INTEGRATION AND ELABORATION OF THE DE GOEDE (2007) AND BURGER (2012) LEARNING POTENTIAL STRUCTURAL MODELS

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DECLARATION

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ABSTRACT

South Africa's turbulent past has left Human Resource managers in South Africa with a unique challenge. Apartheid legislation unfairly discriminated against certain groups of people, which led to these groups' skills and competencies being underdeveloped. The consequence of this is that the skills of a large number of employees in the South African labour market are underdeveloped, which has subsequently led to adverse impact in valid, fair strict-top-down selection. This has fundamentally been caused by the fact that the competence and human capital in South Africa has not been uniformly developed across groups.

The current situation should be addressed by organisations, not only because it is required by legislation, but because it is central to the economic survival of South African organisations. In the final analysis it should be addressed by organisations because it is the morally correct thing to do. Unrest is growing in South Africa especially under those South African groups that have been previously disadvantaged. The masses are tired of not having the opportunity to productively take part in economic activities and experience economic freedom. A testimony to this is the meteoric rise of the Economic Freedom Fighters (EFF) party that, in its first national election as an official party, obtained 9% of the total votes. To address this unrest individuals from previously disadvantaged groups, with the necessary learning potential, need to be identified and developed. Therefore, a method is needed in South Africa that will identify individuals who display a high potential to learn and that will gain maximum benefit from affirmative development opportunities. In order to successfully address the negative effects of South Africa's past through affirmative development the complex nomological network of latent variables underlying learning performance needs to be understood. It will be possible to rationally contribute to successful accelerated affirmative development when a comprehensive understanding of the factors that underlie learning performance, and how these factors combine to determine learning performance, exists.

The primary objective of this study is to integrate the De Goede (2007) and Burger (2012) learning potential structural models and to expand and modify the integrated De Goede-Burger model. More specifically the objective of the current research was to:

- Identify additional latent variables not currently included in the integrated De Goede- Burger learning potential structural model that might directly or indirectly influence classroom learning performance and learning performance during evaluation;

- Develop hypotheses on the manner in which these additional latent variables should be embedded in the integrated De Goede- Burger learning potential structural model;
- Empirically test the expanded De Goede- Burger learning potential structural model by evaluating the model's absolute fit and the testing the statistical significance of hypothesised paths in the model.

Once additional latent variables were identified and hypotheses were developed on the manner in which these additional latent variables are embedded in the integrated De Goede-Burger learning potential structural model, the expanded model was empirically tested. The attempt to obtain measurement model fit was constrained by the fact that the number of observations (114) that were obtained were smaller than the number of freed parameters in the congeneric measurement model in which the intercepts were not modelled. The measurement model was subsequently fitted as a tau-equivalent model. The fitted measurement model did not provide a sufficiently credible description of the process that generated the observed inter-item parcel covariance matrix to have faith in the measurement model parameter estimates. The researchers consequently deemed it pointless to proceed with the fit of the structural model via structural equation modelling. In-order to remedy the situation the decision was made to take a more robust approach by evaluating the path specific substantive hypotheses via multiple regression analysis. This meant dissecting the structural model into 7 separate regression models, fitting each of these via multiple linear regression analysis and testing the path-specific substantive hypotheses by testing the significance of the partial regression slope coefficient estimates.

The regression analysis results indicated that most of the independent variables explained unique variance, which was found to be statistically significant ($p < .05$), in the specific dependent variables that the independent variables are proposed to influence. However, no support was obtained for the path-specific substantive research hypotheses that *learning performance,* exerts a unique positive influence on *academic self-efficacy.* Also, no support was found for the path-specific substantive research hypotheses that the *information processing capacity*time cognitively engaged* interaction effect exerts a unique positive influence on *automisation.* Limitations to the research methodology are noted. Practical recommendations are made. Recommendations for future research are made.

OPSOMMING

Suid-Afrika se onstuimige verlede het menslike hulpbronbestuurders in Suid-Afrika gelos met `n unieke uitdaging. Wetgewing gedurende Apartheid het op `n onregverdige wyse gediskrimineer teenoor sekere bevolkingsgroepe wat daartoe gelei het dat dié groepe se vaardighede en bevoegdhede onderontwikkel is. Die gevolg hiervan is dat die vaardighede van `n groot hoeveelheid werknemers in die Suid-Afrikaanse arbeidsmark onderontwikkel is wat gelei het tot nadelige impak in geldige en billike bo-na-onder seleksie. Die fundamentele oorsaak hiervan is die feit dat die bevoegdhede en intellektuele kapitaal in Suid-Afrika nie eenvormig oor groepe ontwikkel is nie.

