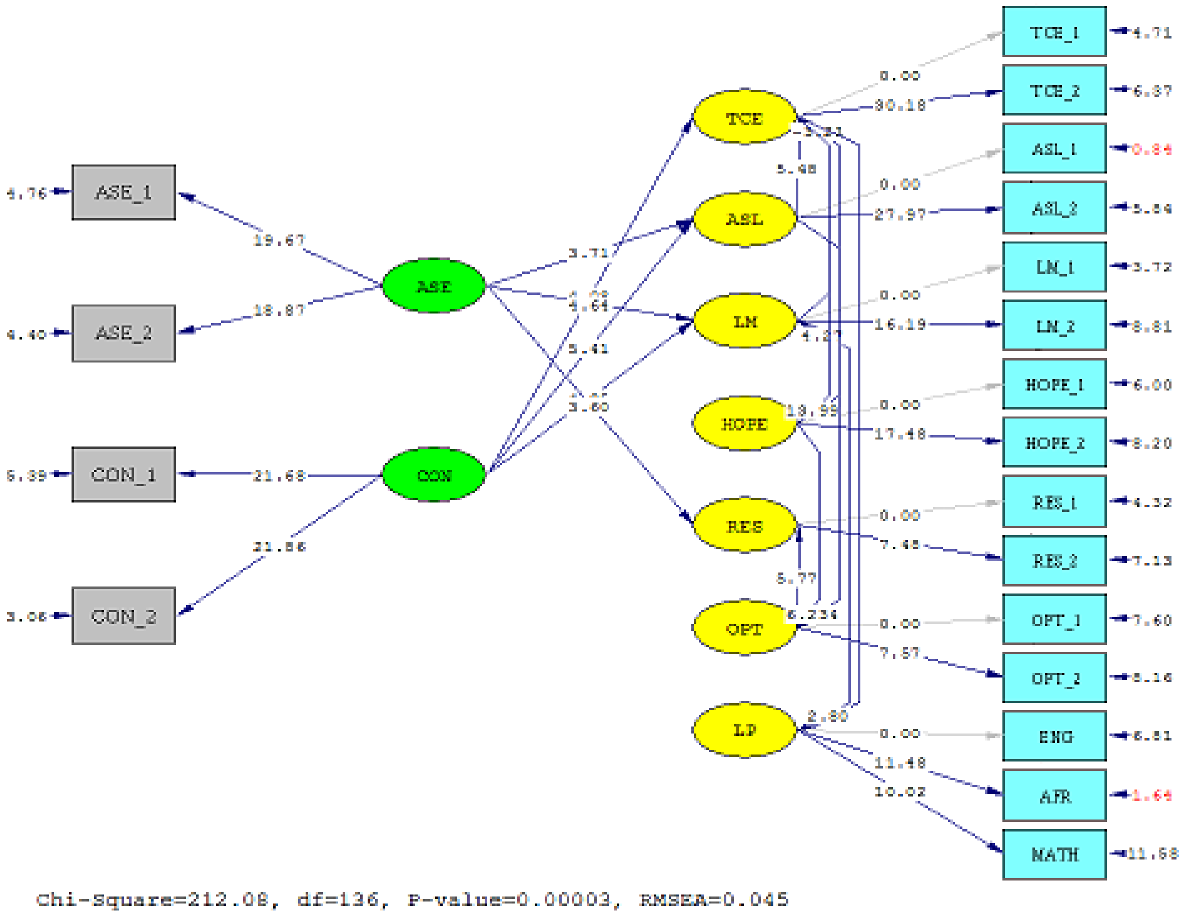

Figure 4.12 Representation of the modified fitted learning potential structural model (model E)

Table 4.93

Goodness of fit statistics for the modified learning potential model (model E)

Degrees of Freedom	136
Minimum Fit Function Chi-Square	236.073 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	228.007 (p = 0.00)
Satorra-Bentler Scaled Chi-square	**212.079 (p = 0.00)**
Chi-square Corrected for NON-Normality	433.895 (p = 0.0)
Estimated Non-centrality Parameter (NCP)	76.079
90 Percent Confidence Interval for NCP	(40.512 ; 119.587)
Minimum Fit Function Value	0.846
Population Discrepancy Function Value (FO)	0.273
90 Percent Confidence Interval for FO	(0.145 ; 0.429)
Root Mean Square Error of Approximation (RMSEA)	**0.0448**
90 Percent Confidence Interval for RMSEA	**(0.0327 ; 0.0561)**
P-value for test of Close Fit (RMSEA < .05)	**0.764**
Expected Cross-Validation Index (ECVI)	**1.147**
90 Percent Confidence Interval for ECVI	(1.020 ; 1.303)
ECVI for Saturated Model	**1.362**
ECVI for Independence model	**34.517**
Chi-square for Independence Model with 253 Degrees of Freedom	9592.369
Independence AIC	**9630.369**
Model AIC	**320.079**
Saturated AIC	**380.000**
Independence CAIC	**9718.430**
Model CAIC	**570.358**
Saturated CAIC	**1260.610**
Normed Fit Index (NFI)	**.978**
Non-Normed Fit Index (NNFI)	**.990**
Parsimony Normed Fit Index (PNFI)	**.778**
Comparative Fit Index (CFI)	**.992**
Incremental Fit Index (IFI)	**.992**
Relative Fit Index (RFI)	**.972**
Critical N (CN)	**234.220**
Root Mean Square Residual (RMR)	**0.911**
Standardised RMR	**.0633**
Goodness of Fit Index (GFI)	**.921**
Adjusted Goodness of Fit Index (AGFI)	**.889**
Parsimony Goodness of Fit Index	**.659**

The Satorra-Bentler Chi-square (p = 0.00) illustrated in Table 4.93 (212.079) justified the decision to reject the exact fit null hypothesis. The close fit null hypothesis was not rejected (p > .05). The RMSEA value of .0448 indicated a good fit in the sample, which signalled a slight improvement in the fit of this model. Supporting these results was the fact that the upper bound of the 90 percent confidence interval for the RMSEA (0.0327; 0.0561), fell only slightly above the .05 cut-off value.

The critical N (CN) improved even more from the previous modification, and the results presented in Table 4.93 revealed a CN value of 234.220, which is above the critical cut-off value of 200, and therefore regarded as pleasing.

This model produced a SRMR-value of .0633, which was somewhat lower than the previous model's fit SRMR-value (.0649), but was still above the critical cut-off value (.05). This revealed that even though the model fit did improve, the remaining results produced by LISREL needed to be investigated to determine whether ways to improve this modified model's fit actually existed. Consequently, the parameter estimates for beta and gamma, as well as the modification indices were explored; to determine whether possible ways to modify this model existed, that would possible result in an improved fit.

4.10.13 Modification of structural model (model F)

The *Unstandardised Beta Matrix* shown in Table 4.94 illustrated that none of the current paths included in the model (model E) should be deleted. All the paths were supported. All the hypothesised pathways were found to be statistically significant (p < .05).

The results also revealed that empirical support was found for the theoretically sound positive relationship between *academic self-leadership* and *optimism*, which was added in the previous modification (modification of model E).

Table 4.94
Learning potential structural modified model unstandardised beta matrix (model E)

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE		0.439 (0.080) 5.476	0.518 (0.106) 4.889	-0.489 (0.152) -3.209			
ASL							
LM							0.203 (0.048) 4.272
HOPE	0.906 (0.065) 13.994						
RES						0.570 (0.099) 5.768	
OPT		0.239 (0.087) 2.741		0.650 (0.104) 6.226			
LP	0.184 (0.066) 2.798						

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

Table 4.95 depicts the unstandardised gamma matrix. Table 4.95 revealed that all of the freed gamma paths were statistically significant ($p < .05$).

Table 4.95
Learning potential structural modified model unstandardised gamma matrix (model E)

	ASE	CON
TCE	-	0.448 (0.110) 4.081
ASL	0.302 (0.081) 3.708	0.465 (0.086) 5.405
LM	0.388 (0.084) 4.640	0.402 (0.083) 4.845
HOPE	-	-
RES	0.268 (0.074 3.602	-
OPT	-	-
LP	-	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The results reflected in Tables 4.94 and 4.95, showed that none of the existing paths needed to be deleted to improve the fit of the structural model. The modification indices for the beta matrix are presented in Table 4.96, and the MI-values for the fixed Gamma parameters in model E are shown in Table 4.97.

Table 4.96
Modified learning potential structural model modification indices for beta matrix (model E)

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE	-	-	-	-	1.427	3.860	0.002
ASL	-	-	3.908	0.079	0.417	0.000	0.722
LM	0.467	5.931	-	0.669	4.696	5.860	-
HOPE	-	0.247	0.739	-	1.136	0.589	0.209
RES	2.651	4.591	4.631	-	-	-	**10.275**
OPT	2.786	-	4.526	-	5.087	-	0.368
LP	-	0.083	1.384	0.190	8.811	0.005	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The currently fixed parameter β_{57} was found to have the highest MI-value and was therefore first considered for modification purposes. This parameter describes the slope of the regression of *resilience* on *learning performance during evaluation* (10.275). The completely standardised expected change for the beta coefficient was of sufficient magnitude (0.195) to justify freeing the parameter.

The proposed modification was therefore the addition of a feedback path reflecting the positive influence of *learning performance during evaluation* on *resilience.* This path was part of the original proposed structural model. However, in the original structure, no statistical support for this path was obtained, and it was therefore deleted during the first modification of the original model. More specifically it was deleted because it failed to significantly explain variance in *resilience* in a model that included all the other effects that formed part of the model at the time. The model has, however, since been modified with specific effects removed and others added. The path originally made theoretical sense based on an argument presented in Chapter 2. In defence of the return of this specific path to the model this argument is presented again in the next paragraph.

If individuals are faced with adverse situations and they overcome the adversity successfully, a possibility exists that the particular individuals will overcome future adversity even quicker. Herbert (2011) supports this notion by explaining that individuals may actually become more resilient to an adverse circumstance each time they effectively “bounce back” from the previous setback.

In a study completed by Richardson (2002), it was found that the *resilience* of an individual can increase and even grow when the individual returns to levels above homeostasis after an adverse situation. Consequently, if an individual is provided with a difficult/challenging learning opportunity, and the individual achieves success at it, i.e. achieve high *learning performance during evaluation*; their *resilience* most probably will definitely improve and their ability to recover from adversity in the future may advance. Accordingly, it is argued that if an individual makes a success of an opportunity, and achieves a high level of *learning performance during evaluation*, their *resilience* will also improve. Therefore, it could be argued that *learning performance during evaluation* positively influences *Resilience*, thereby supporting the inclusion of this positive relationship in the modified structural model (model F).

The modification indices for Γ did not reveal a MI-value greater than those calculated for **B**.

Table 4.97
Modified learning potential structural model modification indices for gamma matrix (model E)

	ASE	**CON**
TCE	1.934	-
ASL	-	-
LM	-	-
HOPE	1.084	0.249
RES	-	2.701
OPT	0.315	0.004
LP	6.952	0.205

The results illustrated up to this point warranted the return of an original path depicting the positive relationship between *learning performance* and *resilience*, to the modified structural model (model F). This path made theoretical sense, the magnitude of the expected change was satisfactory (0.195), and the sign of the expected change was in line with the theorised argument. The results further revealed that none of the existing paths should be deleted from this model. The modified model (model F) was subsequently fitted; and a visual representation of this fitted model, as well as the fit indices is presented in Section 4.10.14.

4.10.14 Assessing the overall fit statistics of the modified structural model (model F)

A graphic presentation of the modified, model (model F) is presented in Figure 4.13. The full range of fit indices for the sixth modified model (model F) is illustrated in Table 4.98, followed by a discussion on the results.

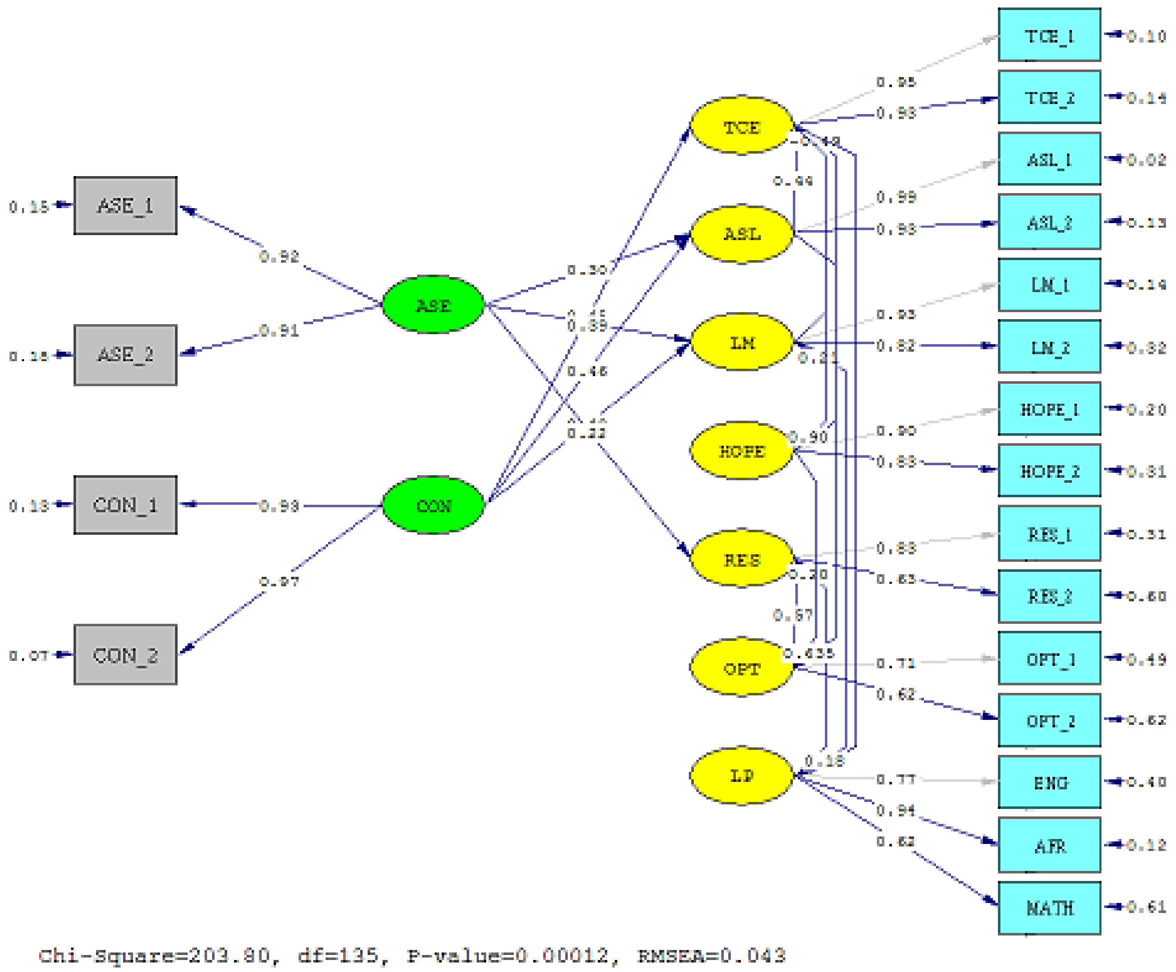

Figure 4.13 Representation of the modified fitted learning potential structural model (model F)

Table 4.98

Goodness of fit statistics for the modified learning potential model (model F)

Degrees of Freedom	135
Minimum Fit Function Chi-Square	225.217 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	218.857 (p = 0.00)
Satorra-Bentler Scaled Chi-square	**203.795 (p = 0.00)**
Chi-square Corrected for NON-Normality	429.625 (p = 0.0)
Estimated Non-centrality Parameter (NCP)	68.795
90 Percent Confidence Interval for NCP	(34.323 ; 111.236)
Minimum Fit Function Value	0.807
Population Discrepancy Function Value (FO)	0.247
90 Percent Confidence Interval for FO	(0.123 ; 0.399)
Root Mean Square Error of Approximation (RMSEA)	**0.0427**
90 Percent Confidence Interval for RMSEA	**(0.0302 ; 0.0543)**
P-value for test of Close Fit (RMSEA < .05)	**0.841**
Expected Cross-Validation Index (ECVI)	**1.125**
90 Percent Confidence Interval for ECVI	(1.001 ; 1.277)
ECVI for Saturated Model	**1.362**
ECVI for Independence model	**34.517**
Chi-square for Independence Model with 253 Degrees of Freedom	9592.369

Independence AIC	**9630.369**
Model AIC	**313.795**
Saturated AIC	**380.000**
Independence CAIC	**9718.430**
Model CAIC	**568.709**
Saturated CAIC	**1260.610**
Normed Fit Index (NFI)	**.979**
Non-Normed Fit Index (NNFI)	**.991**
Parsimony Normed Fit Index (PNFI)	**.773**
Comparative Fit Index (CFI)	**.993**
Incremental Fit Index (IFI)	**.993**
Relative Fit Index (RFI)	**.973**
Critical N (CN)	**242.138**
Root Mean Square Residual (RMR)	**0.863**
Standardised RMR	**.0592**
Goodness of Fit Index (GFI)	**.924**
Adjusted Goodness of Fit Index (AGFI)	**.893**
Parsimony Goodness of Fit Index	**.656**

The Satorra-Bentler Chi-square (p = 0.00) depicted in Table 4.98 (203.795) supported the decision to reject the exact fit null hypothesis. The close fit null hypothesis was not rejected (p > .05). The sample RMSEA value of .0427 indicated a very good fit, which showed an improvement in the fit of this model since the previous modification. Supporting these results was the fact that the upper bound of the 90 percent confidence interval for RMSEA (0.0302; 0.0543), fell only marginally above, the .05 cut-off value. The upper bound of the confidence interval fell closer to the critical RMSEA value than the previous version of this model, and therefore provided additional support for this good fitting model.

The critical N (CN) improved even more from the previous modification, and the results revealed a CN value of 242.138, which was substantially above the threshold value of 200, and further supported the good fit achieved. Moreover, this model produced a SRMR-value of .0592, which was much lower than the previous modification's fit indices, however still marginally above the critical cut-off value.

This revealed that even though the model fit did improve, the remaining results produced by LISREL needed to be investigated to determine whether ways existed to improve this modified model's fit even further. The parameter estimates for beta and gamma, as well as the modification indices were consequently explored, to determine whether possible ways to modify this model (model F) existed, which would result in an improved fit.

4.10.15 Modification of structural model (model G)

The unstandardised beta matrix portrayed in Table 4.99 illustrated that none of the paths included in the model should be deleted. All the paths were supported. All the hypothesised pathways were found to be significant ($p < .05$). The portrayed results also disclosed empirical support for the theoretically sound positive relationship between *learning performance* and *resilience*, which was added in the previous section. This finding was gratifying. Finding support for this path to some degree vindicated the original theorising put forward in this study.

Table 4.99
Learning potential structural modified model unstandardised beta matrix (model F)

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE		0.438 (0.080) 5.493	0.514 (0.106) 4.873	-0.486 (0.152) -3.205			
ASL							
LM							0.208 (0.048) 4.336
HOPE	0.905 (0.065) 13.975						
RES						0.567 (0.099) 5.712	0.202 (0.059) 3.387
OPT		0.246 (0.087) 2.847		0.631 (0.103) 6.125			
LP	0.182 (0.066) 2.750						

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The Unstandardised gamma matrix depicted in Table 4.100 revealed that all of the paths between the exogenous and endogenous latent variables in model F were significant ($p < .05$).

Table 4.100
Learning potential structural modified model unstandardised gamma matrix (model F)

	ASE	CON
TCE	-	0.449 (0.110) 4.094
ASL	0.302 (0.082) 3.703	0.465 (0.086) 5.395
LM	0.385 (0.083) 4.618	0.403 (0.083) 4.862
HOPE	-	-
RES	0.221 (0.074) 2.990	-
OPT	-	-
LP	-	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The results reflected in Table 4.99 and Table 4.100, showed that no need existed for the deletion of any of the existing paths in the modified learning potential structural model (model F). The modification indices for the beta matrix are presented in Table 4.101, and the modification indices for gamma are shown in Table 4.102.

Table 4.101
Modified learning potential structural model modification indices for beta matrix (model F)

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE	-	-	-	-	2.183	3.891	0.003
ASL	-	-	3.910	0.069	0.777	0.006	0.718
LM	0.508	5.979	-	0.698	4.492	6.119	-
HOPE	-	0.231	0.679	-	1.887	0.781	0.098
RES	6.174	4.187	0.543	-	-	-	-
OPT	3.123	-	2.987	-	2.015	-	3.483
LP	-	0.079	1.374	0.089	0.155	0.749	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The currently fixed parameter with the highest MI-value was found in the gamma matrix presented in Table 4.101.

Table 4.102
Modified learning potential structural model modification indices for gamma matrix (model F)

	ASE	**CON**
TCE	1.998	-
ASL	-	-
LM	-	-
HOPE	1.133	0.217
RES	-	2.084
OPT	0.411	0.032
LP	**6.793**	0.175

The parameter γ_{71} had the highest MI-value. This suggested that freeing the parameter γ_{71} will result in the inclusion of a path from *academic self-efficacy* to *learning performance* (6.793). The completely standardised expected change for the gamma coefficient was of sufficient magnitude (0.223), to justify the inclusion of this path. The critical question was whether the addition of a direct path reflecting a positive influence of *academic self-efficacy* on *learning performance during evaluation* made substantive theoretical sense.