Die huidige situasie behoort aangespreek te word deur organisasies, nie net omdat dit vereis word deur wetgewing nie, maar omdat dit van kardinale belang is vir die ekonomiese oorlewing van Suid-Afrikaanse organisasies. Nie net is dit die ekonomiese regte ding om te doen nie, maar dit is ook die morele regte ding om te doen. Daar is `n onrus wat besig is om te groei in Suid-Afrika, veral onder voorheen benadeelde groepe. Dié groepe se ongelukkigheid is besig om te groei omdat hulle nie die geleentheid gegin word om deel te neem aan ekonomiese aktiwiteite en om ekonomiese vryheid te ervaar nie. Die feit dat die Ekonomiese Vryheidsvegters (EFF) in hulle eerste nasionale verkiesing 9% van totale stemme ingepalm het, is getuienis van die feit dat voorheen benadeelde groepe honger is vir ekonomiese geleentheid en vryheid. Om hierdie onrus aan te spreek moet individue van voorheen benadeelde groepe, wat beskik oor die nodige potensiaal, geïdentifiseer word en ontwikkel word. Om die identifiseering van potensiaal te bewerkstellig word `n metode in Suid-Afrika benodig wat individue wat `n hoë potensiaal het om te leer, en wat maksimum voordeel uit regstellende ontwikkelinggeleenthede sal kry, te kan identifiseer. Om die negatiewe gevolge van Suid-Afrika se verlede op `n suksesvolle wyse reg te stel deur regstellende ontwikkeling moet die komplekse nomologiese netwerk van latente veranderliks onderliggend aan leerprestasie verstaan word. Dit sal moontlik wees om op `n rasionele vlak by te dra tot suksesvolle versnelde regstellende ontwikkeling wanneer `n omvattende verstaan ontwikkel is oor die faktore wat onderliggend is aan leerprestasie, asook hoe die faktore kombineer om leerprestasie te bepaal.

Die primêre doelwit van die studie is om die De Goede (2007) en Burger (2012) leerpotensiaal strukturele modelle te integreer en om die geïntegreerde De Goede- Burger model uit te brei en aan te pas. Meer spesifiek was die doelwit van dié huidige navorsing om:

- Addisionele latente veranderlikes te identifiseer wat nie tans in die geïntegreerde De Goede-Burger leerpotensiaal strukturele model ingesluit is nie, maar wat

moontlik direk of indirek `n invloed het op leerprestasie in die klaskamer en leerprestasie gedurende evaluasie;

- Hipoteses te ontwikkel oor die wyse waarop dié addisionele latente veranderlikes ingesluit moet word in die geïntegreerde De Goede-Burger leerpotensiaal strukturele model.
- Empiries die uitgebreide De Goede-Burger leerpotensiaal strukturele model te toets deur die model se absolute passing te evalueer en deur die statistiese beduidenheid van die voorgestelde paaie in die model te toets.

Na addisionele latente veranderlikes identifiseer is en hipotesese ontwikkel is oor die wyse waarop dié addisionele latente veranderlikes ingesluit is in die geïntegreerde De Goede-Burger leerpotensiaal strukturele model, was die uitgebreide model empiries getoets. Die poging om aanvaarbare metingsmodelpasgehalte te vind is aan bande gelê deur die feit dat die getal waarnemeings (114) gelyk was aan die getal vrygestelde parameters in die kongeneriese metingsmodel waarin die afsnitte nie gemodelleer is nie. Die model is vervolgens as ‘n tau-ekwivalente model gepas. Die gepasde model het nie ‘n genoegsaam oortuigende beskrywing gebied van die proses wat die waargenome inter-itempakkie-kovariansiematrys gegenereer het om vertroue in die metinsmodelparameter-skattings te hê nie. Die navorsers het gevolglik besluit dat daar geen punt daarin is om voort te gaan met die passing van die strukturele model nie.. Aangesien daar nie passing vir die metingsmodel verkry is nie, het die navorsers het besluit om `n meer robuuste benadering te neem deur die baanspesifieke substantiewe hipoteses te evalueer via meervoudige regressie-analise, Dit het beteken dat die strukturele model vereenvoudig moes word na 7 afsonderlike regressie-modelle. Elkeen van die modelle is gepas word met behulp van meervoudige lineêre regressie-analise en die baan-spesifieke substantiewe hipotesese is getoets deur die statistiese beduidenheid van die gedeeltelike regressie-helling-koëffisiënt-ramings te toets.

Die resultate van die regressie-analise het aangedui dat meeste van die onafhanklike veranderlikes unieke variansie in die spesifieke afhanklike veranderlikes wat die onafhanklike veranderlikes voorgestel is om te beïnvloed verklaar, wat as statisties beduidend gevind is ($p < .05$. Daar was egter geen ondersteuning gevind vir die baanspesifieke substantiewe navorsinghipotesese dat *leerprestasie*, unieke positiewe invloed uitoefen op *akademiese selfdoeltreffendheid* nie. Daar is ook geen ondersteuning gevind vir die baanspesifieke substantiewe navorsinghipotesese dat die *informasie prosessering kapasiteit*tyd kognitief ingespan* interaksie effek ‘n unieke positiewe invloed uitoefen op *outomatisasie* nie. Tekortkominge in die navorsingsmetodiek word uitgewys.. Praktiese aanbevelings word gemaak. Aanbevelings vir toekomstige navorsing word gemaak.

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CHAPTER 1

INTRODUCTORY ARGUMENT

1.1 INTRODUCTION

A strong national economy correlates strongly with stable social factors like low unemployment rates, low poverty rates and high levels of education. Economic Anthropology written by Stuart Plattner gives a general explanation of economics as the study of how men and society end up choosing, with or without the use of money, how to allocate scarce productive resources which could have alternative uses, to produce various commodities and distribute them for consumption, now or in the future, among various groups and people in society (Plattner, 1989). It is through the effective allocation of scarce productive resources within various groups in society that economies flourish and contribute to a stable functional society.

Businesses provide a platform to distribute resources to various groups in society. Businesses combine and transform scarce resources to provide society with goods and services that add value to society and in return businesses generate profit and economic value for people who are stakeholders in the business. Economic Value Added (EVA) is one of the financial performance measures that comes the closest to capturing the true economic profit of an enterprise. The EVA measure indicates how much economic value is added for shareholders by management, who has been entrusted to act in the best interest of shareholders (Shil, 2009). In order for businesses to create sufficient economic value businesses need to implement strategies that will distinguish them from competitors which will give them a competitive edge. A strategy generally implemented by businesses to gain a competitive edge is a competitive strategy. Competitive strategy aims to establish a profitable and sustainable position against the forces that determine industry competition (Porter, 1985). To optimise economic value, businesses need to develop a competitive advantage over competitors in terms of the product that the business provides. Competitive advantage grows fundamentally out of value a firm is able to create for its consumers and the inability of other businesses to recreate this value. It is this value that businesses create for consumers that motivates consumers to buy the product of one business instead of the products of competitors.

Labour serves as a possible way for a business to gain competitive advantage over its competitors. The human resource function is one of the business functions that are

responsible for various activities, one of which is the effective development and allocation of labour. This function utilises human resources as a key success factor for sustained organisational performance (Prinsloo, 2013). The human resource function therefore has the task to develop, allocate and utilise human resources in such a way that it has a significant impact on an organisation's performance. Paci and Marrorcu (2003) stated that a skilled and highly educated labour force has been indicated as the key driver of economic performance, seeing that it increases the efficiency of existing production as well as stimulates the creation of new products and processes. Creating competitive advantage through people requires careful attention to the practices that best leverage these assets (Wright, Gardner & Moynihan, 2003). Strategic human resource management refers to the development and design of specific human resource programs that are aligned with the specific business strategy of the company. The concept of strategic human resource management tends to focus on organisation-wide human resource concerns and addresses issues that are related to the firm's business, both short-term and long-term (Tsui, 1987). Businesses can gain competitive advantage by aligning the strategic human resources strategy of the company with the business strategy of the company which will lead to an increase of economic value received by stakeholders.

The view that the human resource function plays an important role in adding value to businesses is, however, a view that has being criticised. Dave Ulrich (1997) argued in the Harvard Business review that the human resource function in its current state is ineffective, incompetent, and costly. This is unfortunately a view that is widely held in the business world.

Studies have, however, found that businesses do in fact rely on human resources to add economic value. A majority of the research done on the relationship between HR practices and business performance has demonstrated a statistically significant ($p<.05$) relationship between measures of HR practices and firm profitability (Wright et al, 2003). One of the roles that the human resource function needs to play is adding value to businesses through promoting effective employee performance and ensuring that employees are allocated to the jobs that they would be the most effective in. Human resource managers firstly influence employee performance by selecting employees are that are capable and competent to perform the tasks that are required of them. The training and development function of human resources secondly also has a crucial role to play in enhancing employee performance by equipping employees to function optimally in their jobs. Organisations should therefore prioritise selecting the best employees, invest in their training and development and create an organisational culture that promotes high employee work performance if they want to succeed.