The theoretical argument supporting the proposition made by the modification index for gamma, consists of an argument pertaining that when an individual believe in their own ability to succeed in their academic task, their chances of actualising that belief and achieving high levels of *learning performance during evaluation,* increases. For example, Tenaw (2013) reported a meta-analysis of 39 studies from 1977 to 1988; that revealed a positive and statistically significant relationship between self-efficacy and academic performance. This is based on the idea that individual's high on self-efficacy attempt challenging tasks more often, persist longer at them, and exert more effort. If there are failures, highly efficacious individuals attribute it to a lack of effort or an adverse environment (Tenaw, 2013). The initial argument in this study, with reference to the relationship between these two variables, was that they do influence each other, but not in a direct way. This study thought it more realistic that these two latent variables influence each other in an indirect manner, seeing that it seemed rather unlikely that high *academic self-efficacy* would in and by itself result in academic achievement and success. However, despite this, the modification indices output provided by LISREL, as well as the empirical support found in literature, show otherwise. Consequently, a possibility exists for a direct link between these two constructs, and therefore at least warrants an attempt to find a theoretical argument to support the inclusion of this path in the modified structural model.

It could be argued that individuals only need to believe in their own ability to succeed in their academic tasks. This line of reasoning can be justified by the fact that individuals' high on self-efficacy attempt challenging tasks more often, persist longer at them, and exert more effort (Tenaw, 2013). Reference to exerting effort and persistence; however, tend to point towards *learning motivation*. This again suggests that *learning motivation* mediates the effect of self-efficacy on *learning performance during evaluation*. Despite the somewhat theoretically contentious nature of the proposed path it was nonetheless decided to include the path in addition to the already included mediated path. Following the inclusion of the pathway depicting the positive influence of *academic self-efficacy* on *learning performance*, the modified model (model G) was fitted again, and the results are depicted in the next section.

4.10.16 Assessing the overall fit statistics of the modified structural model (model G)

A visual presentation of the modified model is presented in Figure 4.14, and the full range of fit indices for the modified model (model G) is illustrated in Table 4.103, followed by a detailed discussion of the results.

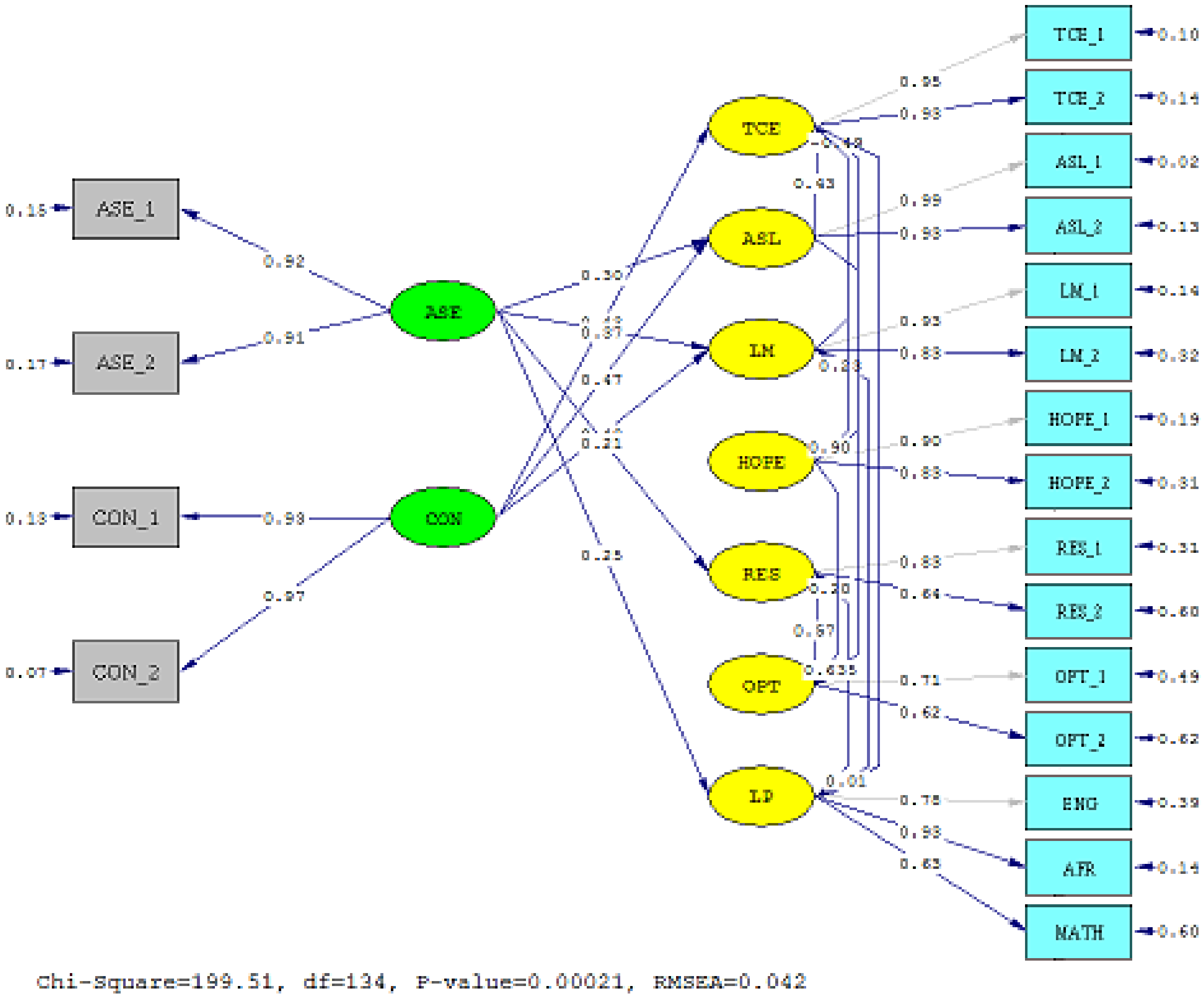

Figure 4.14 Representation *of the modified fitted learning potential structural model (model G)*

Table 4.103

Goodness of fit statistics for the modified learning potential model (model G)

Degrees of Freedom	134
Minimum Fit Function Chi-Square	217.698 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	214.501 (p = 0.00)
Satorra-Bentler Scaled Chi-square	**199.510 (p = 0.000209)**
Chi-square Corrected for NON-Normality	399.413 (p = 0.0)
Estimated Non-centrality Parameter (NCP)	65.510
90 Percent Confidence Interval for NCP	(31.580 ; 107.419)
Minimum Fit Function Value	0.780
Population Discrepancy Function Value (FO)	0.235
90 Percent Confidence Interval for FO	(0.113 ; 0.385)
Root Mean Square Error of Approximation (RMSEA)	**0.0419**
90 Percent Confidence Interval for RMSEA	**(0.0291 ; 0.0536)**
P-value for test of Close Fit (RMSEA < .05)	**0.867**
Expected Cross-Validation Index (ECVI)	**1.117**
90 Percent Confidence Interval for ECVI	(0.995; 1.267)
ECVI for Saturated Model	**1.362**
ECVI for Independence model	**34.517**
Independence AIC	**9630.369**
Model AIC	**311.510**

Saturated AIC	**380.000**
Independence CAIC	**9718.430**
Model CAIC	**571.058**
Saturated CAIC	**1260.610**
Normed Fit Index (NFI)	**.979**
Non-Normed Fit Index (NNFI)	**.991**
Parsimony Normed Fit Index (PNFI)	**.767**
Comparative Fit Index (CFI)	**.993**
Incremental Fit Index (IFI)	**.993**
Relative Fit Index (RFI)	**.973**
Critical N (CN)	**245.720**
Root Mean Square Residual (RMR)	**0.783**
Standardised RMR	**.0527**
Goodness of Fit Index (GFI)	**.925**
Adjusted Goodness of Fit Index (AGFI)	**.894**
Parsimony Goodness of Fit Index	**.652**

The Satorra-Bentler Chi-square value depicted in Table 4.103 (199.510) supported the decision to reject the exact fit null hypothesis ($p = 0.000209$). The close fit null hypothesis was not rejected ($p > .05$). The sample RMSEA value of .0419 indicated an extremely good close fit, which indicated another improvement in the fit of this model since the previous modification. Supporting these results was the fact that the upper bound of the 90 percent confidence interval for RMSEA (0.0291; 0.0536), only fell marginally above the .05 cut-off value.

This is again better than the previous version of this model, and therefore provided additional support for this good fitting model. The critical N (CN) improved even more from the previous modification, and the results revealed a CN value of 245.720, which was above the threshold of 200, and further supported the good fit achieved.

This model produced a SRMR-value of .0527, which was regarded as acceptable, even though it was still slightly above the critical cut-off value. However, despite the acceptability of these fit indices, and the support for a very good close fit, the remaining results produced by LISREL needed to be investigated to determine whether all the included paths were significant, and whether any additional modifications were suggested. The parameter estimates for beta and gamma, as well as the modification indices were therefore explored, to ensure that the best version of the modified structural model was established.

4.10.17 Modification of structural model (model H)

The unstandardised beta matrix is illustrated in Table 4.104.

Table 4.104
Learning potential structural modified model unstandardised beta matrix (model G)

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE		0.430 (0.079) 5.430	0.549 (0.107) 5.153	-0.485 (0.150) -3.231			
ASL							
LM							0.235 (0.049) 4.760
HOPE	0.902 (0.064) 14.089						
RES						0.565 (0.098) 5.777	0.201 (0.062) 3.236
OPT		0.247 (0.086) 2.874		0.632 (0.102) 6.188			
LP	0.007 (0.101) **0.067**						

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The beta matrix revealed a very interesting result, as it identified one pathway that was consistently statistically significant (p < .05) in the earlier models but now no longer was statistically significant (p > .05). This pathway was the hypothesis depicting the positive influence that *time cognitively engaged* has on *learning performance during evaluation*. Normal practice would be to delete this hypothesised relationship, seeing that the data does not support it. However, in this case, this would mean removing one of the core arguments of the proposed structural model.

Cognitive engagement, according to Burger (2012), generally results in higher levels of learning. It is a deceptively simple premise, perhaps self-evident, but the more students study or practice, the more they tend to learn. This specific variable is specifically important to individuals of the previously disadvantaged group, due to their lower levels of crystallised abilities, as a result, it is required of them to exert more effort and spend more time cognitively engaged in their studies (Burger, 2012).

This notion was supported by a study conducted by Carini et al., (2004), where they found that low ability students benefit more from engagement than their individuals who retain a higher ability. Despite the emphasis on previously disadvantaged individuals with possible lower levels of crystallised abilities; any individual who engages in a learning task needs to sit down and study to succeed. It is unrealistic to think that *learning performance during evaluation* will just occur by only being motivated, optimistic, hopeful, confident, and/or resilient. Consequently, it was decided to not delete this pathway, because firstly, the theoretical argument for the exclusion of this path in the proposed model does not make sense. Secondly, the loss of this hypothesised relationship will be greater than the gain of having a model without this vital path[68]. Thirdly the path only became problematic after the introduction of a path for which the theoretical rational was not very convincing. Lastly, this path obtained satisfactory statistical support in the Burger (2012) study. Since the problem was precipitated by the introduction of a path from *academic self-efficacy*, it was decided to take a step back to the previous modification that resulted in the output proposing the deletion of this path.

To determine whether the gain of adding this direct path (*academic self-efficacy* on *learning performance*) is greater than the cost of deleting the relationship of *time cognitively engaged* and *learning performance*, it was decided to revisit and review the theoretical argument presented earlier to warrant the inclusion of this direct effect.

The theoretical argument emphasised the idea that individuals only need to believe in their own ability to succeed in their academic task, to actually realise this belief, and perform, which will result in a high levels of *learning performance during evaluation*. This is based on the idea that individual's high on self-efficacy attempt challenging tasks more often, persist longer at them, and exert more effort (Tenaw, 2013). This, to some degree, does make sense. The direct effect nonetheless does seem a bit unrealistic.

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[68] The rest of the output produced by LISREL for this modified model (model G) was satisfactory. The unstandardised gamma matrix revealed that all the paths were supported. This then included the direct path from *academic self-efficacy* to *learning performance during evaluation*. The modification indices for beta and gamma did not reveal any additional paths to be added to the structural model. Despite this, it was decided to not delete this path.

This study initially had confidence in the idea that the relationship between *academic self-efficacy* and *learning performance during evaluation* was more complex than what a direct effect will allow. This study argued that *academic self-efficacy* would rather work through the effects of *learning motivation* and *time cognitively engaged* to influence *learning performance during evaluation*. This initial idea were substantiated by the notion presented by Tenaw (2013), stating that individual's high on self-efficacy attempt challenging tasks more often, persist longer at them, and exert more effort. More challenging tasks, longer persistence and exerting more effort can also be regarded as high levels of *learning motivation* and/or high levels of *time cognitively engaged*. A more realistic notion is that *academic self-efficacy* works through the *learning motivation* and *time cognitively engaged* latent variables to affect an increase in *learning performance during evaluation*. This line of reasoning does not as much warrant the conclusion that a direct relationship could not possibly exist; than it suggests that an indirect relationship is more likely and theoretically rational. This is further emphasised by the following argument. Chemers, Hu, and Garcia (2001), found that *academic self-efficacy* directly influences *learning performance during evaluation*, but that an indirect effect is more realistic through the implementation of expectations and coping perceptions.

This links to the research findings obtained by Pintrich and De Groot (1990). They found that students who believed they were capable were more likely to persist more often at difficult or uninteresting academic tasks, and more likely to achieve success at that. This study suggested that *academic self-efficacy* played a facilitative role in relation to cognitive engagement and that the cognitive engagement variables were more directly tied to actual performance.

Teaching students about different cognitive and self-regulatory strategies would be very important for improving actual performance on academic tasks. However, Pintrich and De Groot (1990) suggested that the improvement of individuals' *academic self-efficacy* beliefs would result in them using these cognitive strategies more frequently. Consequently, it seems that a direct positive influence of *academic self-efficacy* on *learning performance* could possible exist, but suggest that the indirect effect is more realistic.

Moreover by considering the results produced by this study, the indirect effect of *academic self-efficacy* on *learning performance* is actually already included in the structural model and is represented by the positive influence of *academic self-efficacy* on *learning motivation, learning motivation* on *time cognitively engaged,* and ultimately *time cognitively engaged* on *learning performance during evaluation*[69].

Consequently, the argument presented in this section warranted the exclusion of the direct pathway between *academic self-efficacy* and *learning performance during evaluation* seeing that the indirect influence of *academic self-efficacy* on *learning performance during evaluation* via the mediating influence of *learning motivation* and *time cognitively engaged* makes theoretically more sense, it was already included in the proposed model, and the benefits of excluding this direct relationship from the model was greater than keeping it and losing the pivotal path between *time cognitively engaged* and *learning performance during evaluation*. Therefore, the final modified model (model F) would be regarded as the final adjusted structural model, and the LISREL output of this model will discussed in detail in the next section. This includes a discussion on the overall model fit based on the array of fit indices produced by LISREL. A final decision will be made on the credibility of the structural model parameter estimates, and the parameter estimates of the fitted model will also be discussed, and will result in the interpretation of the structural model.

Lastly, an evaluation of the standardised residuals and an interpretation of the modification indices will be included to amplify that no other possibilities exist to further modify and improve this final structural model.

4.11 ASSESSING THE OVERALL GOODNESS-OF-FIT OF THE FINAL MODIFIED LEARNING POTENTIAL STRUCTURAL MODEL

4.11.1 Overall fit statistics

An admissible final solution of the parameter estimates for the modified learning potential structural model (model F) was obtained after 19 iterations. The completely standardised LISREL model is shown in Figure 4.15. The full range of fit indices produced by LISREL, to provide a final assessment of the overall fit of the model is presented in Table 4.105.

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[69] Empirical support was found for each of these relationships in models A - F. The results will be presented in Section 4.11.17.

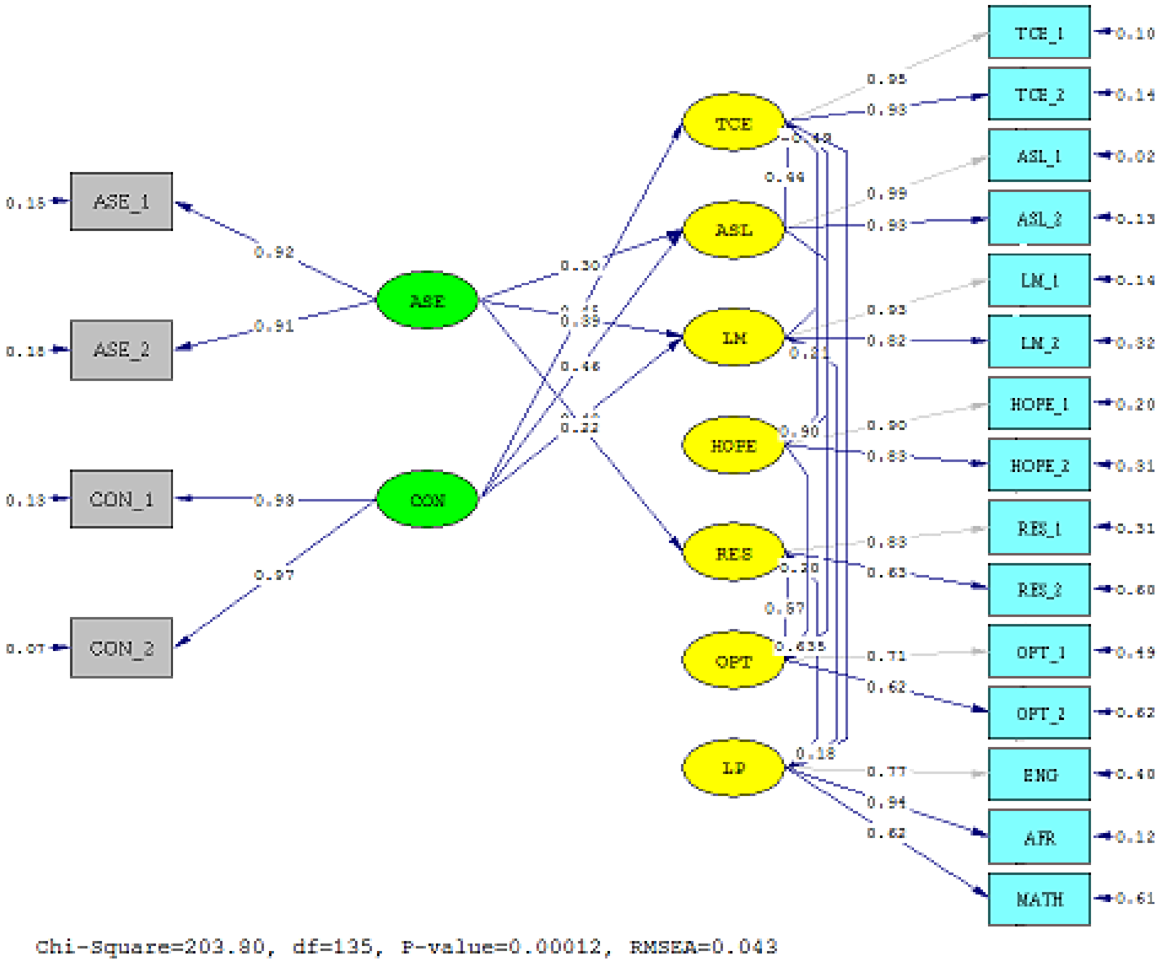

Figure 4.15 Representation of the final adjusted ***Burger – Prinsloo*** learning potential structural model (model F)

Following the final implementation of the suggested changes and modification, the final goodness-of-fit statistics are presented in Table 4.105.

Table 4.105
Goodness of fit statistics for the modified Burger – Prinsloo learning potential model (model F)

Degrees of Freedom	135
Minimum Fit Function Chi-Square	225.217 (p = 0.00)
Normal Theory Weighted Least Square Chi-square	218.857 (p = 0.00)
Satorra-Bentler Scaled Chi-square	**203.795 (p = 0.00)**
Chi-square Corrected for NON-Normality	429.625 (p = 0.0)
Estimated Non-centrality Parameter (NCP)	68.795
90 Percent Confidence Interval for NCP	(34.323 ; 111.236)
Minimum Fit Function Value	0.807
Population Discrepancy Function Value (FO)	0.247
90 Percent Confidence Interval for FO	(0.123 ; 0.399)
Root Mean Square Error of Approximation (RMSEA)	**0.0427**
90 Percent Confidence Interval for RMSEA	**(0.0302 ; 0.0543)**
P-value for test of Close Fit (RMSEA < .05)	**0.841**

Expected Cross-Validation Index (ECVI)	**1.125**
90 Percent Confidence Interval for ECVI	(1.001 ; 1.277)
ECVI for Saturated Model	**1.362**
ECVI for Independence model	**34.517**
Chi-square for Independence Model with 253 Degrees of Freedom	9592.369
Independence AIC	**9630.369**
Model AIC	**313.795**
Saturated AIC	**380.000**
Independence CAIC	**9718.430**
Model CAIC	**568.709**
Saturated CAIC	**1260.610**
Normed Fit Index (NFI)	**.979**
Non-Normed Fit Index (NNFI)	**.991**
Parsimony Normed Fit Index (PNFI)	**.773**
Comparative Fit Index (CFI)	**.993**
Incremental Fit Index (IFI)	**.993**
Relative Fit Index (RFI)	**.973**
Critical N (CN)	**242.138**
Root Mean Square Residual (RMR)	**0.863**
Standardised RMR	**.0592**
Goodness of Fit Index (GFI)	**.924**
Adjusted Goodness of Fit Index (AGFI)	**.893**
Parsimony Goodness of Fit Index	**.656**

Table 4.105 revealed that this model achieved a Satorra-Bentler Chi-square value of 203.795 (P = 0.00). This necessitated the deletion of the null hypothesis of exact fit (H_0: RMSEA=0). A statistically significant chi-square resulting in the rejection of the null hypothesis means imperfect model fit in the parameter and possible rejection of the model. The assumption made by the exact fit null hypothesis constitutes a rather ambitious unrealistic position. So, the null hypothesis of close fit was tested. This model achieved a sample RMSEA value of .0427. The probability of obtaining this RMSEA value in a sample if the close fit null hypothesis would be true was sufficiently large (.841) not to reject the close fit null hypothesis. Consequently, the position that this model displays close fit in the parameter was a tenable position. The fit of the model in the sample could be regarded as very good close fit.

The 90 percent confidence interval for RMSEA (0.0302; 0.0543) was narrow and its upper bound fell only marginally above the critical cut-off close fit RMSEA target value of .05. Hence, further support for this model's achieved fit was obtained. Based on these results, it was concluded that the model provided a plausible explanation and a close reproduction of the observed covariance matrix.

The expected cross-validation index (ECVI) focused on the overall error. This value showed the difference between the reproduced sample covariance matrix derived from fitting the model on the sample at hand, and the expected covariance that would be obtained in another sample of equivalent size, from the same population (Byrne, 1998; Diamantopoulos & Siguaw, 2000). So, to assess the model's ECVI, it must be compared to the independence- and saturated model.

Table 4.105 revealed that the model ECVI (1.125) was smaller than the value obtained for the independence model (34.517). The model ECVI (1.125) was also smaller than the value obtained for the saturated model (1.362). So, this suggested that a model more closely resembling the fitted model seemed to have a better chance of being replicated in a cross-validation sample than the independence- or saturated models.

The assessment of a parsimonious fit acknowledge that model fit can always be improved by adding more paths to the model, and estimating more parameters until perfect fit is achieved in the form of a saturated or just-identified model with no degrees of freedom (Kelloway, 1998). Throughout the process of defining and fitting models, it would seem essential to find the most parsimonious model that achieved satisfactory fit with as few model parameters as possible (Jöreskog & Sörbom, 1993).

The parsimonious normed fit index (PNFI = .773) and the parsimonious goodness-of-fit index (PGFI = .656) approach model fit from this perspective. These two values should range from 0 to 1.0, with higher values indicating a more parsimonious fit. There is no standard for how high either index should be to indicate a more parsimonious fit (Kelloway, 1998). However, the both PNFI and PGFI were above .65, which was regarded as acceptable for this study, seeing that these indices generally tend to have somewhat lower values. The parsimonious normed fit index and the parsimonious goodness-of-fit index, according to Kelloway (1998) and Hair et al., (2006) are more meaningfully used when comparing two competing theoretical models. Nonetheless, it is important to report on the complete range of fit indices produced by LISREL.

Akaike's information criterion (AIC) and the consistent version of AIC (CAIC) comprises what are known as information criteria and are used to compare models (Van Heerden, 2013). Parallel to the EVCI, the AIC and CAIC must be contrasted to the independence- and the saturated models. Table 4.105 revealed that the model AIC (313.795) suggested that the fitted structural model provided a more parsimonious fit than the independent model (9630.369) and the saturated model (380.00). Similarly, the CAIC (568.709) also achieved a value lower than both the independence model (9718.430) and the saturated model (1260.610). These results provided additional support for the fit achieved by the structural model.

The comparative fit indices (CFI) contrast how much better the given model fit reproduced the observed covariance matrix than a baseline model which is usually an independence or null model ('*a priori*') (Van Heerden, 2013). The fit indices presented in Table 4.105 illustrated a normed fit index value of .979, a non-normed fit index value of .991, a comparative fit index value of .993, an incremental fit index value of .993, and a relative fit index value of .973. The closer these values are to unity (1.00); the better the fit of the structural model. Despite this, Diamantopoulos and Siguaw (2000) recommend that .90 provides a strong suggestion of a well-fitting model. The results showed that all these values fell comfortable above the .90 level. This was indicative of a satisfactory comparative fit relative to the independent model.

The critical N (CN) shows the size that a sample must achieve in order to acknowledge the data fit of a given model on a statistical basis (Van Heerden, 2013). As a rule-of-thumb, a critical N greater than 200 is expressive of sufficient representation of the data by the specific model. The results showed that a CN value of 242.138 was achieved; this was well above the threshold.

The standardised root mean residual (SRMR) is regarded as a summary measure of standardised residuals, which represented the average difference between the elements of the sample covariance matrix and the fitted covariance matrix. Lower SRMR values are regarded as indicative of a better fit and higher values symbolised worse fit. So, if the model fit is good, the fitted residuals should be small in comparison to the enormity of the elements (Diamantopoulos & Siguaw, 2000). Based on this, Kelloway (1998) suggested that SRMR-values that are smaller than .05 are indicative of an acceptable fit.

The model produced a SRMR of .0592, which was only slightly above the .05 cut-off value, but still quite small. This was therefore regarded as satisfactory, and thus emphasised the acceptability of the fit achieved by the structural model.

The goodness-of-fit index (GFI) and the adjusted goodness-of-fit index (AGFI) reflect how closely the model comes to perfectly reproducing the sample covariance matrix (Diamantopoulos & Siguaw, 2000). The AGFI (.893) adjusts the GFI (.924) for the degrees of freedom in the model and should be between 0 and 1.0; with values exceeding .90. This is indicative of good model fit (Jöreskog & Sörbom, 1993). The AGFI for this model was slightly below the .90 cut-off value, but were regarded as adequate. Consequently, the GFI and the AGFI produced by this model was regarded as satisfactory and indicative of good model fit.

In conclusion, with regards to the fit of the final modified learning potential structural model, the results seemed to support the notion of good close fit indicated by the range of fit indices presented in Table 4.105. The results also suggested that the proposed structural model clearly outperformed the independence and the saturated models. However, the evaluation for the standardised residuals, the interpretation of the parameter estimates, and the assessment of the produced modification indices were first evaluated before deriving the final conclusion on the overall fit of the modified learning potential structural model.

4.11.2 Evaluation of the modified learning potential structural model standardised residuals

Standardised residual values can be considered as positively large if they exceed +2.58 or negatively large if they are smaller than -2.58 (Diamantopoulos & Siguaw, 2000). Residuals should also be dispersed more or less symmetrical around zero. This is due to the fact that the standardised residual-values can be interpreted as standard normal deviates. Five modifications were made to the original structural model based on large, statistically significant and theoretically meaningful modification index values calculated for B and Γ. This modification resulted in the achievement of good close fit; as illustrated in the fit statistics and interpretation thereof presented in the previous section. It is therefore expected that the percentage of large positive and large negative residuals should be small.

The standardised residuals resulting from the covariance estimates derived from the estimated model parameters obtained for the modified structural model are shown in Table 4.106.

Table 4.106

Modified learning potential Burger – Prinsloo structural model standardised residuals

	TCE_1	**TCE_2**	**ASL_1**	**ASL_2**	**LM_1**	**LM_2**	**HOPE_1**	**HOPE_2**	**RES_1**	**RES_2**
TCE_1	-									
TCE_2	0.762	-								
ASL_1	1.092	0.400	-							
ASL_2	0.820	0.205	-	-						
LM_1	-	0.929	1.873	1.818	-					
LM_2	1.296	1.830	**3.005**	**2.699**	-	-				
HOPE_1	-	-	0.696	0.186	-	0.763	-			
HOPE_2	**3.696**	**8.442**	-0,055	-0.512	-	0.882	-	-		
RES_1	-2.388	-1.942	-1.988	-1.303	1.885	0.649	0.352	-0.203	-	
RES_2	0.884	-0.528	1.266	0.048	1.182	0.851	-0.789	-1.279	0.341	-
OPT_1	0.510	0.928	1.507	0.600	1.569	2.122	-0.429	1.031	0.019	1.049
OPT_2	-2.460	-1.841	0.600	0.806	1.343	1.394	1.226	-0.013	1.293	-0.394
ENG	-2.481	-2.067	-1.638	-1.398	0.501	0.419	-1.348	-0.629	-0.480	-0.763
AFR	-	-	-0.081	-0.215	-	1.547	-0.034	1.513	0.305	-0.754
MATH	**3.657**	**3.865**	1.161	1710	**4.120**	**3.359**	2.528	**3.693**	**3.187**	0.688
ASE_1	1.129	0.899	**-2.590**	**-3.118**	1.122	0.497	1.666	1.578	1.606	0.662
ASE_2	-0.197	-0.334	0.903	1.228	0.304	1.059	0.868	0.656	0.599	2.378
CON_1	-	-1.305	-	-0.377	1.105	0.225	-	0.546	-1.453	0.802
CON_2	-	-0.529	0.859	0.480	0.318	1.456	-	-0.834	-1.698	0.847

	OPT_1	**OPT_2**	**ENG**	**AFR**	**MATH**	**ASE_1**	**ASE_2**	**CON_1**	**CON_2**
OPT_1	-								
OPT_2	-1.387	-							
ENG	4.284	1.477	-						
AFR	-3.152	1.105	0.221	-					
MATH	-0.114	1.604	1.925	0.900	-				
ASE_1	1.013	-0.364	1.419	2.570	5.108	-			
ASE_2	0.820	0.105	2.003	2.497	4.901	-	**-**		
CON_1	0.452	0,683	-0.876	0.036	2.429	0.572	**-0.850**	**-**	
CON_2	-0.198	0.463	-1.533	-0.903	2.294	0.847	**-0.495**	**-**	**-**

TCE= Time Cognitively Engaged (TCE_1/2); ASL= Academic Self-leadership (ASL_1/2; ASE= Academic Self-efficacy (ASE_1/2); CON= Conscientiousness (CON_1/2); LM= Learning Motivation (LM_1/2l; RES= Resilience (RES_1/2); OPT= Optimism (OPT_1/2).

Table 4.106 revealed that twelve of the covariance terms in the observed covariance matrix were substantially underestimated (>2.58), while four terms were substantially overestimated (>-2.58). Despite the overestimation, these results were interpreted as a favourable comment on the fit of the modified model. However, the presence of two covariance terms that suggest overestimation had to be kept in mind when considering the rest of the output produced by LISREL.

A good fitting model would be characterised by a stem-and leaf plot where the residuals are distributed approximately symmetrical around zero and with a minimum spread (Burger, 2012). The stem-and-leaf plot for this model is portrayed in Figure 4.16.

```
- 4|3
- 3|21
- 2|65541
- 1|99876555443333
-0|99988888655555554444433322222211100000000000000000000000000000000000000000000000+04
0|1223344555555666667777788888888899999999
1|00011111122222233333445555666667 7899
2|013445567
3|0247779
4|19
5|1
6|
7|
8|4
```

Figure 4.16 **Stem-and-leaf plot of the standardised residuals**

The results revealed in the stem-and-leaf plot showed that the distribution of the standardised residuals appeared slightly to be slightly positively skewed. So in general, the estimated model parameters therefore tended to underestimate the observed covariance matrix, more than they tended to overestimate it.

These results are highlighted in Table 4.107 that provides a summary of the standardised residuals obtained.

Table 4.107

Summary statistics for the final Burger – Prinsloo learning potential structural model standardized residuals

Description	Values
Smallest Standardised Residual	-4.284
Median Standardised Residual	0.009
Largest Standardised Residual	8.442
Largest Negative Standardised Residuals	
Residual for ENG and OPT_1	-4.284
Residual for AFE and OPT_1	-3.152
Residual for ASE_1 and ASL_1	-2.590
Residual for ASE_1 and ASL_2	-3.118
Largest Positive Standardised Residuals	
Residual for LM_2 and ASL_1	3.005
Residual for LM_2 and ASL_2	2.699
Residual for HOPE_2 and TCE_1	3.696
Residual for HOPE_2 and TCE_2	8.442
Residual for MATH and TCE_1	3.657
Residual for MATH and TCE_2	3.865
Residual for MATH and LM_1	4.120
Residual for MATH and LM_2	3.359
Residual for MATH and HOPE_2	3.693
Residual for MATH and RES_2	3.187
Residual for ASE_1 and MATH	5.108
Residual for ASE_2 and MATH	4.901

TCE_1 & TCE_2 = Time Cognitively Engaged; ASL_1 &ASL_2 = Academic Self-Leadership; ASE_1 & ASE_2 = Academic Self-efficacy; CON_1 & CON_2 = Conscientiousness; LM_1 & LM_2 = Learning Motivation; HOPE_1 & HOPE_2 = Hope; RES_1 & RES_2 = Resilience; OPT_1 & OPT_2 = Optimism; ENG = English First Additional Language; AFR = Afrikaans Home Language; MATH = Mathematics.

From the results presented in Table 4.107 it follows that 8.42% (16/190) of the variance and covariance terms were poorly estimated from the model parameter estimates. Also, it should be noted that the prevalence of large positive residuals was substantially greater than the occurrence of large negative residuals. This suggested that the covariance terms in the observed covariance matrix were typically underestimated by the derived model parameter estimates. The median standardised residual of .009 was indicative of the slightly positively skewed distribution already observed in the stem-and-leaf plot that follows from the dominance of large positive residuals.

The Q-plot, presented in Figure 4.17, served as an additional graphical display of the residuals. The data points did swivel away from the 45-degree reference line, which was a somewhat negative comment on the fit of the model. However, the deviation was only really evident mostly in the upper regions, and a little in the lower regions on the X-axis. These findings are in line with the results reported in Figure 4.17, Table 4.106 and Table 4.107.

The findings on the standardised residuals report favourably on the fit of the model, however, the rest of the LISREL output will also be evaluated.

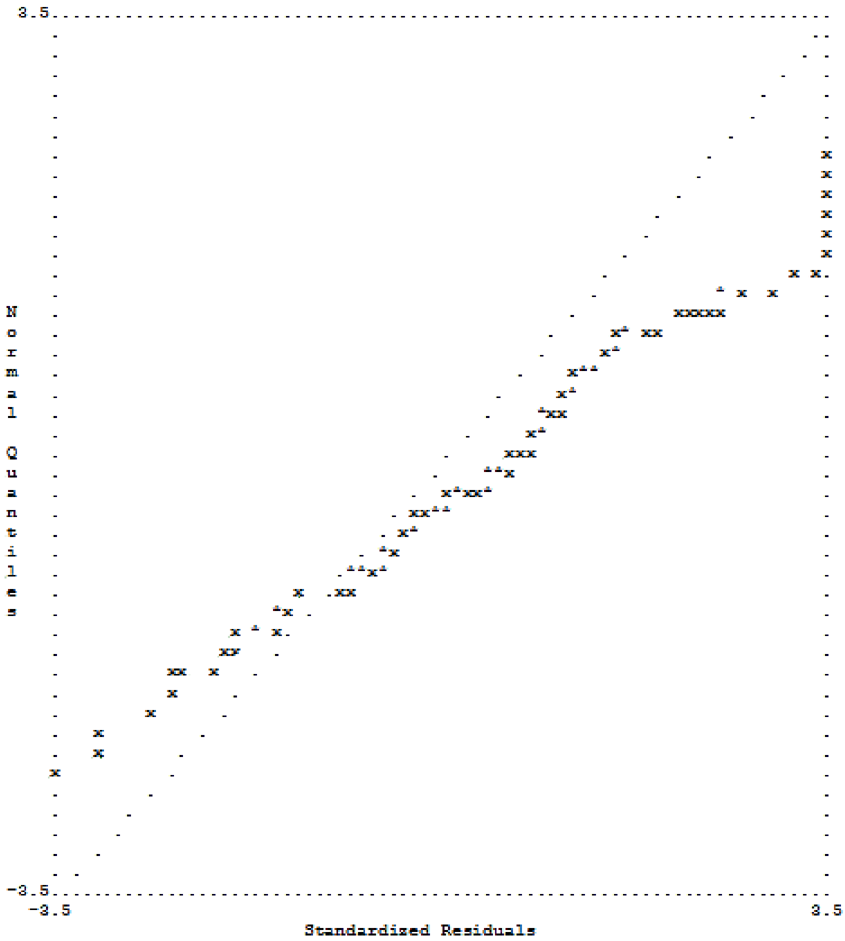

Figure 4.17 **Q-plot for the final Burger – Prinsloo learning potential standardised residuals**

4.11.3 Interpretation of the modified structural model

Based on the results presented up to this point, the modified learning potential structural model has achieved good close fit, where the range of fit indices strongly supported this conclusion. The LISREL output further revealed that the standardised residuals of this model also provided acceptable support for good model fit. The aim of the continuing investigation of the structural model results was to determine whether each of the hypothesised theoretical relationships was supported by the collected data (Diamantopoulos & Siguaw, 2000). The focus was therefore on the linkages between the various endogenous (η) latent variables and between the exogenous (ξ) and endogenous latent variables.

Four issues are relevant when assessing the structural model parameter estimates (Diamantopoulos & Sigauw, 2000). Firstly, it is crucial to assess whether the signs of the parameters representing the paths between the latent variables are in agreement with the nature of the causal effects hypothesised to exist between the latent variables (positive or negative). Secondly, it is important to assess whether the parameter estimates are statistically significant ($p < .05$). Thirdly, assuming statistical significance, it is vital to evaluate the magnitude of the parameter estimates showing the strength of the hypothesised relationships. Lastly, it is very important to assess the squared multiple correlation (R^2) for each of the endogenous latent variables in the model, which provides an indication of the amount of variance in each endogenous latent variable that is accounted for by the latent variables that are structurally linked to it in the model. The higher the squared multiple correlation, the greater the joint explanatory power of the hypothesised antecedents (Van Heerden, 2013).

The parameters that are of interest in evaluating the structural model are the freed parameters of **Γ** (gamma) and **B** (beta). The beta matrix describes the slope of the relationships amid the endogenous latent variables. The unstandardised beta matrix, depicted in Table 4.108, was used to assess the significance of the estimated path coefficients β_{ij} expressing the strength of the influence of η_j on η_i. The unstandardised β_{ij} estimates are significant ($p < .05$) if the t-value is greater that 1.96 (Diamantopoulos & Siguaw, 2000). A significant β estimate would imply that the corresponding H_0-hypothesis should be rejected in favour of the relevant H_a-hypothesis[70].

[70] It is important to emphasise that obtaining a significant beta or gamma path coefficient estimate does not mean proof of causal effect. When using correlational data obtained via an ex-post-factor correlation design, it is impossible to isolate the empirical system sufficiently so that the nature among the variables can be described as causal. This design therefore precludes the drawing of causal inferences from significant path coefficients (Theron, 2010).

Table 4.108
Final Burger – Prinsloo learning potential structural modified model unstandardised beta matrix

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE		0.438 (0.080) 5.493	0.514 (0.106) 4.873	-0.486 (0.152) **-3.205**			
ASL							
LM							0.208 (0.048) 4.336
HOPE	0.905 (0.065) 13.975						
RES						0.567 (0.099) 5.712	0.202 (0.059) 3.387
OPT		0.246 (0.087) 2.847		0.631 (0.103) 6.125			
LP	0.182 (0.066) 2.750						

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

Originally 23 path-specific hypotheses were formulated. These were translated into 23 statistical null hypotheses.

Ten of these statistical null hypotheses could not be rejected in the original model because the parameter estimates were found to be statistically insignificant; these were H_{012}, H_{09}, H_{021}, H_{020}, H_{025}, H_{024}, H_{017}, H_{015}, H_{01}, and H_{027}. These ten paths where the parameter estimates were found to be statistically insignificant were subsequently deleted from the model.

The eleven paths where the parameter estimates were found to be statistically significant were retained. These included; H_{05}, H_{06}, H_{04}, H_{08}, H_{010}, H_{011}, H_{013}, H_{014}, H_{078}, H_{018}, H_{022}, H_{023}, and H_{026}. The two paths where the parameter estimates were found to be statistically significant, but where the nature of the relationship was incorrectly anticipated to be positive were also retained, but now under a revised expectation as to the nature of the relationships (H_{010}, and H_{016}). A number of additional paths that were not originally hypothesised were then also added in a stepwise fashion based on feedback from the structural model output.

Two important points need to be stressed prior to the interpretation of the β estimates in Table 4.108. Although the original path specific hypotheses were formulated by describing the structural relationship between two latent variables only the implicit subtext accompanying each hypothesis was that ξ_j or η_j positively or negatively affects η_i *in a structural model containing all the reaming structural relations* (especially the ones affecting η_j and η_i). In a complex structural model the meaning (or explanation) is spread across the whole of the model rather than being the sum of separate path-specific explanation. The explanation provided by any specific path is inextricably tied in with all the other paths in the model. If paths in the original structural model are deleted and/or if additional paths not originally included are added the precise meaning of the path-specific hypotheses that were originally included therefore change because the structural model in which those paths are embedded changed. The original path-specific hypotheses and their associated null hypotheses can therefore strictly speaking only be tested via the unstandardised Γ and B matrices obtained for the original model.

The paths that were added to the original model were suggested by the current data via modification indices calculated for Γ and $\mathbf{B}$. Although the extent to which the suggested paths made substantive theoretical sense was considered the added paths cannot be considered hypotheses that can be convincingly empirically tested in the current study. In a subsequent study utilising an independent sample and fresh data these added paths can be treated as true hypotheses that can be convincingly empirically tested. Taken together these two points argue the need to cross-validate the final model derived in this study (model F).