Selection is the process of discovery of candidate qualifications and its characteristics in order to determine their suitability for the vacancy. Selection means to be selective and pick and choose from a pool of available candidates (Florea & Mihai, 2014). Employees are selected based on the fit between the requirements of the job they've applied for and their characteristics and abilities. Through human resource interventions managers can exercise influence over employee that enter the organisation and how the organisation will further train or develop its employees (Du Toit, 2014). It is important that HRM helps select employees that will empower businesses to reach set goals. Selection procedures should therefore be used by HRM to ensure employees are selected that will maximise organisational performance and also help add economic value to stakeholders. HRM should have a value-oriented personnel policy and that policy must begin with rigorous selection (Florea & Mihai, 2014).

Selection in South Africa does, however, pose a unique challenge to human resource managers. Organisations have an obligation towards stakeholders to select employees that will maximise stakeholder economic value but organisations also have a legislative obligation to diversify their workforce. This creates a paradoxical situation brought about by the implementation of legislation by the Apartheid regime that led to certain groups not getting access to proper education and not getting the opportunity to develop their human capital. 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[1] of South Africa were limited and the minority rule by White South Africans was maintained (Prinsloo, 2013).

The implementation of acts like the Bantu Education Act led to the underdevelopment of specifically Black[2] human capital. The Bantu Education Act No. 47 of 1953 established a Black Education Department in the Department of Native Affairs which would compile a curriculum that, as it was then phrased, “suited the nature and requirements of Black people” (Glucksmann, 2010). The aim of this Act was to develop Black employees for the jobs they were eligible for, under Apartheid legislation, and not waste time and money to develop Black labourers’ skills for jobs that were reserved for White South Africans. The shortage of skills that was created by Acts like these possess a challenge for the current selection procedures of companies. Companies have an obligation towards stakeholders to select employees with the necessary skills that will maximise organisational performance. However, selection

[1] It is acknowledged that the term “non-White” is an intrinsically offensive term that wrongfully defines people relative to a specific group.

[2] The term Black South African is used to refer to Black African, Coloured, Indian and Chinese South Africans

procedures designed to select the cream of the crop in terms of skills will lead to adverse impact against previously disadvantaged groups.

Adverse impact refers to the situation where a specific selection strategy implemented by an organisation leads to members of a specific group having a lower likelihood of selection in comparison to another group (Theron, 2009). In the situation where companies feel pressured to select employees with the best skills, to optimise stakeholders' interests, members of previously advantaged groups will always tend to be selected above members of previously disadvantaged groups. This will lead to previously disadvantaged groups consistently being deprived of the opportunity to further develop their skills thereby perpetuating the systematic disadvantagement. A question can be posed whether adverse impact should be addressed by taking active steps to reduce adverse impact or whether the approach of time heals all wounds should be adopted?

With the fall of Apartheid in 1994 the effects of Apartheid legislation, like the Bantu Education Act, on disadvantaged groups were not fully comprehended. Political sanctions on South Africa were lifted in 1991 that allowed South Africa to do business with other countries again, but the lack of educated and skilled employees made it difficult to adapt in a highly competitive global economy. This left the newly appointed government with various challenges. The African National Congress (ANC), under the guidance of president Nelson Mandela, was elected as the new governing political party of South Africa in the first democratic elections in South Africa in 1994. The ANC was confronted with the difficult task of having to correct the wrongs of the past by addressing the damaging effect Apartheid legislation had on South Africa and specifically on certain groups of people in South Africa. Previously disadvantaged groups saw the ANC as their saviour, a messiah that would deliver them from their circumstances and give them back what was taken from them and give them a seat at the table of opportunity. However, it seems that not much has changed for the majority of previously disadvantaged groups. Between 1997 and 2006 a slight increase in the overall unemployment rate was experienced, but the various demographic groups experienced very different changes in their respective unemployment probabilities. Black African men and women both saw a slight decrease in their unemployment rates (Black African men: a decrease from 36.7% in 1997 to 35.3% in 2006, Black African women: a decrease from 53.7% in 1997 to 51.3% in 2006), whereas these percentages increased markedly for Coloured men and women (Burger & Jafta, 2010). The question as to whether it is necessary to actively address adverse impact or to just let it sort it-self out over time requires a two-part answer. Firstly, for South Africa to be able to compete on a global scale it is of crucial importance to develop the human capital that South Africa currently has available. Secondly, the concern

exists that previously disadvantaged groups are growing tired of being denied the opportunity to meaningfully participate in the formal economy and to share in its benefits. The current study is concerned that previously disadvantaged Black South Africans are growing tired of being denied a seat at the table and not getting a chance to dip their finger in the honey pot[3].