The unstandardised beta matrix portrayed in Table 4.108 illustrated that all of the freed β parameter estimates in the final learning potential structural model were statistically significant ($p < .05$) and the signs that were theoretically expected for each relationship was also achieved. The influence of *hope* on *time cognitively engaged* was theoretically argued to be a negative relationship and empirical support for this was found, while all the other relationships were theorised to be positive, and supported as such. Consequently, the beta matrix indicated that *hope* (η_6) had a statistically significant negative effect *on time cognitively engaged* (η_3).

Furthermore, *time cognitively engaged* (η_3) had a statistically significant positive effect *on hope* (η_6). The beta matrix also revealed that *time cognitively engaged* (η_3) has a statistically significant ($p < .05$) effect on *learning performance during evaluation* (η_5). The positive influences of *academic self-leadership* (β_4) on *time cognitively engaged* (η_3) and *academic self-leadership* (β_4) on *optimism* (η_8) were also found to be statistically significant. Table 4.108 shows that *learning motivation* (η_2) had a statistically significant effect *on time cognitively engaged* (η_3). The positive influence that *hope* (η_6) has on *optimism* (η_8) was also found to be statistically significant. *Optimism* (η_8) had a statistically significant positive effect *on resilience* (η_7). Lastly, the positive influences of *learning performance during evaluation* (β_5) on *learning motivation* (η_2) and *learning performance during evaluation* (β_5) on *resilience* (η_7) were also found to be statistically significant.

The unstandardised gamma matrix, illustrated in Table 4.109, was used to assess the significance of the estimated path coefficients γ_{ij}, expressing the strength of the influence of ξ_j on η_i.

Table 4.109
Final Burger – Prinsloo learning potential structural modified model unstandardised gamma matrix

	ASE	CON
TCE	-	0.449
		(0.110)
		4.094
ASL	0.302	0.465
	(0.082)	(0.086)
	3.703	5.395
LM	0.385	0.403
	(0.083)	(0.083)
	4.618	4.862
HOPE	-	-
RES	0.221	-
	(0.074)	
	2.990	
OPT	-	-
LP	-	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The results depicted in the gamma matrix showed that all the freed γ parameter estimates were statistically significant ($p < .05$), and all were positive except for the relationship between *academic self-efficacy* and *academic self-leadership.* For all these paths the sign of the parameter estimate corresponded to the theorising that underpinned these paths.

The relationship between *academic self-efficacy* and *academic self-leadership* was initially hypothesised as a positive relationship following a seemingly sound theoretical argument. However, after the first fitting of the structural model, the results suggested that this relationship is significant, but that it should rather be negative in nature. This was also found during the Burger (2012) study. Therefore, considering the argument produced by Burger (2012) and additional literature, it made theoretical sense to revise the argument underpinning this relationship and rather expect *academic self-efficacy* to have a negative influence on *academic self-leadership*. Based on this revised theoretical argument, this path was not deleted from the structural model.

The results achieved through the revision of the original model right from the outset illustrated the fact that the explanation provided by any specific path is inextricably tied in with all the other paths in the model. At the same time fascinating and frustrating the original statistically significant and negative parameter estimate describing the relationship between *academic self-efficacy* and *academic self-leadership* changed into a statistically significant and positive estimate upon the first modifications made to the original model (model A) and remained a statistically significant and positive estimate throughout all the subsequent models (models B – F).

The results produced in Table 4.109 indicated that the relationship between *academic self-efficacy* and *academic self-leadership* in the final structural model should be a positive relationship. The gamma matrix indicated that *academic self-efficacy* (ξ_2) had a statistically significant effect on *academic self-leadership* (η_4). Therefore, the final conclusion with regards to this relationship remains elusive. There is research evidence that supports both a positive and negative relationship.

The critical challenge is to refine the formulation of the relationship. In each of the structural models the β estimates are partial regression coefficients. They describe the regression of *academic self-leadership* on *academic self-efficacy when holding specific other latent variables constant.* When viewed in this fashion it is not the same relationship that in one model was found to be negative and positive in another.

Additionally, the gamma matrix revealed that *academic self-efficacy* (ξ_2) had a statistically significant and positive effect on *learning motivation* (η_2). The relationship between *academic self-efficacy* (ξ_2) and *resilience* (η_7) was also found to be statistically significant. With reference to the construct of *conscientiousness*; the gamma matrix revealed that the positive influence of *conscientiousness* (ξ_1) on *time cognitively engaged* (η_3) was statistically significant. The positive influences of *conscientiousness* (ξ_1) on *academic self-leadership* (η_4) and *conscientiousness* (ξ_1) on *learning motivation* (η_2) were also found to be statistically significant.

Diamantopoulos and Siguaw (2000) suggested that additional insights on the strength of the structural relationships in the structural model can be obtained by considering the completely standardised beta and gamma parameter estimates provided by LISREL. This is because this output is not affected by differences in the unit of measurement of the latent variables and can therefore be compared across structural equations. The completely standardised beta and gamma parameter estimates reflect the average change, expressed in standard deviation units, in the endogenous latent variables, directly resulting from a one standard deviation change in an endogenous or exogenous latent variable to which it has been linked, holding the effect of all other variables constant (Diamantopoulos & Siguaw, 2000). The completely standardised beta and gamma parameter estimates are presented in Table 4.110 and Table 4.111.

Table 4.110

Final Burger – Prinsloo learning potential structural model completely standardised beta estimates

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE	-	0.438	**0.514**	**-0.486**	-	-	-
ASL	-	-	-	-	-	-	-
LM	-	-	-	-	-	-	0.208
HOPE	**0.905**	-	-	-	-	-	-
RES	-	-	-	-	-	**0.567**	0.202
OPT	-	0.246	-	**0.631**	-	-	-
LP	0.182	-	-	-	-	-	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

Table 4.111

Final Burger – Prinsloo learning potential structural model completely standardised gamma estimates

	ASE	CON
TCE	-	0.449
ASL	0.302	0.465
LM	0.385	0.403
HOPE	-	-
RES	0.221	-
OPT	-	-
LP	-	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

The completely standardised parameter estimates revealed that of all the significant effects, the influence of *time cognitively engaged* on *hope* was the most pronounced (.905). This is followed by the effect of *hope* on *optimism* (.631); the influence of *optimism* on *resilience* (.567) and the effect of *learning motivation* on *time cognitively engaged* (.514). The negative relationship of *hope* on *time cognitively engaged* also appears to be reasonable robust (-.486) when compared with the magnitude of the other estimates presented. It is important to take note of the fact that the most pronounced relationship was not originally hypothesised, and was only added after the evaluation of the modification indices during the modification of the structural model. It is also interesting to note that the relationship between the Psycap variables were so pronounced. What was, however, somewhat disconcerting was the small effect of *time cognitively engaged* on *learning performance during evaluation* (.182).

The inter-latent variable correlation matrix represented in Table 4.112 suggested that a number of the latent variables included in this model are strongly related to each other. The strongest correlation was found between *optimism* on *hope* (.786).

Table 4.112

Inter-latent variable correlation matrix for the final Burger – Prinsloo learning potential structural model

	TCE	ASL	LM	HOPE	RES	OPT	LP	ASE	CON
TCE	1.000								
ASL	0.695	1.000							
LM	0.737	0.520	1.000						
HOPE	0.741	0.629	0.661	1.000					
RES	0.549	0.522	0.523	0.609	1.000				
OPT	0.639	0.643	0.545	**0.786**	0.708	1.000			
LP	0.253	0.127	0.333	0.199	0.315	0.157	1.000		
ASE	0.616	0.596	0.663	0.557	0.526	0.499	0.112	1.000	
CON	0.753	0.656	0.675	0.681	0.503	0.592	0.137	0.632	1.000

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

Table 4.113, presented below, illustrated the R^2 values for the seven endogenous latent variables. Van Heerden (2013) explained that R^2 signifies the proportion of variance in the endogenous latent variables that is accounted for by the learning potential structural model.

Table 4.113
R^2 values of the seven endogenous latent variables in the final Burger – Prinsloo learning potentiial structural model

TCE	ASL	LM	HOPE	RES	OPT	LP
0.481	**0.515**	0.398	0.477	0.419	0.345	**0.941**

As is shown by the results displayed in Table 4.113, the learning potential structural model successfully explained variance in *academic self-leadership* and *learning performance during evaluation*. Especially the proportion of variance that was explained in *learning performance during evaluation* was somewhat surprising seeing that only a single non-cognitive latent variable served as a predictor in the structural equation for the *learning performance during evaluation* latent variable. Fluid intelligence, t*ransfer of knowledge, information processing capacity* and *automisation* that were argued to be critical cognitive learning competencies and learning competency potential latent variables were not included in the model. The Burger (2012) and the Van Heerden (2013) learning potential structural models did not achieve nearly comparable results. However, the structural model was less successful in explaining variance in *time cognitively engaged, learning motivation, hope, resilience* and *optimism*. The model's inability to account for variance in these variables is rather disappointing. However, the R^2 values for *time cognitively engaged* and *hope*, were still reasonably high, even though it didn't make the critical cut off value of .50.

4.11.4 Structural model modification indices

The modified learning potential structural model presented in Figure 4.15 seemed to fit the data well. The assessment of the standardised residuals did however reveal that the addition of one or more paths could actually improve the fit of the model. Consequently, it was decided to again assess the modification indices produced by LISREL. The modification indices for the beta (β) matrix are presented in Table 4.1144, and the modification indices for gamma (Γ) are shown in Table 4.115.

Table 4.114
Final Burger – Prinsloo learning potential structural model modification indices calculated for beta

	TCE	ASL	LM	HOPE	RES	OPT	LP
TCE	-	-	-	-	2.183	3.891	0.003
ASL	-	-	3.910	0.069	0.777	0.006	0.718
LM	0.508	5.979	-	0.698	4.492	6.119	-
HOPE	-	0.231	0.679	-	1.887	0.781	0.098
RES	6.174	4.187	0.543	-	-	-	-
OPT	3.123	-	2.987	-	2.015	-	3.483
LP	-	0.079	1.374	0.089	0.155	0,749	-

TCE= Time Cognitively Engaged; ASE= Academic Self-efficacy; CON= Conscientiousness; LM= Learning Motivation; ASL= Academic Self-leadership; PSYCAP= Psychological Capital; RES= Resilience; OPT= Optimism

Table 4.115
Final Burger – Prinsloo learning potential structural model modification indices calculated for gamma

	ASE	CON
TCE	1.998	-
ASL	-	-
LM	-	-
HOPE	1.133	0.217
RES	-	2.084
OPT	0.411	0.032
LP	**6.793**	0.175

The modification indices calculated for the fixed beta parameters in the beta matrix revealed that no additional paths between any endogenous latent variables would significantly improve the fit of the structural model. The modification indices calculated for the fixed gamma parameters in the gamma matrix, on the other hand, depicted in Table 4.115, revealed the parameter with the highest MI-value, and therefore suggested the addition of a path allowing *academic self-efficacy* to exert a positive influence on *learning performance during evaluation*. This path would result in a significant improvement in the fit of the model. The possibility of adding this path had been considered earlier.

Initially this direct effect, explaining that confidence in oneself would in and by itself result in learning performance and success, was theorised as a possibility, and therefore included in the modified learning potential structural model. However, after the inclusion of this path the model was tested again, and LISREL revealed that with the inclusion of the direct path between *academic self-efficacy* and *learning performance during evaluation* the direct influence of *time cognitively engaged* on *learning performance* became statistically insignificant.

The possibility of effectively removing the latent variable *time cognitively engaged* from the structural model did not make theoretical sense, seeing that an individual cannot solely rely on variables such as *learning motivation*, *optimism*, *hope*, *academic self-efficacy* and *resilience* to perform well in a learning task. A person needs to spend time, and mental effort to succeed at a learning task. Consequently, it was decided to back-track to the previous modified model that resulted in the suggestion to delete this important path. Therefore the argument for the modification, where it was suggested to add the direct effect of *academic self-efficacy* on *learning performance during evaluation,* was revised.

Initially, it was suggested that a direct positive influence of *academic self-efficacy* on *learning performance during evaluation* could possible exist and does make to some degree theoretical sense. However, after contemplation, it was realised that the relationship is more complex than what a direct effect will allow. Therefore, it was argued that an indirect effect is more realistic; and by considering the results produced by this study, the indirect effect of *academic self-efficacy* on *learning performance* via *learning motivation* and *time cognitively engaged* actually had been demonstrated in the structural model.

This is demonstrated by the statistically significant and positive influence of *academic self-efficacy* on *learning motivation,* the statistically significant and positive influence of *learning motivation* on *time cognitively engaged,* and finally the statistically significant and positive influence of *time cognitively engaged* on *learning performance during evaluation.* Based on this argument and empirical findings, the pathway between *academic self-efficacy* and *learning performance during evaluation* was not included in the final Burger – Prinsloo learning potential structural model. The remaining modification indices didn't reveal any additional modifications that were significant.

4.12 POWER ASSESSMENT

When evaluating the findings on the fit of the proposed model, it is crucial to evaluate the statistical power associated with testing the model. Statistical power refers to the conditional probability of rejecting the null hypothesis given that it is false (P [reject H_0: RMSEA = 0|H_0 false]). With regards to structural equation modeling, statistical power refers to the probability of rejecting an incorrect model.

According to Diamantopoulos and Siguaw (2000) when considering the fit of the model using the chi-square test, the probability of making a Type I error (rejecting a correct model when it is wrong) is emphasised. This probability is captured by the significance level α that is usually set at .05. A significant chi- square result indicates that *if* the null hypothesis is true (i.e., the model is correct in the population), then the probability of incorrectly rejecting it is low (i.e., less than five times out of 100 if α = .05). However, another error that can occur is *not* to reject an incorrect model, which is known as Type II error and the probability related to it is denoted as β. The probability of avoiding a Type II error is, therefore, 1 - β and it is this probability that indicates the power of the test used to evaluate the fit of the structural model. Consequently, the power of the test explains how likely it is that a false null hypothesis (i.e., incorrect model) will be rejected (Diamantopoulos & Siguaw, 2000).

This issue is more often than not neglected, which is a serious matter seeing that any model assessment would be incomplete when ignoring power considerations. The importance of instigating power analysis is based on the vital role that sample size plays in the decision made in model testing (Diamantopoulos & Siguaw, 2000). This is especially true for large samples, where the power tend to be high. The decision to reject the null hypothesis of exact/close fit then becomes problematic because it is unclear whether the model was rejected because of severe misspecifications, or because of the too high sensitivity of the test to detect even minor flaws in the model. In small samples, where low power is normally the case, the decision not to reject the null hypothesis of exact/close fit results in ambiguity. This is due to the fact it is unclear whether the decision was due to the accuracy of the model, or to the insensitivity of the test to detect specification errors in the model.

In this study the close fit null hypothesis was not rejected. This leads to the question whether the decision to not reject the null hypothesis was the correct decision. The close fit null hypothesis explains that the proposed model closely reflects reality. However, the model only truly achieves good fit if the statistical power of the close fit evaluation is reasonable high. The application of the chi-square test, had already accounted for Type I errors. Consequently, Diamantopoulos and Siguaw (2000) suggested that a power analysis must be conducted to also account for the probability of Type II errors.

The MacCullum, Browne, and Sugawara (1996) assembled power tables only make provision for degrees of freedom less than or equal to 100 and a sample size of less than or equal to 500. Consequently, this method was not used, and the syntax developed by Preacher and Coffman (2006) in R was rather implemented. This syntax is available from http://www.quantsy.org/rmsea/rmsea.htm, and was utilized to determine the statistical power of the test of close fit. For these analyses, a significance level of .05 was specified, a sample size (N) of 280, the degrees of freedom were set to 135, the value of RMSEA was set to .05 under H_0 and the value of RMSEA under H_a was set to .08.

The Preacher and Coffman (2006) software returned a power value of .992988. This suggested that the probability of rejecting the close fit null hypothesis if the model in reality demonstrated mediocre fit (RMSEA = .08), was quite high. This finding, in collaboration with the fact that the close fit null hypothesis was in fact not rejected; boosts the confidence in the merits of this model. This meant that the statistical analysis was sensitive enough, and therefore free from the danger of not rejecting the close fit null hypothesis due to an insensitive test. These results provided adequate trust in the structural model’s ability to truly fit in the population, and it was concluded that the decision to reject the close fit null hypothesis couldn’t be attributed to a lack of statistical power.

4.13 SUMMARY

The purpose of this chapter was to report on the basket of evidence obtained from the data analyses procedures implemented in this study. The final chapter of this dissertation will discuss the results in detail, which will assist in drawing the general conclusions of this study. The methodological limitations, and practical implications of this study are discussed, after which recommendations for future research and practical managerial action will be presented.

CHAPTER 5

CONCLUSIONS, RECOMMENDATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

5.1 INTRODUCTION

In the final chapter of this research dissertation, the objectives of this study will be briefly reviewed, after which the research results as presented in Chapter 4 will be discussed in detail. A discussion of the results of the evaluation of the measurement model will be included, as well as a reflection of the results of the structural model. A representation of the final modified learning potential structural model will be presented in Figure 5.1. This chapter will then conclude with a discussion on the limitations of the research methodology, the practical implications for organisations and society in general, and lastly recommendations for future research will be made.

5.2 BACKGROUND OF THIS STUDY

With reference to personnel selection, organisations have two obligations to comply with. They firstly have a duty towards society to produce goods and deliver services of high economic utility, and to meet this obligation they need to employ the 'best' employees that are the most competent, productive, efficient and effective. Organisations secondly have a moral, legal and political obligation to diversify their workforce. However, South African companies are struggling to simultaneously comply with these two obligations, due to the fundamental challenges which arise from South Africa's socio-political past. South Africa has a history of racial discrimination that was led by the Apartheid system which was characterised by legal racial segregation and designed for the sole purpose of benefiting White South African citizens and discriminating against Black South Africans. This was achieved by segregating amenities and public services and providing Black South Africans with services inferior to those of White South Africans. The segregation deprived this group of many things, including; proper education, adequate healthcare, access to enriching activities, proper sanitation, and acceptable living arrangements. Despite these, the worst wrongdoing ever inflicted upon these individuals was the deprivation of the opportunities to accumulate human capital (Burger, 2012).

Due to the unmistakable negative consequences of the Apartheid system, South Africa, even today, is left with having a shortage of critical skills in the marketplace, high unemployment and poverty rates, inequality in terms of income distribution and unequal racial representation in the workplace as well as other social challenges such as high crime rate and increasing dependence on social grants (Van Heerden, 2013).

South Africa is desperately trying to fight the consequences of an unfair political system but unfortunately, too often with the wrong measures. The affirmative action policy is a good example of such an initiative that has a strong rationale and the need therefore exists; however, the current implementation thereof should be seriously questioned. Consequently, it was proposed that a fundamental mind shift is needed in South Africa; the focus should not fall on employing the individual with the right skin colour, but rather to provide those previously disadvantaged individuals with the opportunity to receive a proper education, and develop the necessary abilities and skills to succeed in the world of work. Training and development will lead to growth, which is the best method for correction (Joubert & Calldo, 2008). Consequently, the implementation of affirmative development programs are proposed, which will assist organisations to comply with the two responsibilities expected of them. It would, in addition, aid South Africa in fighting the challenges resulting from the Apartheid regime as well as contributing to the millennium developmental goals, and contribute to the global competitiveness of the country.

Affirmative development programs depend on a number of different resources and as a result they are very expensive. So, despite the fact that millions of previously disadvantaged individuals require access to such a program, South Africa has limited resources, which means that only a relatively limited number of individuals will have the opportunity to take part in these programs. Therefore, it is crucial that all attempts should be made to ensure that those that are given the opportunity of participation in such a program will succeed in both the program and their job thereafter (Burger, 2012). Therefore, individuals who have the *potential to learn*, who show the greatest probability to acquire the deficient attainments and dispositions, and who would subsequently gain maximum benefit from such opportunities, should be identified (De Goede & Theron, 2010).

Thus, it is necessary to determine which of the individuals considered for an affirmative development opportunity will achieve the highest level of *classroom learning performance* and eventually *learning performance during evaluation*.

It is important to take note of the fact that this study agreed with Van Heerden (2013, p.16) that "it is by no means implied that skills development has gone unacknowledged by the government thus far". In reality the government has attached great importance to this initiative. The government has also invested the largest portion of the budget into the improvement and development of education and training in South Africa. However, to ensure an increased urgency for the implementation of these affirmative development initiatives, a close collaboration between government and the private sector should exist. Organisations are suffering due to the lack of education that is directly evident in the present skills shortage. Furthermore, businesses are negatively affected by social issues such as poverty and unemployment through increased crime rates and decreased spending on economic development (Van Heerden, 2013). Consequently, active participation and commitment is required from the private sector, in addition to that already showed by the government. Every Human Resource department and industrial psychologist need to acknowledge past wrongdoings and take ownership thereof. These professionals play a crucial role in skills development and the implementation of affirmative development programs (Burger, 2012).

The level of learning performance an individual achieve when provided with a developmental opportunity is not a random event. It is systematically, though complexly determined, by a complex nomological network of latent variables characterising the individual and the context/situation in which the learning takes place (Smuts, 2011). In order to successfully ensure that the selected individual will make a success of the training and developmental opportunity, it is crucial to identify as many of these latent variables as possible and also to develop a thorough understanding of the manner in which they combine to affect *classroom learning performance* and eventually *learning performance during evaluation*. A single explanatory research study is unlikely to result in an accurate understanding of the comprehensive nomological network of latent variables that determine learning performance (Burger, 2012).

So, despite the fact that the construct of learning performance has been researched by De Goede (2007), Burger (2012), and Van Heerden (2013); meaningful progress will only be achieved if explicit attempts are made at successive research studies, which takes effort in expanding and elaborating the latest version of the explanatory learning potential structural model (Smuts, 2011).

Therefore, following on the work of De Goede (2007) and Burger (2012), this research study added additional non-cognitive variables to propose an expanded learning potential structural model. This model aimed to answer the question why variance in learning performance of previously disadvantaged individuals participating in an affirmative developmental opportunity occurs? Consequently, the study developed an elaborated structural model based on a reasoned funnel-like argument that explicates the nature of the casual relationships existing between the learning competency potential variables, between the learning competencies, as well as between the learning competency potential latent variables and the learning competencies. This study empirically evaluated the fit of the proposed theoretically derived learning potential structural model by first testing the fit of the combined endogenous and exogenous measurement model, and thereafter the structural model. The fit was evaluated and modifications were implemented where necessary, based on the modification indices provided by the statistical analysis.

5.3 RESULTS

5.3.1 Evaluation of the measurement model

The fit of the measurement model was analysed to determine the extent to which the indicator variables successfully operationalised the learning potential latent variables. The overall goodness-of-fit of the measurement model was tested with structural equation modelling (SEM). The full range of fit statistics produced by LISREL was interpreted to assess the goodness-of-fit of the learning potential measurement model. The results provided concrete evidence that the measurement model fitted the data well, as good close fit was obtained. The null hypothesis of exact fit was rejected; subsequently, the null hypothesis for close fit was tested and not rejected. The interpretation of the array of measurement model fit statistics, the standardised residuals and the modification indices all indicated good model fit.

The factor loadings were statistically significant and mostly satisfactorily large and the error variances were statistically significant and mostly acceptably small. The portfolio of results obtained seemed to validate the claim that the specific indicator variables reflected the specific latent variables they were meant to reflect.

All of the item parcels loaded statistically significantly on the latent variables they were designed to reflect. The results also revealed that the values of the squared multiple correlations for the indicator variables were generally high, and the measurement error variances were generally low, therefore legitimising the use of the proposed operationalisation of the latent variables to empirically test the learning potential structural model. However, four indicator variables; i.e. RES_2, OPT_1, OPT_2, and MATH, were the exception. For these variables more variance was explained by measurement error than by the latent variable in question. In addition, the standardised residuals and modification indices commented favourable on the fit of the model.

The discriminant validity was also tested and the results obtained revealed that it was highly unlikely that any of the inter-latent variable correlations were equal to 1 in the parameter. This meant that each latent variable may be regarded as a separate qualitatively distinct variable although they do share variance.

Based on these findings, it was concluded that sufficient merit for the measurement model existed, and that the operationalisation of the hypothesised Burger – Prinsloo learning potential model was successful. It would therefore be possible to derive a verdict on the fit of the structural model from the fit of the comprehensive LISREL model. Consequently, the proposed Burger – Prinsloo structural model depicted in Figure 2.5 was tested using SEM.

5.3.2 Evaluation of the structural model

5.3.2.1 Modification process and change rationale

The proposed learning potential structural model was fitted to the data and the initial fit was reasonably well, however the unstandardised beta and gamma matrices revealed that twelve of the twenty-three paths were not supported. Two of these paths were significant, however, both the paths were hypothesised as positive and the results revealed that the relationships were negative in nature.

The first of these was the hypothesised influence of *academic self-efficacy* on *academic self-leadership*. This relationship was hypothesised in the current as well as the Burger (2012) study as a positive: an increase in an individual's belief in their academic ability would result in an increase in their *academic self-leadership*. However, the results of the Burger (2012) study indicated that it should be a negative relationship. A theoretical argument was subsequently presented to support this proposed negative relationship. If an individual believes that she/he is capable of succeeding in an academic or learning task, that individual may not see the need to implement *academic self-leadership* strategies as this person may feel that they are capable of performing successfully without the implementation of such strategies. Despite this, Burger (2012) suggested that cross-validation research should be conducted to resolve this debate. However, this study cannot be regarded as cross-validation, it can rather be seen as a way to 're-test' the paths hypothesised by Burger (2012). This study rather serves as a way to confirm the paths supported by the Burger (2012) research. Consequently, this relationship was hypothesised as positive, seeing that the positive relationship makes more theoretical sense to the author of this study. But, the successive results suggesting a negative relationship increased the predictive validity of this relationship. Therefore, this path was not deleted from the model, and was regarded as a negative relationship and kept in the model.

The other relationship that was proposed as being positive but where the results statistically supported a negative relationship was the hypothesised relationship of *learning performance during evaluation* and *optimism*. The positive relationship between these constructs was hypothesised based on the idea that the success achieved by the individual will result in a more positive attributional style. However, after considering the argument for the negative relationship between *academic self-efficacy* and *academic self-leadership*, this line of thinking made substantive theoretical sense for this particular relationship. If individuals achieve success in their learning opportunities, and achieve a high level of *learning performance during evaluation*, they don't necessarily see the need to implement a positive attribution style, as the 'boost' generated by the achievement/success related to a successful performance would be enough. *Optimism* is not seen as necessary when achievement and success are high. Accordingly, this hypothesised path was also not deleted from the model although it was now interpreted as a negative relationship.

The other ten paths that were not significant and that were therefore deleted from the model were the hypotheses that *academic self-leadership* positively influences *academic self-efficacy* (H_{09}); that *academic self-leadership* positively influences *learning motivation* (H_{06}); that *hope* positively influences *academic self-leadership* (H_{019}); that *hope* positively influences *learning motivation* (H_{018}); that *hope* positively influence *resilience* (H_{023}); that *resilience* positively influences *academic self-efficacy* (H_{024}); that *optimism* positively influences *academic self-leadership* (H_{015}); that *optimism* positively influences *learning motivation* (H_{013}); that *optimism* positively influences *hope* (H_{017}); and that *learning performance during evaluation* positively influences *resilience* (H_{025}). The remaining paths were all statistically significant and therefore supported and not rejected.

After the first modification, the fit of the structural model (model A) was subsequently re-evaluated and even though a reasonable good fit was again achieved, the fit results were poorer than the results obtained for the original model. All the paths were found to be significant and therefore supported, except for the negative influence of *learning performance during evaluation* on *optimism*[71]. Therefore this path was deleted from the proposed structural model. The modification indices for beta contained the parameter with the largest MI-value, thus suggesting that a relationship should be added depicting the positive influence of *time cognitively engaged* on *hope*. This made substantial theoretical sense, as *hope*'s one component, i.e. willpower; assist an individual in setting their goals and determining the way in which they are going to achieve these goals. This part of the *hope* definition is supported by another definition of *hope* provided by Snyder (2002); *Hope* is a person's generalised expectancy to achieve their goals. *Time cognitively engaged* refers to the extent to which an individual attend to and extend mental effort in a learning task. Therefore, an increase in *time cognitively engaged* could be expected to result in an increase in learning, which will ultimately lead to performance and probable success. Therefore, if an individual is more cognitively engaged in a learning opportunity, their expectancy to achieve their goals will increase.

[71] This was the relationship originally hypothesised as being positive in nature, however, the first fit results revealed that this relationship should indeed be negative, this change in the sign did however make theoretical sense and the model was not deleted. However, the current fit results revealed that this negative relationship is not supported statistically.

This is due to the fact that an increase in cognitive engagement will result in probable success; which is very likely to serve as a person's primary goal throughout a developmental opportunity. Therefore, based on this argument it made theoretical sense to include this positive relationship of *time cognitively engaged* and *hope*.

After the deletion and the addition of the two suggested paths, the model (model B) was fitted again and the fit deteriorated from a good to a reasonable fit. Despite the fact that the beta and gamma matrices revealed that support was obtained for all the included paths, the modification indices suggested that the structural model could be further expanded to improve the fit of the model. The parameter with the highest MI-value was presented for the influence of *hope* on *time cognitively engaged*. However, this time, the standardized expected change revealed that this relationship should be negative. Consequently, in line with the previous modification, it was explained that as an individual increase their *time cognitively engaged*, it will result in them being more hopeful. However, as soon as their levels of *hope* are heightened, and they are expecting positive goals with a very strong likelihood of achievement, it can be argued that they might decrease the time they cognitively engage, as they will not see the need for it. Therefore, the negative relationship made sense and was included.

After the fit of the modified structural model (model C) was again evaluated the model fit improved substantially. However, opportunity for improvement still existed. The positive influence of *academic self-efficacy* on *hope* was not statistically supported and therefore deleted. Additionally, it was suggested to include the pathway depicting the positive influence of *learning performance during evaluation* on *learning motivation*. So, if a learner performs well on a learning task she/he may be more motivated to learn, assuming that high learning performance is intrinsically rewarding. Achieving success in the learning task should increase the expectancy that effort translate to performance and thereby increase motivation.

The fit of the revised model (model D) was re-evaluated and the model fit improved even more; a good close fit was achieved. However, the modification indices for beta revealed that the fit would improve if a positive relationship between *academic self-leadership* and *optimism* was added.

This made substantial theoretical sense seeing that an individual high on *academic self-leadership* will display cognitive-thought pattern strategies in the form of creating and maintaining functional constructive patterns of habitual thinking, i.e. self-management of beliefs and assumptions through self-talk- and mental imagery strategies; as well as behavioural-focussed by engaging in self-goal setting. *Optimism* is associated with a positive outcome, outlook or attribution of events, which includes positive emotions and motivation. So, an individual that reveals high levels of *academic self-leadership* will probably show high levels of *optimism*. This is because the key components of *academic self-leadership* will encourage an optimistic approach to life. Consequently, it was safe to include this relationship. The original proposed model did hypothesise this positive relationship, but in the opposite direction.

The fit of the modified model (model E) was re-evaluated and the fit improved even more. The modification indices, however, revealed that the fit would improve further if a pathway was added depicting the positive influence of *learning performance during evaluation* on *Resilience*. This path was part of the original proposed structural model, and after the first modification, no statistical support for this path was obtained, and it was therefore deleted. This path did originally make theoretical sense and was based on the argument that if individuals are faced with adverse situations, and they overcome the adversity successfully, a possibility exists that the particular individuals will overcome future adversity even quicker. Individuals become more resilient to an adverse circumstance each time they effectively “bounce back” from the previous setback. So, if an individual is provided with a difficult/challenging learning opportunity, and the individual is successful, i.e. achieve high level of *learning performance*; their *resilience* can be expected to improve and their ability to recover from adversity in the future will advance, therefore supporting the inclusion of this positive relationship in the modified structural model.

After the inclusion of this pathway the fit of the modified model (model F) was evaluated for the last time. Good model fit was obtained. However, the modification indices revealed that the fit would improve if a **direct** positive influence of *academic self-efficacy* on *learning performance* was added. This path was not added for three important reasons.

Firstly, a direct pathway between these two latent variables did make theoretical sense, however, the author believed this relationship to be more complex that what a direct influence would allow. Consequently, this study thought it more realistic that these two latent variables are structurally related to each other in an indirect manner, seeing that it seemed a bit idealistic that high *academic self-efficacy* would in and by itself result in academic achievement and success.

Secondly, when considering the results of this study, an indirect effect of *academic self-efficacy* on *learning performance* was already included and found to be statistically significant in the model. It is represented by the positive influence of *academic self-efficacy* on *learning motivation, learning motivation* on *time cognitively engaged,* and ultimately *time cognitively engaged* on *learning performance during evaluation.*

Lastly, the author experimented, and did add this direct relationship to the model (model G) and re-evaluated the fit of the model. The beta matrix revealed one path that was not significant: the positive influence that *time cognitively engaged* have on *learning performance*. Normal practice would be to delete this hypothesised relationship, seeing that the data does not support it. However, in this case, this would mean removing one of the core arguments of the proposed learning potential structural model. Cognitive engagement, results in higher levels of learning. It is a deceptively simple self-evident premise, but the more students study or practice, the more they tend to learn. It is unrealistic to think that *learning performance during evaluation* will directly occur by only being motivated, optimistic, hopeful, confident, and/or resilient. This path could therefore not be deleted, and consequently, it provided another reason for not adding the positive direct influence of *academic self-efficacy* on *learning performance.*

5.3.2.2. Modified learning potential structural model

The modification of the learning potential structural model resulted in the initial twenty-three paths being reduced to a final sixteen paths. Eight of the originally hypothesised paths were completely deleted from the final structural model. Five paths were added to the model of which two were new hypothesised paths (i.e. the reciprocal relationship between *hope* and *time cognitively engaged*), while the other three were paths that were initially deleted and then brought back either in its original hypothesised form (i.e. *learning performance* on *resilience*), or as hypothesised in the opposite direction (i.e. *academic self-efficacy* on *optimism*), or as a combination of two original hypothesised paths (i.e. *learning performance* on *learning motivation*)[72]. The modified learning potential structural model achieved good model fit. The fit indices revealed statistical support for all the paths included in this model. The stem-and-leaf plot did however indicate that the distribution of the standardized residuals appeared slightly positively skewed. Thus indicating that the estimated model parameters did, on average, underestimate the covariance terms; indicating that this modified model still failed to account for one or more influential paths. Additionally, less than perfect fit was indicated by the fact that the standardized residuals for all pairs of observed variables tended to deviate slightly from the 45-degree reference line, presented by the Q-plot. Despite these results, all the null hypotheses were supported and all the signs were in-line with the theorising related to the paths. The final proposed and tested learning potential Burger – Prinsloo structural model is presented in Figure 5.1.

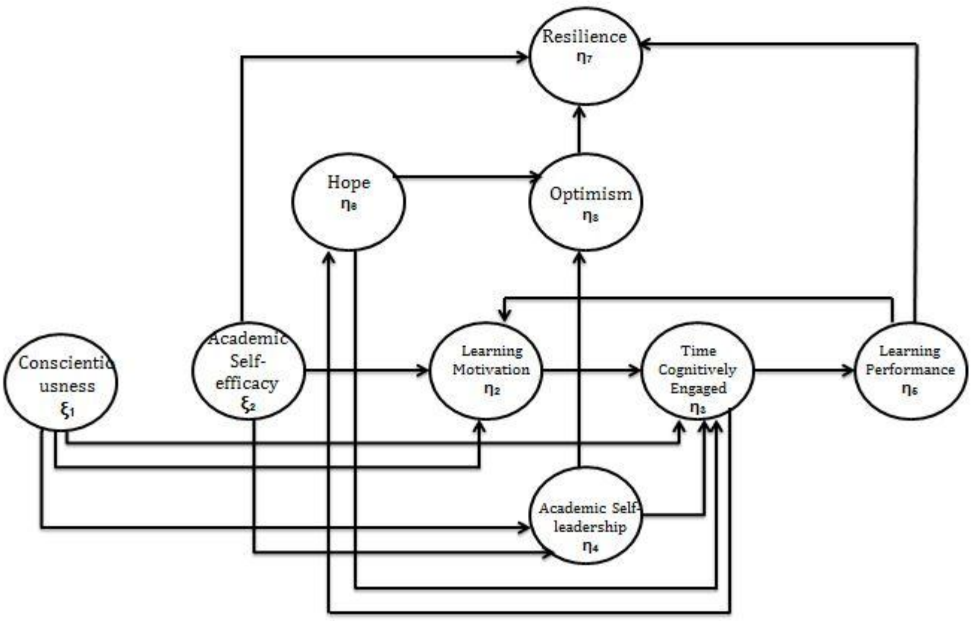

Figure 5.1 **Final proposed and tested Burger – Prinsloo learning potential structural model**

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[72] Burger (2012) hypothesised that *learning performance during evaluation* positively influences *learning motivation*. This study divided this hypothesised path into two separate paths to introduce the mediating effect of *optimism*. Consequently, it was hypothesised that *learning performance during evaluation* positively influences *optimism*, and *optimism* positively influences *learning motivation*. However, these two separately hypothesised relationships were both deleted because no support for them was found, and the modification indices suggested the addition of the original path hypothesised by Burger (2012).

Conscientiousness was found to positively influence *time cognitively engaged*. This corroborated research conducted by Nakayama, Yamamoto and Santiago (2007), who found that diligent students made an effort to learn and to engage with their study material. These authors found that conscientious students exert more effort and spent more time on their study material. They concluded by explaining that conscientious students direct their energy towards the learning task in an attempt to form structure and ultimately to transfer existing knowledge to the current task, which allowed them to complete more modules that their less conscientious counterparts.

Conscientiousness was also found to positively influence *academic self-leadership*. Houghton, Bonham, Neck and Singh (2004) found that *conscientiousness* was significantly related with the behaviour focused skills factor (r = .57), the natural rewards skills factor (r = .33), and the constructive thought-pattern processes skills factor (r = .29); which all formed part of the *academic self-leadership* multi-dimensional construct. *Conscientiousness* was further found to positively influence *learning motivation*. This finding made substantial theoretical sense as individuals who are highly conscientious, are more likely to set higher standards for themselves, are more likely to be willing to work hard on tasks, and generally have a stronger desire to learn (Chen et al., 2001; Colquitt & Simmering, 1998; as cited in Burger, 2012).

Academic self-efficacy, the confidence in one's own academic capability, was shown to positively influence *academic self-leadership*. This relationship was initially hypothesised as positive, however after the first modification it was suggested that the relationship should be negative, which according to the Burger (2012) made theoretical and empirical sense. From the second modification to the final modification, the results provided strong empirical support for a positive relationship. A substantive theoretical argument for a positive relationship also does exist. It could be argued that an increase in an individual's *academic self-efficacy*, the belief in their own academic capability, would result in the strengthening of the person's way in which they influence themselves to achieve self-direction, and motivation necessary to perform, i.e. their *academic self-leadership*. In addition it was argued that strictly speaking when the same relationship is embedded in different structural models containing the same latent variables but different paths, the path-specific hypothesis being tested is different since other latent variables are being controlled.

An individual with a higher level of self-confidence is more likely to self-regulate, self-control, and self-manage, thus emphasising the fact that an individual needs a high level of belief in their own academic capability to become a successful self-leader. Due to the confusion with regards to the nature of the relationship between these two constructs, it is suggested that cross-validation research should be conducted to resolve the debate.

Academic Self-efficacy was also shown to positively influence *learning motivation*. This finding is in line with research conducted by Chapman and Tunner (as cited in Burger, 2012); where it was discovered that students' self-efficacy influences school performance by impacting motivation. This is based on the fact that self-perceptions of competence affect motivation in an activity (Bandura, 1977, 1997).

The results further revealed that *academic self-efficacy* positively influences *resilience*. This is based on the theoretical argument stating that confidence in one's ability classifies as an asset factor in a person's life. Asset factors attribute to the development of *resilience*. The stronger asset factor an individual has, i.e. a higher level of *academic self-efficacy*, the better prepared and more likely an individual is to survive adverse circumstances, i.e. show *resilience* (Stewart, Reid & Mangham, 1997; Luthans et al., 2007).

Furthermore, the results of this study suggested that *learning motivation* positively influences *time cognitively engaged*. This relationship was based on the theoretical argument stating that the more a person is motivated to learn, the more time they will spend, and mental effort they will invest in the learning task at hand (Ryman & Biersner, 1975). Consequently, *learning motivation* was found to serve as the force that brings an individual's intention to learn into action (Burger, 2012).

Time cognitively engaged was shown to positively influence *learning performance during evaluation*. Consequently, the amount of time spent on a learning task, will directly result in higher academic marks, i.e. a higher level of learning performance, which makes substantial theoretical sense. *Time cognitively engaged* was also proved to positively relate to *hope*. This is based on the fact that *hope* is a person's generalized expectancy to achieve their goals (Snyder, 2002).

Time cognitively engaged refers to the extent to which an individual attend to and extend mental effort in a learning task. So, if an individual is more cognitively engaged in a learning opportunity, their expectancy to achieve their goals will increase.

Academic self-leadership was found to positively influence *time cognitively engaged*, and *optimism*. Individuals high on *academic self-leadership* are more likely to show a higher level of self-direction, self-control and self-management, which would assist them to increase the amount of time and effort invested in the learning task. With reference to the positive influence of this construct on *optimism*, the results amplified that the construct of *optimism* is associated with a positive outcome, outlook or attribution of events, which includes positive emotions and motivation (Luthans, 2002a). An individual that show high levels of *academic self-leadership* are more prone to show high levels of *optimism*, seeing that the key components of *academic self-leadership* will encourage an optimistic approach to life.

Learning performance during evaluation was also found to positively influence *learning motivation*, as well as *resilience*. Both these relationship represent feedback-effects in the structural model. Despite the fact that the feedback loop to *learning motivation* made substantive theoretical sense, it was not initially hypothesised as a direct relationship in the proposed structural model. It was rather hypothesised as a relationship mediated by the construct of *optimism*. However, the results did not support the two separate hypothesised relationships, i.e. from *learning performance* to *optimism*, and from *optimism* to *learning motivation*. Consequently, the direct relationship was proposed and made statistical sense, and was therefore included in the model. It made substantial theoretical sense that when a person achieves academic success, their motivation increases and vice versa (Anderson, 1983). The feedback loop to *resilience* emphasised the idea that if an individual is faced with an adverse situation, and they overcome the adversity successfully, a possibility exists that the particular individual will overcome future adversity even quicker. So, if an individual is provided with a difficult/challenging learning opportunity, and the individual is successful, i.e. achieve high level of *learning performance during evaluation*; their *resilience* will most likely improve and their ability to recover from adversity in the future will advance.

Hope showed to positively influence *optimism* and negatively influence *time cognitively engaged*. These relationships made substantial theoretical sense, with reference to *optimism*. Optimists are those individuals who have the agency (willpower) component of *hope*, thus, they have the positive expectations and specific goals in mind.