The establishment of a political party like the Economic Freedom Fighters (EFF), and the fact that it managed to draw substantial number of votes in its very first national election, is a testimony that previously disadvantaged people are growing tired of their circumstances. The EFF's proposed policy includes the nationalisation of strategic sectors of the economy like the mining – and banking industry, which is seen by the EFF as the foundation for sustainable economic growth in South Africa (EFFighters.org.za, 2016). Also included in the policy of the EFF is promise of free education up to undergraduate level and the introduction of minimum wages that will improve the living conditions of South Africans, specifically the lives of blue-collar workers like miners, domestic workers and petrol attendants (EFFighters.org.za, 2016).It is clear that the policy proposed by the EFF resonates with a large group of South Africans seeing that they obtained 9% of the overall votes in their first national election as a registered party. The EFF portrays itself as the voice of those who are still disadvantaged and advocates that it wants to uplift the disadvantaged through its proposed policy.

The Employment Equity Act 55 of 1998 (Republic of South Africa, 1998) was implemented to give previously disadvantaged groups the opportunity to share in the economic wealth of South Africa. The overall objective of the Act is to ensure fair treatment and achieve equity in employment, through promoting equal opportunities and implementing affirmative action measures to redress disadvantages of the past experienced by people from designated groups (Finnemore, 2013).The Affirmative Action policy was a source of great hope for many Black South Africans, but at the same time it developed into an intense resentment by those Whites who perceive themselves as the new victims of reverse discrimination (Prinsloo, 2013). The necessity of affirmative action is, however, unavoidable seeing that it has an essential role to play in the development of under developed human capital in South Africa as well as giving previously disadvantaged groups the opportunity to take part in- and benefit from economic activities.

The concern exists that aggressive affirmative action, as it is traditionally interpreted benefits an already privileged few, but ultimately hurts the people it is meant to help through the gradual systematic implosion of organisations (especially in the public sector) due to the lack of

[3] It is acknowledged that ideally these concerns should be rooted in verifiable statistics. Unfortunately the current study was unable to substantiate these concerns with scientific empirical evidence.

motivated and competent personnel and a loss of institutional memory (Esterhuyse, 2008). One can only imagine that the implementation of affirmative action as described by Du Toit (2014) and Van Heerden (2013) can be a cause of frustration and concern for organisations that have been subjected to this type of implementation of affirmative action. Affirmative action in its current state requires companies to employ a certain number of previously disadvantaged employees. This begs the question whether organisations that are selecting previously disadvantaged employees purely based on the numbers that they require, are also making sure that these individuals have the necessary skills to do the specific jobs they have been selected for? Affirmative action should not be seen as a short-term solution that tries to get as many people from previously disadvantaged groups into jobs just for the sake of numbers. The concern exists that in too many cases it is simply treated as a necessary bureaucratic procedure imposed by legislation. Approaching affirmative action implemented in such a manner will only lead to employees who are in over their heads, organisations that become less effective and businesses that view affirmative action in a negative light. It is argued here that affirmative action should have more of a developmental focus that over the long term addresses the development of previously disadvantage groups from the ground up instead of selecting a certain number of previously disadvantaged employees into an organisation because the organisation is required to do so in order to mechanically comply with legislation[4]. The traditional interpretation of affirmative action tends to ignore the fundamental cause of adverse impact and the under-representation of Black South Africans in the economy.

When considering the causes of adverse impact in South Africa and the under-representation of Black South Africans in the economy, a developmental interpretation of affirmative action is required rather than an interpretation where previously disadvantaged employees are selected merely so that the organisation can comply with the required numbers[5]. Fundamentally adverse impact is caused by systematic differences in the current work performance levels that previously advantaged and previously disadvantaged South Africans can achieve due to

[4] It is thereby not implied that there are no organisation that are leading by example. The current study is aware of inspiring anecdotal examples where organisations (like Solms Delta wine estate) and individuals have invested in the development of previously disadvantaged individuals in the belief that fundamental talent is not correlated with race, gender or creed. The comments raised under [2] and [3] both testify to the need for a systematic scientific survey on the manner in which affirmative action is interpreted and implemented and managed in private- and public-sector organisations in South Africa.

[5] The current study contrasts a developmental interpretation of affirmative action with a quota interpretation of affirmative action. Under the former interpretation the emphasis falls on rectifying the fundamental causes of the underrepresentation of specific groups in private- and public-sector organisations in South Africa with the long-term purpose of ensuring equitable representation without compromising on organisational efficiency and effectiveness. Under the latter interpretation the current study sees the emphasis falls on complying with agreed upon number of employees that will be appointed from specific racial and gender groups in specific job categories by typically being willing to make some sacrifices on individual employee performance.