As a result, it is transparent that *optimism* is structurally related to one of the two components of *hope*. This conclusion highlights the idea that when an individual's level of *hope* increases, both the agency (willpower) and pathway (waypower) components of *hope* will increase, and therefore it is evident that an individual's *optimism* will also increase. With regards to the negative influence of *hope* on *time cognitively engaged*, the reciprocal relationship between these constructs should be considered. As an individual increase their *time cognitively engaged*, it will result in them being more hopeful. However, as soon as their levels of *hope* are heightened, and they are expecting positive goals with a strong likelihood of achievement, they will decrease the time they cognitively engage, as they will not see the need for it.

Lastly, the results of this study revealed that *optimism* positively influences *resilience*. *Optimism*, similar to *academic self-efficacy*, can be regarded as an asset factor, and therefore attributing to the development of *resilience* (Luthans et al., 2007). So, *Optimism* will attribute to the increases in a person's *resilience*.

All of these constructs were shown to play a significant role in the learning potential structural model, in that it directly and indirectly determined whether a learner would perform well academically or not. Additionally, these constructs were shown to influence each other in a complex manner.

5.4 LIMITATIONS OF THIS STUDY

Most of the limitations of the research methodology were already mentioned and discussed throughout the text; nonetheless, the most important issues will be emphasised again in this section.

Firstly, the fact that good model fit in structural equation modelling does not imply causality should be highlighted. Even though the structural model being evaluated hypothesised particular causal paths between the latent variables constituting the model; good model fit and significant path coefficients comprise insufficient evidence to deduce that these causal paths have been confirmed (Kerlinger & Lee, 2000). In the final analysis this is not due to limitations in the analysis technique implemented, but rather owing to the *ex post facto* nature of the study that precludes the experimental manipulation of the relevant latent exogenous and endogenous variables.

Secondly, the learning potential structural model was tested on a non-probability, convenience sample of Grade 11 learners from seven different secondary schools under the Western Cape Department of Education (DOE). These schools were also selected on a non-probability, convenience basis. Due to this non-probability sampling procedure implemented to select the specific sample used in this study, it cannot be claimed that the sample is representative of the target population. Additionally, with reference to sampling limitations, the affirmative action perspective from which this study stems amplifies the ideal to have a sample that consists of participants that qualify as affirmative development candidates. Despite the fact that five of the seven participating schools are classified as previously disadvantaged schools, the division between learners in terms of this category are not that obvious. This classification implies that previously disadvantaged individuals are in previously advantaged schools, and vice versa. This was not the case. Therefore, to obtain a sample of only affirmative development candidates are a much more challenging task than anticipated. This sample of respondents were not solely individuals from disadvantaged backgrounds, but was a mixture of previously advantaged and disadvantaged learners. Although it was argued in Chapter 3, that it is deemed sufficient to draw a sample that includes participants that do not qualify as affirmative development candidates, it still remains a limitation of this study. Therefore, replication of this study in different developmental contexts are therefore recommended and promoted.

In the third instance, it is encouraged to not only replicate this study in different developmental contexts, but also in different provinces. This is based on the following limitation; the inclusion of the additional non-cognitive variables in this study stems from a strong argument amplifying the effects of adverse living conditions. This study argues that due to previously disadvantaged individuals living in the worst living conditions, and poverty stricken areas; it is an unrealistic expectation to expect of them to succeed and flourish in a provided learning opportunity. However, this study used a sample of Western Cape schools, but the Western Cape has some of the best statistics in terms of poverty, education, employment and municipal services in the whole of South Africa. Consequently, it is limiting to this study that the sample is not as representative of the disadvantaged population, as what would be desired based on the proposed argument. Nonetheless, studying in normal circumstances and even favourable living conditions is also tiring and demanding of any learner. Thus, despite the fact that this study utilised a Western Cape sample, it will still contribute tremendously to the available body of knowledge.

Fourthly, the final Burger – Prinsloo learning potential structural model depicted in Figure 5.1 was derived from the original Burger – Prinsloo learning potential structural model depicted in Figure 2.5.The modifications made to the original model, both in terms of deleting existing paths or adding new paths were suggested by the sample data analysed in this study. The same data that suggested the modifications cannot be used convincingly and definitively to test the path-specific hypotheses. The final Burger – Prinsloo learning potential structural model and its paths should therefore be seen as a revised overarching substantive research hypothesis and a revised array of path specific hypotheses. These revised hypotheses should be tested by confronting the final Burger – Prinsloo learning potential structural model with new data. The sample limitations of this study should be taken into account when selecting the new data.

The fifth limitation refers to the measurement instruments used in this study. All of the instruments are self-report instruments, and this normally runs a few risks.

(1) A risk of social desirability or impression management is a strong reality with self-reporting instruments. Social desirability/Impression management refer to the risk that learners may be tempted to manipulate the answers in order to create a more/less favourable impression when completing the self-report questionnaires.

This, according to Elmes, Kantowitz and Roediger (2003), influences the reported levels of each construct measured and therefore the results.

(2) The use of self-reports poses a possible limitation to this study as it presents the question as to whether the reported results are an individual's actual experiences or mainly illustrate their perceptions. A person's perceptions may be different from their actual state of being, thus resulting in them rating themselves higher (or lower) on the constructs due to false perceptions (Van Heerden, 2013). Also, the average age of the participating candidates is 17 years, which is quite young, and their personal knowledge with regards to the difference in their perceptions of themselves and their actual states are not well developed yet. These concerns with regards to the instruments are especially relevant in this study that took place in a Grade 11 classroom, which is a competitive environment filled with uncertainty, peer pressure and rivalry.

Therefore, students may be tempted to create a more/less desirable impression in order to appear on par with their peers or just because they don't know the difference between who they actually are, and their perception of who they want to be really.

(3) In addition to the other two concerns with regards to the measurement instruments, the exclusive reliance on self-reporting measures can, in addition, also create method bias. However, this study did take notice of this fact and measured the *learning performance during evaluation* construct by not using self-reports, but by rather relying on objective academic results obtained for *English first additional language, Afrikaans Home language,* and *Mathematics* for the first semester of each learner.

The last limitation of this study has to do with the method of testing the discriminant validity. This study considered the phi matrix; however, this was not strong evidence of discriminant validity. Consequently, this study calculated a 95% confidence interval for each sample estimate in Φ utilising an Excel macro developed by Scientific Software International (Mels, 2009), to assess the discriminant validity. The results revealed that discriminant validity for this study was identified. However, this method is very lenient and doesn't hold very stringent assumptions like other existing methods.

The reason why the use of this method to test the discriminant validity poses a limitation is because the range of constructs included in this study are closely related and defined, especially the Psycap constructs, and therefore a more stringent method to test the discriminant validity can be to the studies' advantage. A more stringent approach to the evaluation of discriminant validity would entail the comparison of the average variance extracted calculated for each latent variable with the squared inter-latent variable correlation (Diamantopoulos & Siguaw, 2000). Therefore, the current practices do pose a limitation to this study.

5.5 PRACTICAL IMPLICATIONS FOR THIS STUDY

This section describes the practical stance on the usefulness of the results achieved by this study. These will be discussed in detail in the next few paragraphs.

This study was motivated by the argument that affirmative development is critical to the future of South Africa. The study further argued that the level of learning performance achieved by learners admitted to these opportunities are not random events, but rather systematically determined by a complex nomological network of latent variables characterising the learner and his/her learning environment. In addition, it was also mentioned that the reality of scarce resources for these learning opportunities does exist. Consequently, the resources that can be devoted to affirmative development need to be utilised in an optimal manner. This implies that individuals who show the greatest potential to be successful in a development program/opportunity need to be identified, and once identified the malleable determinants of learning performance residing in the learner as well as in the learning environment need to be manipulated through appropriate human resource interventions to levels optimal for effective *classroom learning performance* and *learning performance during evaluation*. Both the selection of individuals into affirmative development opportunities based on learning potential as well as the post selection interventions amplify the crucial role and responsibility of human resources professional and the I/O psychologists in affirmative development.

So, to assist these professionals in identifying the individuals that will gain maximum benefit from such an opportunity, organizations need to be empowered with relevant predictors according to which all applicants for a development opportunity need to be assessed and subsequently seem suitable or not.

Determination of these predictors depends on the development of an understanding of the factors that determine whether or not a person is successful when entered into an Affirmative Development opportunity.

The Burger – Prinsloo learning potential structural model holds the possibility of providing evidence on the identity of some of the latent variables, i.e. the predictors that determine the level of learning performance an individual achieves and the manner in which they combine to determine the learning potential an individual has. The results of this study have revealed that *conscientiousness, academic self-efficacy, learning motivation, academic self-leadership, hope, optimism, resilience* and *time cognitively engaged*, influence the success of a learner during an affirmative development opportunity.

Based on the discussion up to this point, the first practical implication of the results of this study would be to use the identified 'predictors' as tools throughout the recruitment and selection of candidates for an affirmative development opportunity. The results of this study can be used to identify and select individuals who possess what it takes to optimally benefit from the learning opportunity. This study suggest that *conscientiousness*, *academic self-efficacy*, *learning motivation, academic self-leadership, hope, optimism, resilience* and *time cognitively engaged,* could be considered for inclusion in the selection procedure aimed at optimising *learning performance*. It should, however, be taken into consideration that the range of 'predictors' identified in this study consists of malleable, and non-malleable latent variables, and therefore their usefulness for recruitment and selection purposes differ.

In agreement with the proposal made by Van Heerden (2013), the non-malleable determinants of *classroom learning performance* and eventual *learning performance during evaluation* can rightfully serve as predictor constructs that warrant consideration for inclusion in the learning potential selection battery that is used to select individuals into these developmental opportunities.

From this study *conscientiousness* can be included; however, in collaboration with other research on this topic, the following non-malleable person-centered variables should be able to control the level of classroom learning performance by controlling the quality of the candidates that flow into the developmental opportunity.

These include; *learning goal-orientation* and *internal locus of control* (Van Heerden, 2013), and some cognitive predictors would include *fluid intelligence* and *information processing capacity* (De Goede, 2007)[73]. The question should, however, be considered whether selection into affirmative development opportunities should only utilise non-malleable learning potential latent variables as predictors. On the one hand it could be argued that individuals should not be denied access to development opportunities based on deficiencies that can be corrected. This line of reasoning would exclude the use of malleable latent variables as predictors from affirmative development selection procedures.

In terms of this line of reasoning, the results on the malleable latent variables offer the possibility to affect *classroom learning performance* by manipulating the quality of learners **before** they are admitted onto the affirmative development program. Consequently, this study proposed *academic self-efficacy*, *learning motivation, academic self-leadership, hope, optimism, resilience* and *time cognitively engaged* as variables that should be considered in this regard.[74] Suggestions with regards to the enhancements of these malleable variables will be subsequently discussed.

Also flowing from the same line of reasoning is a second practical implication of this study. This involves using the results of this study to design specific interventions to develop the latent malleable competency potential variables of the learners admitted into affirmative development programs, for the sole purpose of improving the effectiveness of the training provided. This study proposed *academic self-efficacy*, *learning motivation, academic self-leadership, hope, optimism, resilience* and *time cognitively engaged* as variables that should be considered in this regard. Suggestions with regards to the enhancements of these malleable variables will be discussed in the next few paragraphs.

[73] However, Burger (2012) reported that De Goede (2007) did not provide adequate empirical justification for the confident inclusion of *Information Processing capacity* in the selection battery. Despite the fact that Van Heerden (2013) proposed this variable based on the results produced in her study; additional research is required on this learning competency potential latent variable. If adequate empirical support is achieved, then it would be a valuable addition to the Learning Potential selection battery.

[74] Burger (2012) reported that skill development programs are hampered by challenges such as mismatch between learner expectations and actual program, high absenteeism and turnover among learners, high dismissal rate of learners, and learners displaying poor attitudes. Letsoalo (2007) reported that that 80% of learners registered for SETA learnerships did not complete their training. A range of factors could contribute to this, however, Alexander (2006) explained that a frequently mentioned reason include poor recruitment and selection of learners into these programs. Consequently, the assessors could assess whether the candidates have the identified malleable and non-malleable constructs, which were shown to influence *learning performance*, to increase the chances of selecting the individual that will most likely a success at such a developmental opportunity.

Academic self-efficacy can be affected by five primary sources; learning experiences, vicarious experiences, imaginal experiences, social persuasion, and physiological states (Bandura, 1997). Self-efficacy can therefore be developed through the interpretation of one's previous performance or learning experiences. It can also be influenced by one's observations of the behaviour of others and the consequences of such behaviours. Self-efficacy can be enhanced through imaginal experiences, which influences self-efficacy beliefs by imagining oneself or others behaving effectively or ineffectively in hypothesised situations. Social persuasion will enhance self-efficacy through the encouragement and/or discouragement from other individuals. Positive persuasions will increase self-efficacy, and vice versa. Lastly, learners base their self-efficacy judgements on their perceived physiological state (i.e. butterflies in the stomach prior to a public speaking competition).

So, a learner's belief about the implications of their physiological state may alter their self-efficacy (i.e. someone low on self-efficacy may see the butterflies as a sign of their own inability). This model showed, that the construct of *academic self-efficacy* is crucial to the learner's potential to learn, and should therefore be a prime focus throughout selection and training.

Learning motivation could be enhanced by considering Vroom's (1964) expectancy theory. When trying to motivate learners more, certain questions need to be asked: would the learners find the training valuable; what positive outcomes could this training lead to for the learners; what are the expectations of the learners of achieving success. It is important to ensure that the expectancy of the learners is high, also to ensure that a clear link between *learning performance during evaluation* and value rewards exist. Consequently, if learners have high expectations that effort will translate into learning success, and if *learning performance during evaluation* has valence for trainees and is instrumental in opening up valued doors; learners should be more motivated (Burger, 2012).

With reference to *Time cognitively engaged,* this is the most crucial construct as it is the only latent variable that in the current model[75] directly influences *learning performance during evaluation*. Trainers should be aware of the learner's schedules and how motivated they are to learn. Trainers, most importantly, should make a decision with regards to how much work will have to be studied on their own time, and how much instruction time exists. Instruction time refers to the proportion of time spent on instructional activities. If *time cognitively engaged* is not high outside the classroom; then instruction time serves as the primary place for *transfer of knowledge* to occur. *Time cognitively engaged can also be enhanced by learning motivation, conscientiousness, academic self-leadership,* and *hope*.

Academic self-leadership is the key to employees' enthusiasm for, commitment toward and performance in the developmental opportunity and in the organization. Consequently, the organization should train learners in general self-leadership strategies of which the principals could be applied in the affirmative development program and the job thereafter.

The *academic self-leadership* construct is also strongly related to *time cognitively engaged,* and will strongly influence their *learning performance during evaluation* through the influence of this variable.

With regards to the positive psychological capital variables, i.e. *hope, optimism,* and *resilience*; the results revealed that the most influential of these is the *hope* construct. Almost none of the hypothesised paths for *optimism* and *resilience* were supported. Consequently, this study encourages the focus on the construct of *hope* as this construct have a direct relationship with *time cognitively engaged* and therefore a significantly supported effect on *learning performance during evaluation*. Avey, Luthans and Jensen (2009) reported that training efforts include realistic goal design, pathway generation and overcoming obstacles; thus professionals need to influence learners' perceptions of challenges versus hindrances present in a competitive learning environment.

[75] In an extended model it could be expected that the effect of *time cognitively engaged* on *learning performance during evaluation* would be mediated by *transfer of knowledge and automisation.*

The final practical implication includes the potential benefit of this study to any organisation or schools, i.e. any context where any form of learning takes place. As already mentioned, this study firstly provides ‘clues’ to what will allow an individual to achieve higher levels of *learning performance during evaluation*. Secondly, these ‘clues’ are malleable in nature and therefore open for development. Consequently, organisations (HR managers and industrial psychologists) as well as schools (principals and teachers) should take responsibility for the training and development of these malleable, state-like constructs, as it can be extremely beneficial to schools, organisations and the country as a whole. With specific emphasis on the Psycap constructs, but also with regards to the other included latent variables; these could assist in developing individuals, teams, organisations, and communities to flourish and prosper (Avolio & Gardner, 2005).

The first method of developing these constructs in employees/learners will be through the provision of training opportunities, as explained in the previous paragraphs, which through numerous research studies have proven to be very advantageous (Luthans, Avey, Avolio, Norman & Combs, 2006; Luthans, Youssef & Avolio, 2007; Luthans & Youssef, 2004; Toor & Ofori, 2010). The second method of enhancing these constructs in individuals, is through the reinforcement and modelling of these characteristics by the principals, teachers, managers and psychologists i.e. the ‘leaders’ in the organisations or schools. Research has supported the positive contagion effect that leaders have on their followers (Norman, Luthans & Luthans, 2005; Ross, 2006). Consequently, the results of this study can potentially unlock insights into the learning potential of employees/learners/students that can be of great advantage to any form of learning institution and all organisations that aim to receive return on their investments in training and development.

Returning to the question that arose earlier whether selection into affirmative development opportunities should only utilise non-malleable learning potential latent variables as predictors, it could also be argued that the malleable latent variables can be used for both selection and development. It need not be one or the other. If individuals fail to qualify for admission into a development program based on a too low expected *learning performance during evaluation* score the primary reasons for this low expectation can still be diagnosed from the predictor scores that entered the regression model.

If the too low expected *learning performance during evaluation* score would be attributed to malleable learning potential latent variables the interventions described in the foregoing paragraphs can still be used in an attempt to remedy the situation. Likewise that fact that malleable learning potential latent variables were used to inform the selection decision does not preclude the possibility of further attempts to improve learners' standing on the malleable learning potential latent variable even if they were admitted to a development program.

5.6 RECOMMENDATIONS FOR FUTURE RESEARCH

The first recommendation is that this model and subsequent elaborations of this model should be empirically tested on a new and preferably more representative sample. This will allow the revised overarching substantive research hypothesis and the range of path-specific substantive research hypotheses to be formally and empirically assessed on data that played no role in the derivation of the revised hypotheses. This recommendation will also assist in achieving a higher degree of generalizability of the study results. At present, the study proposes a sample of schools in the Western Cape. However, the Western Cape has some of the best statistics in terms of poverty, education, employment, and municipal services in the whole of South Africa.

As presented by the South African Institute of Race Relations (2012), the Western Cape has a poverty rate of 20% while the Eastern Cape has an astounding rate of 83%. The unemployment rate in the Western Cape is 16%, while in Kwazulu-Natal it ranges from 37% to 46%. With the highest poverty rate (83%), the Eastern Cape also displays the worst living conditions: some 68% of households do not have access to running water, whilst in the Western Cape it is less than 1%. In the Eastern Cape 66% of households do not have electricity, whereas in the Western Cape only 6% do not have electricity. Lastly, about 95% of the Eastern Cape population do not get their refuse collected, however less than 5% of the Western Cape does not have this service. Based on these statistics, it amplifies the need to conduct this study on a more representative sample, as this will greatly enhance the contribution of this study to the field of Industrial Psychology.

However, this does not deny the massive contribution of this study to the I/O field of knowledge and schools in general, seeing that studying in normal circumstances and even good living conditions is also tiring and demanding on any learner. So, despite the fact that this study relied on a Western Cape sample, it still contributes to the available body of knowledge.

The second recommendation involves the proposal for a future collaborative study with the De Goede (2007), the Burger (2012) and the Van Heerden (2013) results forming one structural model to be tested. This study, and all the others, achieved good model fit, and therefore, it is recommended that future research should try to merge these presented structural models to form the De Goede- Burger- Van Heerden- Prinsloo learning potential structural model. This would contribute significantly to the field of Industrial Psychology and Human Resource Management, as it will simultaneously consider both the cognitive and non-cognitive aspects of learning potential. Consequently, it would provide an even better representation of the complex nomological network of variables comprising the learning potential of an individual. The third recommendation involves the suggestions with regards to additional latent variables that could be incorporated in the endeavour to further expand the learning potential structural model and thereby to more closely approximate the complex psychological process that determines *learning performance during learning potential*. The proposed latent variables that should be considered for inclusion comprise the following:

5.6.1 Adversity of living and learning conditions

Future elaborations of the learning potential structural model should also formally model the *adversity of the living and learning conditions* of the learner. This latent variable was explicitly considered and formed the core argument for the relevance of the inclusion of the Psycap latent variables in this study. This is based on the fact that a range of studies have revealed the negative impact of an adverse living and learning environment on the development, learning and performance of a learner (Visser, 2009). The adversity of the learner’s living conditions has not been formally modelled and based on the arguments provided in Chapter 2, a need for this, in the South African context, definitely exists.

The possibility should in addition be explored in future research that *adversity of the living conditions* interact with the psychological capital latent variables to affect *learning performance during evaluation* via its effect on *time cognitively engaged*. The importance of Psycap only really comes to the fore when the level of adversity increases.

If this latent variable does, as argued in this study, play an influential role in determining *learning performance* it clearly holds great relevance for practical attempts to create the conditions conducive to successful learning. The morality of attempts to increase the probability of successful learning in the face of adversity solely by focusing on attempts to enhance *psychological capital* should be questioned.

Consequently, it is suggested that additional research on this construct is needed in the context of the learning potential structural model, to attempt to influence the *learning performance* of the previously disadvantaged. Seeing that majority of this group still live in adverse living conditions and has failed to be part of the 'better-for-all' promise.

5.6.2 Prior Knowledge

Future elaborations of the learning potential structural model should also take into account the critical role of *prior knowledge*. This construct has been described as familiarity, expertise, and experience interchangeably. However, it is suggested that it rather refers to the objective knowledge an individual has stored in their memory (Roschelle, 1995).

Prior knowledge exists at the levels of perceptions, focus of attention, procedural skills, modes of reasoning, and beliefs about knowledge (Roschelle, 1995). This constructs often confounds a trainers/educator's best efforts to teach a learner. Also, literature revealed that learning proceeds primarily from *prior knowledge* and only secondary from the presented material (Roschelle, 1995). Consequently, it made sense why various studies demonstrated a positive relationship between *prior knowledge* and learning (Beier & Ackerman, 2005; Lipson, 1982; McNamara & Kintsch, 1996; Shapiro, 2004). These authors also discovered the important role of *prior knowledge* in the process of obtaining new knowledge. Therefore, this construct can play a highly influential role in a learner's *classroom learning performance*.

Again the possibility should be considered that *prior knowledge* interacts with *fluid intelligence* to determine *transfer of knowledge*.

However, Van Heerden (2012) suggested that the quality of *prior learning* will make a difference in the adverse influence this construct has on the learner's *classroom learning performance*. It was suggested that *prior knowledge* consisting mainly of a surface-level understanding of facts was not related to student achievement, whereas higher levels of *prior knowledge* correlated significantly with success in the presented course. Subsequently, because this study focuses on the *classroom learning performance* of a previously disadvantaged individual, who may or may not have had the opportunity to obtain *prior knowledge*, the necessity of this construct in a study of this nature may be questioned.

However, the theoretical argument that *fluid intelligence* plays an influential role in *classroom learning performance* as well as subsequent *learning performance during evaluation* is persuasive (De Goede, 2007). *Transfer of knowledge* occurs when *fluid intelligence* combines and transforms existing crystalized abilities into a solution to a novel problem. However, *fluid intelligence* cannot operate in a vacuum. To successfully solve novel complex learning problems *Transfer of knowledge* has to occur. This requires retrieving crystallised knowledge written to knowledge stations derived from *prior learning* and adapting and transforming these insights to create meaning in the novel learning material. Burger (2012) explained that the distance over which *fluid intelligence* must 'jump' in order to turn *prior knowledge* into solutions increases as the level of *prior knowledge* decreases.

This is exactly the reason why many previously disadvantaged individuals fail when admitted into jobs or training programs. This seems to suggest a *prior learning* x *fluid intelligence* interaction effect on *classroom learning performance* as well as *learning performance during evaluation*.

The foregoing argument suggests the importance of this construct, and the necessity to include it in future studies. It is a critical learning potential latent variable without which one cannot really hope to accurately predict *classroom learning performance* and *learning performance*. To assist learners to make the most of a new learning experiences; trainers/educators need to understand the influence *prior knowledge* has on learning.

5.6.3 Longitudinal Models

A further possibility to consider in future learning potential structural models is to develop and test longitudinal models in which latent variables like *prior learning*, *learning motivation*, *learning performance during evaluation* and *classroom learning performance* are modelled at different time points to more realistically capture the structural feedback loops that exist between these variables (Little, 2013).

5.8 CONCLUSION

South Africa is currently facing a range of challenges that is a direct result of having segregated amenities and public services which characterised this country's socio-political past lead by the Apartheid system. This system was aimed to create a divided society, where some were always advantaged while others were excluded and deprived. These challenges include skills shortages, high unemployment, excessive poverty rates, inequality in income distribution and unequal racial representation in the workplace. These challenges are pervasive and incapacitating, and have had a negative influence on every aspect of society. Addressing the root cause of these challenges; namely the fact that the previously disadvantaged group lack the necessary skills, knowledge and attitudes to succeed in the world of work, is essential and require the government and the private sector's urgent attention and collaborative effort. It is suggested that the government and the private sector's collaborative effort should take on the form of affirmative development programs that consist of training opportunities relevant to the modern world of work presented to previously disadvantaged individuals. These will succeed in providing direct means of addressing the challenges faced by this country. With the provision of education and skills development; the skills shortage should subside, the high unemployment and poverty rates will eventually decrease, and the previously disadvantaged will be better equipped to succeed in the world, consequently resulting in a more equal income distribution in South Africa and racial representation in the workplace.

These programs also have the potential to assist the private sector in complying with the Employment Equity Act (1998). Currently, organizations are placing incompetent individuals in positions just to lessen the increased pressure placed by the government. Affirmative action, as it is traditionally interpreted in terms of quotas and preferential hiring is a cheap, shallow, insincere cop-out solution that denies the severity of the problem (De Goede & Theron, 2010). Affirmative development programs will assist to empower the previously disadvantaged to rely on their own skills and competencies to enter and succeed in the workplace, thus lessening the necessity for the powerful government to force the placement of disempowered individuals in jobs they cannot perform well.

Affirmative development programs have the additional advantage of assisting organisations to select the 'best' employee for the job without resulting in adverse impact. This phenomenon is not the result of an unfair selection procedure, but rather because of the past, leaving Black South Africans with underdeveloped competency potential. As a result of the unfair playing field within the South African context, choosing the 'best' employee results in the *previously advantaged* group being more advantaged, while leaving the *previously disadvantaged* group further deprived. This reality lies in the fact that South Africa has a vast untapped reservoir of human potential that need to be unlocked. The fundamental mind shift to a more developmental approach will assist in uncovering the locked potential.

Lastly, the necessity of affirmative development programs goes beyond business considerations or alleviation of economic and social challenges. The necessity focuses rather on a purely moral standpoint by emphasising the possible contribution towards the millennium developmental goals (MDGs). These programs will result in economic growth that has the potential to assist in the realization of the eight MDGs.

This study, in collaboration with three other studies (De Goede, 2007; Burger, 2012 and Van Heerden, 2013), were small steps in the direction of addressing these identified problems inhibiting the growth and success of South Africa. Even though this topic is not a simple matter, it is hoped that the importance of this study and other similar studies (De Goede, 2007; Burger, 2012 and Van Heerden, 2013) are realised, and the results will be converted through synergistic cooperation between practical scientists and scientific practitioners, into practical methods that can be applied by government and private sector organizations to start mining the vast untapped reservoir of human potential in South Africa. The available results of the already existing research studies should not be allowed to stay locked up in theses and academic journals, but should rather be implemented to constructively address the challenges disabling this country and to unlock South Africa's reservoir of human potential.

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APPENDIX 1

EXAMPLE OF PERMISSION LETTER ADDRESSED TO PARTICIPANT SCHOOLS

Department of Industrial Psychology
University of Stellenbosch
Stellenbosch
7600

(Address of school)

16 July 2012

Dear *(Name of principal)*

This letter is addressed to you, for the purpose of asking you to partake in a research study conducted by a Jessica Prinsloo, a Master's (Mcomm) student of the Department of Industrial Psychology at the University of Stellenbosch (US). Rolene Liebenberg from the Division of Community Interaction at the US has encouraged me to approach you regarding the possible participation of *(School's name*) Grade 11 learners in the proposed study.

The objective of the research study is to modify and elaborate on an existing theoretical model developed by Burger (2011), with regards to differences in the Learning *Performance* of learners. Thus, this study aims to elaborate on previous research, by considering the effect of non-cognitive variables in the learning process of a learner. This study will specifically consider the effect of the following variables on a learners learning performance; Time Cognitively Engaged, Learning Motivation, Academic Self-leadership, Academic Self-efficacy, Conscientiousness, Resilience, Hope, and Optimism. For a more thorough description of the proposed study, please consult the attached research proposal. By participating in the proposed study, the following will be required of you:

1. This study needs the participation of Grade 11 learners who have the following three subjects: Afrikaans Home Language, English First Additional Language, and Mathematics (not Mathematics Literacy).
2. Between 30 and 40 minutes with the learners, as this will be enough time for them to complete the fill-in questionnaire.

3. The term 1 and term 2 academic marks of the participating Grade 11 learners for the three subjects. Their academic marks will fulfil a crucial part in this study, as it will serve as measures of the level of *Learning Performance* achieved by learners.

This study will require each learner to provide their name on the questionnaire they need to complete. However, this will only be done to link academic marks with the results obtained on the questionnaire. Research participants will otherwise remain confidential. The information will only be disclosed when permission from both the learner and their parent/guardian is obtained. It is also important to take note of the fact that *(School's name*) identity will not be revealed in my Master's thesis, and will also remain confidential. This study will not be invasive, and will avoid disrupting day-to-day practices at *(School's name)*. I will aim to visit the participating schools as the third term commences (middle July), but will come at a time that will suit you best.

This study has the potential to make an immeasurable difference in how any learning environment approaches the process of learning and succeeds in achieving great learning performance. Consequently, I would encourage you to partake in this study, as it will assist in the improvement of interventions aimed at facilitating successful learning, and therefore, the results of this study will be extremely valuable to your school, you community and future of this country.

If you have any questions or concerns about the proposed study, please feel free to contact Jessica Prinsloo (072 478 4172 or 15056074@sun.ac.za) or my supervisor Prof Callie Theron (021 808 3009 or ccth@sun.ac.za).

Yours sincerely,
Jessica Prinsloo

APPENDIX 2

INFORMED ASSENT FROM LEARNERS

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jou kennisvennoot • your knowledge partner

STELLENBOSCH UNIVERSITY

PARTICIPANT ASSENT FORM

Title of research project	The Modification, Elaboration, and Empirical Evaluation of the Burger Learning Potential Structural model.
Assent Form addressed to:	Grade 11 learners

You are asked to participate in a Research study that will be led by Jessica Prinsloo, a Master's student from the Department of Industrial Psychology at the University of Stellenbosch.

1. What is the Research project about?

The Research project aims to modify, and elaborate previously done research, that attempts to explain differences in Learning Performance. Specifically, the project wishes to look at the *time you spend studying (Time Cognitively Engaged),* you're *Learning Motivation*, your *Academic Self-leadership,* your *Academic Self-efficacy,* your *Conscientiousness*, and your *Resilience, Hope, and Optimism*, and how these things affect your level of Learning Performance.

2. Why have I been invited to participate in this project?

You were selected because you are a Grade 11 learner who has completed the first half (term 1 and term 2) of their Grade 11 course, with the following 3 subjects: Afrikaans Home language, English First Additional language, and Mathematics (not Mathematics Literacy).

3. Who is doing the research?

Jessica Prinsloo, a Master's student from the Department of Industrial Psychology at the University of Stellenbosch, conducts this specific Research Project you are asked to participate in. The results obtained from this study, will contribute to my Master's thesis.

4. What will happen to me in this study?

If you volunteer to participate in this study, you will be asked to fill in a short questionnaire of ±30 minutes. You will be asked to fill in your name and surname, but this information will only be used to link your questionnaire information with your academic marks.

5. Can anything bad happen to me?

There are no expected risks connected with your participation in this study. The results of this study will be treated as confidential, only my supervisor and I will have access to the data. You teachers, principal or school will NOT have access to your information. However, because we need to link your questionnaire data with your academic marks, the completion of the questionnaire cannot be anonymous. This only means that we would definitely need you to write your name on your questionnaire, but this information will remain confidential.

6. Can anything good happen to me?

If you participate in this study, you will NOT receive any direct benefits. However, the results of this study has the potential to help your school, your community and South Africa as a country, because it will help us to develop interventions that assist learners to learn better. This means that this study will help us to discover ways to enable successful learning.

7. Will anyone know I am in the study?

Any information obtained in this study, and any information that can be linked to you, will remain confidential. The information will only be revealed if you and your parent/guardian give permission or if law requires the information to be disclosed. The information will remain confidential, because only me and my supervisor has access to it, it is also stored on a password-protected computer, and in my thesis I will only report aggregate statistics for the sample. Therefore, your data will never be singled out, I will consider the sample as a group, and report the information I obtain as such. The results of this study will be reported in an unrestricted electronic thesis, and by means of an article that will be published in a scientific journal. A summary of the results will be presented to the teachers and principle of your school, as well as the other schools I visit. In none of these cases will your information be revealed, and your academic marks will not be reported. The name of your school will also remain confidential, so no one will know that your school took part in this study.

8. Who can I talk to about the study?

If you have any questions or concerns about this study, you are more than welcome to contact Jessica Prinsloo (072 478 4172 or 15056074@sun.ac.za) or Prof Callie Theron (021 808 3009 or ccth@sun.ac.za), both from the department of Industrial Psychology of the University of Stellenbosch.

9. What if I do not want to do this?

You are not forced to take part in this study, so you may refuse, even if your parents/guardians have given permission for you to participate. You may also stop participating at any time during the study without getting into trouble.

You are also not forced to answer questions that you don't want to answer. You are not waving any legal claims, rights or remedies because you are participating. If you want to talk to anyone about your rights as a research participant, please contact Ms Maléne Fouché (021 808 4622 or mfouche@sun.ac.za) at the Division of Research Development.

Do you understand what will be *expected of you* if you participate in this study?

YES	NO

Are you *willing* to participate?

YES	NO

Has the researcher *answered all your questions*?

YES	NO

Do you understand that you can *pull out* at any time before, or during the study?

YES	NO

Name and Surname

Grade

Signature of Grade 11 learner

Date

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DEELNEMER INSTEMMINGSVORM

Titel van Navorsingsprojek:	Verandering, Uitbreiding en Empiriese Evaluasie van die Burger Leerpotensiaal Strukturele model.
Toestemming gerig aan:	Graad 11 leerders

Jy word versoek om deel te neem aan ‘n navorsingsprojek onder leiding van Jessica Prinsloo, ‘n magisterstudent aan die Universiteit van Stellenbosch, Departement Bedryfsielkunde tans besig met haar meestersgraad (MComm Psig).

1. WAAROOR GAAN HIERDIE STUDIE?

Hierdie studie beoog om vorige navorsing rakend die leerpotensiaal van leerders uit te brei en/of te wysig. Die projek neem die volgende veranderlikes in ag: die *tyd wat jy aan skoolwerk afstaan*, jou *leermotivering*, jou *akademiese self-leierskap*, jou *akademiese selfgeldendheid*, jou *pligsgetrouheid*, jou *veerkragtigheid, hoop en optimisme*. Die invloed van hierdie faktore op jou leerpotensiaal sal ondersoek word.

2. HOEKOM WORD JY UITGENOOI OM DEEL TE NEEM?

Jy is ‘n Graad elf leerder wat die eerste helfte van jou Graad 11 jaar voltooi het, met die volgende 3 vakke: Afrikaans Eerste Taal, Engels Tweede Taal en Wiskunde.

3. WIE DOEN DIE NAVORSING?

Jessica Prinsloo, ‘n student tans besig met haar meestersgraad in Bedryfsielkunde aan die Universiteit van Stellenbosch. Die inligting sal bydra tot haar magistertesis.

4. WAT WORD VAN MY VERWAG?

Indien jy instem om deel te neem, sal jy versoek word om ‘n vraelys te voltooi van om en by 30 minute. Jy moet jou naam en van verskaf, maar hierdie inligting gaan slegs gebruik word om jou akademiese rekord aan jou vraelysresultate te koppel.

5. KAN EK IN HIERDIE PROSES BENADEEL WORD?

Geen risikos word vir jou in hierdie studie voorsien nie. Slegs ek en my toesighouer sal toegang tot jou inligting hê, want dit is vertroulik. Jou onderwysers, skoolhoof en skool sal NIE toegang tot die inligting hê nie. Aangesien ons jou akademiese rekords met jou vraelys moet verbind, kan jou vraelys ongelukkig nie naamloos wees nie. Al is jou naam op die vraelys sal die inligting nogtans vertroulik bly.

6. KAN MY DEELNAME AAN HIERDIE STUDIE VIR MY VOORDELIG WEES?

Indien jy hieraan deelneem, sal daar geen onmiddelike voordele of vergoeding ontvang nie. Hierdie navorsing sal egter jou skool, jou gemeenskap en die hele Suid-Afrika kan help in die toekoms, want die inligting van hierdie navorsing sal ons help om leerders te help om beter te kan leer.

7. SAL ENIGIEMAND WEET DAT EK AAN DIE STUDIE DEELNEEM?

Alle inligting wat tydens die studie bekom word, is vertroulik. Jou inligting kan slegs bekendgemaak word as jy en jou ouer/voog geregtelik toestemming daarvoor gee. Die inligting word gestoor op ‘n rekenaar waarvan slegs ek en my toesighouers die wagwoord ken. In my tesis sal ek slegs die groepstatistiek bekend maak en dit wil sê, geen individuele statistiek word bekend gemaak nie. Die resultate van hierdie studie sal in ‘n onbeperkte elektroniese tesis bekend gemaak word en ‘n artikel sal in ‘n wetenskaplike vaktydskrif hieroor gepubliseer word. ‘n Opsomming van die resultate sal aan die onderwysers en skoolhoofde van die deelnemende skole voorgedra word. Jou persoonlike inligting en akademiese rekords sal nooit bekendgemaak word nie. Jou skool se naam sal ook vertroulik hanteer word.

8. MET WIE KAN EK OOR DIE STUDIE PRAAT?

Indien jy enige vrae het, skakel vir Jessica Prinsloo (072 478 4172 of 15056074@sun.ac.za) of Prof. Callie Theron (021 808 3009 of ccth@sun.ac.za) verbonde aan die Departement Bedryfsielkunde aan die Universiteit Stellenbosch.

9. WAT AS EK NIE WIL DEELNEEM NIE?

Selfs as jou ouer/voog toestemming gee dat jy aan hierdie studie mag deelneem, is jy steeds nie verplig om deel te neem indien jy nie wil nie. Jy het ook die volle reg om jouself op enige tyd tydens of na die invul van die vraelys, van die studie te onttrek. Jy mag enige vrae wat jy nie wil invul nie, uitlos en steeds deel wees van die studie. Indien jy verdere vrae het oor jou regte as deelnemer, kontak asseblief Me. Maléne Fouché (021 808 4622 of mfouche@sun.ac.za) by die Afdeling vir Navorsingsontwikkeling van die Universiteit van Stellenbosch.

Verstaan jy wat jy moet doen?

JA	NEE

Wil jy deelneem aan die studie?

JA	NEE

Is al jou vrae deur die studieleier beantwoord?

JA	NEE

Verstaan jy dat jy enige tyd voor, gedurende of na die studie jouself hiervan kan onttrek?

JA	NEE

Naam en Van

Graad

Handtekening van leerder

Datum

APPENDIX 3

INFORMED CONSENT FROM PARENTS/GUARDIANS OF LEARNERS

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STELLENBOSCH UNIVERSITY

CONSENT TO PARTICIPATE IN RESEARCH

Title of the Research Project:	Modification, Elaboration, and Empirical Evaluation of the Burger Learning Potential Structural Model.
Consent Form addressed to:	Parent/Guardian of Grade 11 learner.

You are asked to give permission to allow your child to participate in a research study conducted by Jessica Prinsloo (master's student, MComm), Prof Callie Theron and Dr Gina Görgens, from the Department of Industrial Psychology at Stellenbosch University. The results of this study will contribute to the thesis of Jessica Prinsloo. Your child is selected as a possible participant in this study because he/she is a Grade 11 learner who has completed their first half of their Grade 11 course with the following subjects: Afrikaans Home language, English First Additional language and Mathematics.

1. PURPOSE OF THE STUDY

The objective of the research study is to modify and elaborate an existing theoretical model developed by Burger (2011), aimed at explaining differences in the *Learning Performance* of learners. More specifically, this study aims to elaborate on the previous research, by considering the effect of non-cognitive variables in the learning process of a learner. This study will specifically consider the effect of the following variables on a learner's learning performance; *Time Cognitively Engaged*, *Learning Motivation*, *Academic Self-leadership*, *Academic Self-efficacy*, *Conscientiousness*, *Resilience*, *Hope*, and *Optimism*.

2. PROCEDURES

If you give permission for your child to participate in this study, we would ask of them to complete a short questionnaire that would take ± 30 minutes to complete. They would be asked to provide their name, as this would allow us to link your child's academic results (for the three subjects for term 1 and term 2) and their questionnaire results.

We will come to your child's school, and provide them with the questionnaire. Completion of the questionnaire will not interfere with the normal school activities of your child.

3. POTENTIAL RISKS AND DISCOMFORTS

There exist no foreseeable risks, discomforts or inconveniences for your child or their school. If your child does not want to partake in the study, they are allowed to withdraw before participating, they can withdraw anytime during the study, even after completion of the questionnaire, they may withdraw their input.

4. POTENTIAL BENEFITS TO SUBJECTS AND/OR SOCIETY

There exist no direct benefits for you or your child. However, the development of this learning potential structural model will assist in the development of interventions aimed at promoting successfully learning. Thus, this research will be very valuable to your child's school, your community, and society as a whole.

5. PAYMENT FOR PARTICIPATION

Not you, your child, nor their school will receive any payment for participating in the research study.

6. CONFIDENTIALITY

Any information that is obtained in connection with this study and that can be identified with your child, will remain confidential, and will only be disclosed with your and your child's permission or as required by law. Confidentiality will be maintained by restricting access to the data to the researchers (Jessica Prinsloo, Prof Callie Theron and Dr Gina Görgens), by storing the data on a password-protected computer, and by only reporting aggregate statistics of the sample. The results of this study will be distributed in an unrestricted electronic thesis, as well as in an article published in an accredited scientific journal. A summary of the findings will be presented to the teachers of the participant schools. Not one of these publications will reveal the identity of any research participant (learner), or the academic marks of any learner. The identity of your child's school will also remain confidential.

7. PARTICIPATION AND WITHDRAWAL

You as parent/guardian can choose whether to allow your child to participate in this study. If you allow your child to participate in the study, you may at any time withdraw your child from the study without suffering any consequences. Your child may refuse to answer any questions that he/she does not want to answer, and still remain in the study. Your child will also give personal permission to partake in the study, by signing an informed assent letter, but he/she will not be allowed to do so without your explicit permission.