systematic differences in the knowledge, abilities and skills needed to succeed in the world of work due to a lack of development opportunity (Theron, 2013). If the fundamental cause lies in underdeveloped job competency potential the intellectually honest treatment of the problem lies in the development of the knowledge, abilities and skills needed to succeed in the world of work. Affirmative development emphasises the creation and enhancement of competence in targeted populations through the development of malleable job competency potential, in contrast to the more traditional emphasis in affirmative action on the equitable representation across the social divisions by which persons are classified (Du Toit, 2014). When approached from a developmental perspective, affirmative action creates a platform to tap into the vast source of underdeveloped human resources in South Africa and increase competitiveness on a global scale. Seeing that businesses are by law required to diversify their work force it only makes sense to support the aims of affirmative action when approached from a developmental perspective. The *Dinokeng Scenario* is a project that emphasised the role that all South Africans need to play in the development of South Africa's human resources. This is done by engaging stakeholders (individuals, communities, business, non-profits and government) with critical questions about the future of South Africa. Some of the questions asked by the *Dinokeng Scenario Team* are as follow (The Dinokeng Scenarios, 2009):

> "How can we as South Africans address our critical challenges before they become time bombs that destroy our accomplishments?" "What can each one of us do – in our homes, communities and workplaces – to help build a future that lives up to the promise of 1994?"

Critical challenges like the under-representation of previously disadvantaged South Africans in especially the private sector in South Africa (Commission for Employment Equity, 2018)[6] can only be successfully addressed if citizens and leaders from all sectors actively engage with the state to improve delivery and enforce an accountable government (The Dinokeng Scenarios, 2009). Businesses can embrace affirmative action by using their human resources function to help train and develop the untapped human capital in South Africa.

Businesses, however, have limited resources and cannot afford to waste money on selecting individuals that will not benefit from affirmative action skills development programs and whose services will in the end will not be of value to the organisation. Affirmative development will be effective when human resource managers select those learners that will most benefit from affirmative action programs. This is however a daunting task seeing that the pool from which

[6] Some of the key findings of the 18th Commission for Employment Equity Report, that illustrate how prevalent under-representation still is in higher-level managerial positions in the public sector in South Africa, are (1) White people occupy 67.7% of top management jobs in SA, (2) Black people occupy 83.5% of positions at unskilled level, (3) Females occupy 43.5% of semi-skilled jobs and (4) In senior management, males occupy 66.2% of the positions

human resource managers can select these learners consists of millions of people. The human resources manager should therefore take up the responsibility of making himself knowledgeable in the area of affirmative development and develop an understanding of the factors that will determine the extent to which a learner will benefit from taking part in affirmative action skills development programs or not. To effectively select candidates into an affirmative development programme especially the non-malleable determinants of learning performance need to be validly understood.

Effective selection as described above is of critical importance but effective selection on its own is not enough to ensure successful affirmative development. Learning performance also depends on malleable learner characteristics as well as malleable situational characteristics. Human resource interventions should therefore also be initiated, prior to development or running concurrently with the development programme, aimed at optimising these malleable determinants of learning performance. Both selection into the affirmative programme and interventions aimed at equipping the learner for developmental success will require that the identity of the factors underlying affirmative development learning performance be understood as well as the manner in which these factors combine to determine learning performance. It is therefore necessary to first get clarity on the fundamental nature of the key behavioural performance areas that forms the learning task. Only if the learning competencies that constitute learning are clear can one attempt to explicate the nomological network of latent variables that characterises the learners and the perception learners have of the learning environment (Burger, 2012) that determine the level of competence that learners will achieve on these learning competencies. What is required, therefore, is the development of a comprehensive learning potential structural model. Such a learning potential structural model, if validated, will not only assist in the selection of candidates into the affirmative development programme but also in other human resource interventions that precede the development programme and/or that run concurrently with the programme aimed at enhancing the learning performance of those candidates admitted onto the programme. The use of such a learning potential structural model will help human resource managers implement affirmative action development interventions that will be able to help identify and develop individuals that will actually benefit from these interventions.

Previous studies have attempted to develop such a learning potential structural model to inform human resource actions aimed at ensuring the success of affirmative development programmes as an intellectual honest way of addressing the inequalities created by South Africa's socio-political past. De Goede (2007) explicated and empirically tested the learning potential structural model implied by the APIL test battery, that was developed by Taylor

(1989,1992,1994,1997), to measure learning potential in the South African context. The learning potential measure developed by Taylor (1989,1992,1994,1997) specifically assessed the cognitive learning competency potential variables (*abstract thinking capacity* and *information processing capacity*) that Taylor (1989,1992,1994,1997) hypothesised to underpin the level of competence that learners achieve on *transfer* and *automisation* as two learning competencies that constitute *learning performance in the classroom* whilst reducing the influence of verbal abilities, cultural meanings and educational qualifications.