8. IDENTIFICATION OF INVESTIGATORS

If you as parent/guardian have any questions or concerns about the particular research study, please feel free to contact Jessica Prinsloo (072 478 4172 or 15056074@sun.ac.za) or Prof Callie Theron (021 808 3009/084 273 4139 or ccth@sun.ac.za).

9. RIGHTS OF RESEARCH SUBJECTS

You may withdraw your consent at any time and your child will discontinue participation without any penalty. You are not waving any legal claims, rights or remedies by allowing your child to participate in this study. If you have any questions regarding your child's rights as research subjects, please contact Ms Maléne Fouché (021 808 4622 or mfouche@sun.ac.za) at the Division for Research Development of Stellenbosch University.

10. SIGNATURE OF PARENT/GUARDIAN OF RESEARCH PARTICIPANT

The information above was described to……………………………………………………..in English and I understood what was described to me. I was given an opportunity to ask questions, and the questions were answered to my satisfaction. I hereby give consent voluntarily that my Grade 11 child participates in the research study.

____

Name of parent/guardian

____

Name of Grade 11 learner

______________________________ ______________________________

Signature of parent/guardian Date

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TOESTEMMING VAN OUER/VOOG

Titel van Navorsingsprojek:	Verandering, Uitbreiding en Empiriese Evaluasie van die Burger Leerpotensiaal Strukturele Model.
Toestemming gerig aan:	Ouers van Graad 11 leerders

U word hiermee versoek om toestemming te verleen dat u kind aan hierdie navorsingsprojek mag deelneem. Die ondersoek word gelei deur Jessica Prinsloo (magisterstudent, MComm), Prof. Callie Theron en Dr. Gina Görgens van die Departement Bedryfsielkunde van die Universiteit van Stellenbosch. Die resultate van hierdie studie sal bydra tot die magistertesis van Jessica Prinsloo. U kind kwalifiseer as moontlike deelnemer aangesien hy/sy die eerste semester (kwartaal 1 en 2) van Graad 11 voltooi het met die volgende vakkeuses: Afrikaans Eerste Taal, Engels Tweede Taal en Wiskunde.

1. DOEL VAN DIE STUDIE

Die doel van die navorsingstudie is om 'n reedsbestaande teoretiese model gerig om die verklaring van verskille in leerprestasie soos ontwikkel deur Burger (2011) uit te brei en/of te wysig. Meer spesifiek poog die studie om die bestaande model uit te brei deur die rol wat nie-kognitiewe veranderlikes sin die leerproses van leerders speel te prober verstaan. Die volgende veranderlikes word in ag geneem: *Tydbesteding*, *Leermotivering*, *Akademiese Self-leierskap*, *Akademiese Selfgelding*, *Pligsgetrouheid*, *Veerkragtigheid*, *Hoop* en *Optimisme*.

2. PROSEDURES

Indien u toestemming verleen dat u kind mag deelneem aan die navorsingstudie sal hy\sy gevra word om 'n kort vraelys te voltooi wat om en by 30minute sal neem. U kind sal sy/haar naam moet verskaf om sodoende u kind se akademiese rekord (in genoemde vakke) en die vraelys se resultate aan mekaar te koppel. Die navorser sal u kind se skool persoonlik besoeken sal daar die vraelyste uitdeel.

3. POTENSIËLE RISIKO'S

Daar bestaan geen voorsienbare risiko's vir u kind of hul skool, wat verband hou met die deelname in hierdie navorsingstudie nie. U kind is geregtig om hom/haar van hierdie studie te onttrek voor deelname, daartydens of selfs na die voltooing van die vraelys.

4. POTENSIËLE VOORDELE

Daar bestaan geen direkte voordele vir u kind nie. Tog sal die uitbreiding van die leerpotensiaal-strukturele model die ontwikkeling van intervensies gerig op suksesvolle studie van leerders bevorder. Daarom sal u kind se skool, u gemeenskap en die algehele samelewing noemenswaardig by hierdie navorsing baat.

5. VERGOEDING

Nog u, nog u kind of sy skool sal enige finansiële of ander vergoeding vir deelname aan hierdie studieontvang nie.

6. VERTROULIKHEID

Alle inligting wat tydens hierdie studie bekom word rakend u kind, is vertroulik en sal slegs met u en u kind se toestemming bekend gemaak word. Beperkte toegang tot inligting aan die navorsers (Jessica Prinsloo, Prof. Callie Theron en Dr. Gina Görgens) word verseker deur data op 'n rekenaar, wat 'n wagwoord benodig, te berg. Slegs die gesamentlike statistiek van die groep word gerapporteer en geen individuele statistiek nie. Die resultate sal gerapporteer word in 'n onbeperkte elektroniese tesis en 'n gepubliseerde artikel in 'n geakkrediteerde wetenskaplike vaktydskrif. 'n Opsomming sal ook aan die onderwysers van die deelnemende skole voorgedra word. Op geen van die bogenoemde publikasies sal die identiteit van enige leerder of hul akademiese rekord bekend gemaak word nie. Die naam van die skool van die deelnemende leerders sal ook vertroulik bly.

7. DEELNAME EN ONTREKKING

Die deelname van die leerder aan hierdie studie is die keuse van u as ouer/voog. Indien u instem dat u kind mag deelneem, behou u die volle reg om u kind enige tyd van die studie te onttrek sonder enige gevolge. U kind mag weier om enige van die vrae op die vraelys nie te antwoord nie en steeds deel te wees van die studie. Daar word ingeligte toestemming van elke leerder ook verkry (waarvoor hy sy handtekening gee) voor deelname aan die studie mag plaasvind. Geen kind mag ten spyte van sy instemming, sonder sy ouer/voog se toestemming aan die navorsingstudie deelneem nie.

8. INDENTITEIT VAN NAVORSERS

Enige navrae in verband met die studie kan aan Jessica Prinsloo (072 478 4172 of 15056074@sun.ac.za) of Prof. Callie Theron (021 808 3009/084 273 4139 of ccth@sun.ac.za) gerig word.

9. REGTE VAN DIE LEERDERS

U of u kind mag ter enige tyd die toestemming kanseleer en die leerder uit die studie onttrek sonder enige gevolge. Deur u kind toe te laat om aan hierdie studie deel te neem verbeur u nog u kind geen wetlike regte, aansprake of voorregte nie. Indien u enige vrae in verband met u kind se regte rakende sy/haar deelname aan hierdie studie het, kontak gerus vir Me. Maléne Fouche (021 808 4622 of mfouche@sun.ac.za) by die Afdeling vir Navorsingsontwikkeling van die Universiteit van Stellenbosch.

10. HANDTEKENING VAN OUR/VOOG VAN DEELNEMER

Bogenoemde inligting is aan my ………………………………………………………..verduidelik in Afrikaans en ek verstaan dit. Ek is die geleentheid gebied om vrae te vra en is bevredigend beantwoord. Hiermee gee ek my toestemming dat my Graad 11 leerder aan hierdie studie mag deelneem.

____

Naam van ouer/voog

____

Naam van Graad 11 leerder

______________________________ ______________________________

Handtekening van ouer/voog Datum

APPENDIX 4

REVISED LEARNING PERFORMANCE QUESTIONAIRE

REVISED LEARNING POTENTIAL QUESTIONNAIRE

[SELF ASSESSMENT FORM]

HERSIENE LEEROTENSIAAL VRAELYS

[SELFASSESSEERING VORM]

CONFIDENTIAL/ VERTROULIK

TIME COGNITIVELY ENGAGED

This section of the questionnaire is to provide an assessment of cognitive engagement. Cognitive (mental) engagement refers to the amount of time spent as well as the effort exerted on academic tasks.

Directions: Listed below is a set of statements about your first half of grade 11 (i.e., term 1 and 2). Please react to each statement as **honestly and truthfully** as possible. **There are no right or wrong answers**.

Indicate how often you performed the following behaviours described in the statements by crossing the number (from 0 to 6) that best describes how frequently performed the following behaviours in the first half of grade 11.

0 Never	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Very Often	6 Always

For example: If you <u>never</u> performed the behaviour described in the statement, cross the box with the number 0.

0 Never	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Very Often	6 Always

Read each statement carefully and choose only ONE answer!
Please respond to all questions

Statement	Never	Almost never	Rarely	Sometimes	Often	Very often	Always
1. I *spent enough time* on my academic work in the first half of grade 11 to reach my learning/academic goals.	0	1	2	3	4	5	6
2. I *exerted enough cognitive effort* on grade 11 learning/academic work to reach my goals.	0	1	2	3	4	5	6
3. In my grade 11 class I actively listened and engaged with my teachers	0	1	2	3	4	5	6

	Never	Almost Never	Rarely	Sometimes	Often	Very Often	Always
4. In my grade 11 class I exerted effort to concentrate and understand what my teacher was saying.	0	1	2	3	4	5	6
5. I was intellectually/mentally engaged with what my teacher was saying in my grade 11 class.	0	1	2	3	4	5	6
6. I was intellectually/mentally engaged with my grade 11 study material outside of compulsory class times.	0	1	2	3	4	5	6
7. I would make sure that when I had set time aside to study I used my time efficiently and exerted effort to learn the material.	0	1	2	3	4	5	6
8. When I got down to work with regards to the first half of grade 11, I worked hard.	0	1	2	3	4	5	6
9. I forced myself to focus if my mind drifted off while I was studying.	0	1	2	3	4	5	6
10. I put enough time and effort into the first half of grade 11 to reach my grade 11 goals.	0	1	2	3	4	5	6
11. I was an active member of my grade 11 class.	0	1	2	3	4	5	6
12. I *listened* intensively/deeply in my grade 11 classes.	0	1	2	3	4	5	6
13. I *concentrated* in my grade 11 classes.	0	1	2	3	4	5	6

	Never	Almost Never	Rarely	Sometimes	Often	Very Often	Always
14. I actively participated in grade 11 academic group activities.	0	1	2	3	4	5	6
15. I kept myself focused when I learnt for my grade 11 tests.	0	1	2	3	4	5	6
16. When I was studying in the first half of grade 11 I really engaged with my grade 11 study material.	0	1	2	3	4	5	6
17. I tried not to get distracted in class.	0	1	2	3	4	5	6

Please turn over to next page

ACADEMIC SELF-LEADERSHIP

This section of the questionnaire is to provide an assessment of self-leadership. Self-leadership refers to how you managed and lead yourself with regards to your first half of grade 11.

Directions: Listed below is a set of statements about your first half of grade 11 (i.e., term 1 and 2). Please react to each statement as **honestly and truthfully** as possible. **There are no right or wrong answers**.

Indicate how often you performed the following behaviours described in the statements by crossing the number (from 0 to 6) that best describes how frequently performed the following behaviours in the first half of grade 11.

0	1	2	3	4	5	6
Never	Almost Never	Rarely	Sometimes	Often	Very Often	Always

For example: If you <u>never</u> performed the behaviour described in the statement, cross the box with the number 0.

0	1	2	3	4	5	6
~~Never~~	Almost Never	Rarely	Sometimes	Often	Very Often	Always

Read each statement carefully and choose only ONE answer!
Please respond to all questions

Statement	Never	Almost Never	Rarely	Sometimes	Often	Very Often	Always
1. I used my *imagination* to picture myself performing well on important grade 11 learning tasks before I actually did them.	0	1	2	3	4	5	6
2. I *visualized* myself successfully performing a grade 11 learning task before I did it.	0	1	2	3	4	5	6
3. I mentally rehearsed the way I planned to deal with a grade 11 learning challenge before I actually faced the challenge.	0	1	2	3	4	5	6
4. I wrote down specific learning goals for grade 11.	0	1	2	3	4	5	6

5. I consciously had my grade 11learning goals in mind when I studied.	0	1	2	3	4	5	6
6. I talked to myself (out loud or in my head) to *work through* difficult learning/academic problems in grade 11.	0	1	2	3	4	5	6
7. I found I was talking to myself (out loud or in my head) to help me *deal* with difficult learning/academic problems I faced in grade 11.	0	1	2	3	4	5	6
8. When I *did* a learning/academic assignment especially well, I would treat myself to something I liked or activity I especially enjoy.	0	1	2	3	4	5	6
9. When I successfully *completed* a grade 11 task, I would often reward myself with something I liked or activity I especially enjoy.	0	1	2	3	4	5	6
10. I evaluated/assessed the correctness of my beliefs and assumptions when I was in difficult situations.	0	1	2	3	4	5	6
11. I evaluate/assess my beliefs and assumptions when I had a disagreement with someone else.	0	1	2	3	4	5	6
12. I was tough on myself in my thinking when I did not do a grade 11 task well.	0	1	2	3	4	5	6
13. I got down on myself when I performed grade 11 tasks poorly.	0	1	2	3	4	5	6
14. I felt guilt when I performed grade 11 tasks poorly.	0	1	2	3	4	5	6
15. I made a point of keeping on track as to how well I was doing in my grade 11 work.	0	1	2	3	4	5	6

16. I was aware of how well I was performing my grade 11 activities.	0	1	2	3	4	5	6
17. I kept track of my progress on grade 11 work.	0	1	2	3	4	5	6
18. I focused my thinking on the pleasant rather than the unpleasant aspects of my grade 11 learning/academic work.	0	1	2	3	4	5	6
19. I surrounded myself with objects and people that brought out the learning behaviours I wanted in myself to help me learn.	0	1	2	3	4	5	6
20. I would try to find activities in my work that I enjoyed doing in order to get my work done.	0	1	2	3	4	5	6
21. I found my own favourite way to get my work done.	0	1	2	3	4	5	6
22. I used *written notes* to remind myself of the things I needed to get done.	0	1	2	3	4	5	6
23. I made *lists* to remind me of the things I needed to get done.	0	1	2	3	4	5	6

Please turn over to next page

ACADEMIC SELF-EFFICACY

This section of the questionnaire is to provide an assessment of academic self-efficacy. Academic self-efficacy refers to the belief you have in your academic ability.

Directions: Listed below is a set of statements about your first half of grade 11 (i.e., term 1 and 2). Please react to each statement as **honestly and truthfully** as possible. **There are no right or wrong answers**.

Indicate how often you performed the following behaviours described in the statements by crossing the number (from 0 to 6) that best describes how frequently performed the following behaviours in the first half of grade 11.

Use the following responses:

0 Never	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Very Often	6 Always

For example: If you never performed the behaviour described in the statement, cross the box with the number 0.

0 ~~Never~~	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Very Often	6 Always

Read each statement carefully and choose only ONE answer!
Please respond to all questions

Statement	Never	Almost Never	Rarely	Sometimes	Often	Very Often	Always
1. I felt that I was able to deal with my grade 11 work.	0	1	2	3	4	5	6
2. I believed if I tried hard enough I could solve difficult problems in my grade 11 course.	0	1	2	3	4	5	6
3. I needed reassurance during the first half of my grade 11 course with regards to the academic work.	0	1	2	3	4	5	6
4. I believed I could handle anything in the first half of my grade 11 course.	0	1	2	3	4	5	6

5. I was confident that I could cope efficiently with the first half of my grade 11 course.	0	1	2	3	4	5	6
6. I believed I could solve most problems with regards to the first half of my grade 11 course if I put in the necessary effort.	0	1	2	3	4	5	6
7. I believed I could handle the first half of my grade 11 course well.	0	1	2	3	4	5	6
8. I felt certain I could achieve the academic goals I set for myself in the first half of my grade 11 course.	0	1	2	3	4	5	6
9. I believed I was capable of reaching the goals I set for the first half of my grade 11 course even when *times were tough*.	0	1	2	3	4	5	6
10. I felt secure about my ability to reach the goals I set for the first half of my grade 11 course.	0	1	2	3	4	5	6
11. I felt capable of dealing with most problems that came up in grade 11.	0	1	2	3	4	5	6
12. I felt I would get good grades in grade 11, if I tried hard enough.	0	1	2	3	4	5	6

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CONSCIENTIOUSNESS

This section of the questionnaire is to provide an assessment of conscientiousness. Conscientiousness refers to the trait of being meticulous self-disciplined, careful, thorough, organized, and deliberating carefully before acting.

Directions: Listed below is a set of statements about your first half of grade 11 (i.e., term 1 and 2). Please react to each statement as **honestly and truthfully** as possible. **There are no right or wrong answers**.

Indicate how often you performed the following behaviours described in the statements by crossing the number (from 0 to 6) that best describes how frequently performed the following behaviours in the first half of grade 11.

Use the following responses:

0 Never	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Very Often	6 Always

For example: If you <u>never</u> performed the behaviour described in the statement, cross the box with the number 0.

0 ~~Never~~	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Very Often	6 Always

Read each statement carefully and choose only ONE answer!
Please respond to all questions

Statement	Never	Almost Never	Rarely	Sometimes	Often	Very Often	Always
1. I was always prepared in grade 11.	0	1	2	3	4	5	6
2. I paid attention to details.	0	1	2	3	4	5	6
3. My parents and/or teachers needed to check up on me in order for me to get started with my work in the first half of grade 11.	0	1	2	3	4	5	6

Statement	Never	Almost Never	Rarely	Someti mes	Often	Very Often	Always
4. I got my grade 11 tasks done efficiently and effectively.	0	1	2	3	4	5	6
5. I successfully completed the first half of my grade 11 tasks in the manner I planned to.	0	1	2	3	4	5	6
6. When I made plans with regards to the first half of grade 11 I stuck to them.	0	1	2	3	4	5	6
7. I planned my study time.	0	1	2	3	4	5	6
8. I was thorough in my academic work.	0	1	2	3	4	5	6
9. I got my academic work competed on time.	0	1	2	3	4	5	6
10. I developed a study timetable to guide my studying.	0	1	2	3	4	5	6
11. I stuck to my developed study timetable.	0	1	2	3	4	5	6
12. The study timetable I set up was well organized.	0	1	2	3	4	5	6

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LEARNING MOTIVATION

This section of the questionnaire is to provide an assessment of learning motivation. Learning motivation refers to the specific desire to learn the content of the curriculum relevant to grade 11.

Directions: Listed below is a set of statements about your first half of grade 11 (i.e., term 1 and 2). Please react to each statement as **honestly and truthfully** as possible. **There are no right or wrong answers**.

Indicate the extent to which you agree or disagree with the following statements by crossing the number (from 1 to 7) that best describes your behaviours in the first half of grade 11.

Use the following responses:

1 Strongly Disagree	2 Disagree	3 Slightly Disagree	4 Neither Agree nor Disagree	5 Slightly Agree	6 Agree	7 Strongly Agree

For example: If you <u>strongly disagree</u> with one statement, cross the box with the number 1.

~~1 Strongly Disagree~~	2 Disagree	3 Slightly Disagree	4 Neither Agree nor Disagree	5 Slightly Agree	6 Agree	7 Strongly Agree

Read each statement carefully and choose only ONE answer!
Please respond to all questions

Statement	Strongly Disagree	Disagree	Slightly Disagree	Neither Agree Nor Disagree	Slightly Agree	Agree	Strongly Agree
1. I intended to increase my knowledge during the first half of grade 11.	1	2	3	4	5	6	7
2. When I didn't understand some part of the first half of grade 11course I tried harder for example by asking questions.	1	2	3	4	5	6	7
3. I was willing to exert considerable effort in order to enhance my knowledge and understanding during the first half of grade 11.	1	2	3	4	5	6	7

4. I wanted to learn as much as I could during the first half of grade 11.	1	2	3	4	5	6	7
5. I was motivated to learn the work covered in the first half of grade 11.	1	2	3	4	5	6	7
6. I intended to do my best in the first half of grade 11.	1	2	3	4	5	6	7

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PSYCHOLOGICAL CAPITAL[76]
(HOPE, OPTIMISM AND RESILIENCE)

This section of the questionnaire provides an assessment of Psychological Capital (Hope, Optimism, Resilience and Self-efficacy). Optimism refers to the way your habitual way in which you explain setbacks and failure, thus it refers to your explanatory style. Hope refers to your desire to get started and "stick to" a goal, as well as your ability to come up with alternative plans of action to reach your goals. Resilience is your capacity to "bounce back" from uncertainty, stress, conflict, failure and even positive change.

Directions: Listed below is a set of statements about your first half of grade 11 (i.e. term 1 and 2). Please react to each statement as **honestly and truthfully** as possible. **There are no right or wrong answers**.

Indicate how often you performed the following behaviours described in the statements by crossing the number (from 1 to 6) that best describes how frequently performed the following behaviours in the first half of grade 11.

1 Strongly Disagree	2 Disagree	3 Somewhat Disagree	4 Somewhat Agree	5 Agree	6 Strongly Agree

For example: If you <u>strongly disagree</u> with the behaviour described in the statement, cross the box with the number 1.

1 Strongly Disagree	2 Disagree	3 Somewhat Disagree	4 Somewhat Agree	5 Agree	6 Strongly Agree

Read each statement carefully and choose only ONE answer!
Please respond to all questions

Statement	Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree
1. I feel confident analyzing a long-term problem to find a solution.	1	2	3	4	5	6
7. If I should find myself in a jam at school, I could think of many ways to get out of it.	1	2	3	4	5	6
13. When I have a setback at school, I have trouble recovering from it, moving on.	1	2	3	4	5	6
18. I feel I can handle many things at a time at school.	1	2	3	4	5	6

[76] Prior to the insertion of the Psycap questionnaire in the Revised Learning Potential Questionnaire, an agreement was signed stating that the full questionnaire will not be published in this thesis. Consequently, only one item per subscale was shown. Permission to use this questionnaire for research purposes can be obtained from www.mindgarden.co.za.