To fully grasp the factors that influence learning performance a single explanatory research study would not suffice. The possibility of fruitful progress towards a more extensive and deeper understanding of the psychological processes underlying the phenomenon of interest improves if successive explicit attempts are made to elaborate on existing formals models describing the structural relations governing the phenomenon of interest (Theron,). It is thus important that a comprehensive learning potential structural model should be developed that will allow for a valid description of the psychological mechanism (i.e. the factors that influence learning performance and the manner in which they structurally combine) that regulates the level of learning performance that learners achieve. This will only be possible if the learning potential model developed by De Goede (2007) is elaborated. Various researchers (Burger, 2012; Du Toit, 2014; Mahembe, 2014; Pretorius, 2015; Prinsloo, 2013; Van Heerden, 2013) have proposed and empirically tested elaborations of the De Goede (2007) model or even elaborations of elaborations of the De Goede (2007) model (e.g. Prinsloo, 2013).

The original structural model that was proposed by De Goede (2007) focused only on the cognitive aspects of learning potential. Burger (2012) argued that focusing purely on cognitive factors that influence learning potential is too restrictive a view to have, and that to truly understand learning potential the structural model should be elaborated to include non-cognitive factors as well. All the studies that directly or indirectly elaborated on the De Goede (2007) model acknowledged in one way or another that *classroom learning performance* and *learning performance during evaluation* in part is comprised of cognitive learning competencies and that the level of competence that is achieved is influentially determined by cognitive learning competency potential latent variables. During the empirical testing of these elaborated learning potential structural models, however, the cognitive competencies and the cognitive learning competency potential latent variables were deleted because of problems associated with the appropriate operationalisation of the two learning competencies, *transfer of knowledge* and *automisation* (De Goede & Theron, 2010).

De Goede (2007) used the APIL subtests to measure *transfer* and *automisation* as the two learning competencies that form the core of *learning performance in the classroom*. The APIL

purposefully uses essentially meaningless learning material to assess the two learning competencies in a simulated learning opportunity so as to ensure that differences in prior learning opportunities do not contaminate the measures (De Goede & Theron, 2010). At the time, however, it was not fully appreciated that these measures cannot be considered valid measures of the extent to which prior learning was successfully transferred on to the specific novel learning material that was covered in the specific development programme in the classroom and the extent to which those insights derived through transfer were successfully automated (De Goede & Theron, 2010). In the final analysis it is the actual *transfer* that takes place in the classroom and the subsequent *automisation* of the insight derived through *transfer*, that determines the *learning performance during evaluation* in actual development programmes.

The current study acknowledges that the elaboration of the original De Goede (2007) learning potential structural model through the inclusion of the non-cognitive factors proposed by Burger (2012), Van Heerden (2013), Prinsloo (2013), Mahembe (2014), Du Toit (2014) and Pretorius (2015) are of definite value. However, the current study also argues that it is imperative that the cognitive competencies and the cognitive learning potential latent variables are returned to the elaborated learning potential structural model. It is also argued that this extended model is then further elaborated on so as to more accurately reflect the intricate manner in which the cognitive part of the psychological mechanism underpinning learning performance operates. The critical problem that will have to be solved though to allow the return of the cognitive competencies and the cognitive learning competency potential latent variables to the learning potential model is the measurability of the cognitive learning competencies of *transfer* and *automisation*.

Although these studies (Burger, 2012; Du Toit, 2014; Mahembe, 2014; Pretorius, 2015; Prinsloo, 2013; Van Heerden, 2013) have contributed to a more comprehensive and penetrating understanding of the nomological net underlying *classroom learning performance* and *learning performance during evaluation* further research on learning potential is still required. More specifically further research is needed on the cognitive hub of *classroom learning performance.* The fact that all of the post-De Goede (2007) learning potential research excluded the cognitive learning competencies of *transfer* and *automisation* from the structural models that were empirically tested inhibited theorising from developing a more penetrating and detailed understanding of the manner in which the cognitive learning competencies of *transfer* and *automisation* create new knowledge that is available for transfer in *learning performance during evaluation.* Therefore, instead of starting with a new model to explain variance in *learning performance during evaluation*, it would be a more a fruitful option to

continue this cumulative process and further elaborate on one or more of the aforementioned elaborations on the De Goede (2007) model by returning the focus to the nucleus of *classroom learning performance* and *learning performance during evaluation.*

RESEARCH-INITIATING QUESTION

The second-generation research-initiating question is the deceptively simple question why variance in learning performance occurs when the learning competency potential influences that have been identified by De Goede (2007) and Burger (2012) have been statistically controlled for. The research-initiating question is therefore which other learning competency potential latent variables and latent learning competencies, not currently included in the integrated De Goede-Burger model, need to be included in the learning potential structural model and how should these additional latent variables be grafted on the integrated model.

The research-initiating question has purposefully been stated as an open-ended question that makes no commitment to any latent variables for inclusion in the elaborated integrated De Goede-Burger model. Latent variables have to earn their inclusion in the elaborated integrated learning potential structural model through logical theoretical argument that suggests that such latent variables are needed to construct a psychological mechanism capable of regulating differences in learning performance. The research-initiating question has therefore purposefully been formulated as an open-ended question so as to enforce theorising[7].

1.2 RESEARCH OBJECTIVE

The primary objective of this study is to integrate the De Goede (2007) and Burger (2012) learning potential structural models and to expand and modify the integrated De Goede-Burger model. More specifically the objective of the research is to:

- Identify additional cognitive latent variables and paths not currently included in the integrated De Goede- Burger learning potential structural model to obtain a more

[7] The term theorising is used here to refer to the explication of a set of latent variables, their constitutive definitions and develop hypotheses on the nature of the structural relations that exist between these latent variables with the objective of explaining a World 1 phenomenon (Babbie & Mouton, 2001) constituted by one or more latent variables.

penetrating and detailed understanding of the manner in which the cognitive learning competencies of *transfer* and *automisation* create new knowledge through *classroom learning performance* and how this new knowledge affects *learning performance during evaluation*;

- Develop hypotheses on the manner in which these additional latent variables are embedded in the integrated De Goede- Burger learning potential structural model and;
- Empirically test the expanded De Goede- Burger learning potential structural model by evaluating the model's absolute fit and the testing the statistical significance of hypothesised paths in the model.

1.3 STRUCTURAL OULINE OF THE THESIS

The theorising in response to the research initiating question is presented in Chapter 2. The theorising in Chapter 2 resulted in the explicit derivation of a number of path-specific substantive research hypotheses that were combine in a single overarching substantive research hypothesis that was presented as a learning potential structural model. In Chapter 3 the research methodology is presented that was used to empirically test the validity of the hypotheses derived through theorising in Chapter 2. In Chapter 4 the results of the empirical testing of the overarching and path-specific hypotheses are presented. Chapter 5 concludes with a discussion of the results, a discussion of managerial implications of the results and a discussion of future research needs.

CHAPTER 2

LITERATURE STUDY

2.1 INTRODUCTION

In this section Burger's (2012) elaboration of the original model of De Goede (2007) will be discussed briefly. Burger (2012) elaborated on the original model of De Goede (2007) by adding a number of non-cognitive latent variables that she hypothesised would influence learning performance, arguing that cognition is not the only factor that plays a role in learning. After the constructs that were added by Burger have been discussed, and her findings on her reduced model have been reported, an argument will be presented why the original proposed Burger (2012) learning potential model should be elaborated by returning the focus to that part of the model as it was originally proposed by De Goede (2007). This section will argue the pivotal role that *transfer of knowledge* plays in learning but that the original De Goede (2007) model failed to capture the intricate manner in which this competency, along with *automisation,* generates new knowledge. This section will moreover argue the need for an alternative approach to the operationalisation of the transfer latent variable is required than the approach that was used in the empirical testing of the original De Goede (2007) model.

In Chapter 1 it was argued that the implementation of Apartheid legislation, like the Bantu Education Act (Republic of South Africa, 1953), led to the underdevelopment of the skills of a large group of South African people. The implementation of Apartheid legislation led to White people in South Africa being unfairly advantaged and Black people in South Africa being denied multiple economic and educational opportunities. It is these past injustices that cause valid and fair strict-top-down selection to create adverse impact against Black South Africans. Under-representation of Black employees in high-end jobs (Commission for Employment Equity, 2018) is not caused by faulty selection procedures. The under-representation of Black employees can rather be explained by the legacy of the previous political dispensation (Burger, 2012). This was and still is one of the primary challenges for the governing party since 1994, to address and rectify these past injustices.

In 1994 the first democratic elections were held and the African National Congress (ANC), under the guidance of President Nelson Mandela, was elected as the new governing party. The newly elected ANC was a breath of fresh air, especially for the people who were oppressed under the Apartheid regime. It marked for them the end of their suffering, the start of something new and as well as their opportunity to gain economic freedom. To rectify past

injustices, the ANC implemented affirmative action legislation, like the Employment Equity Act (Republic of South Africa, 1998). The aim of the Employment Equity Act is to give previously disadvantaged groups the opportunity to share in the economic wealth of South Africa. The overall objective of the Act is to ensure fair treatment and achieve equity in employment, through promoting equal opportunities and implementing affirmative action measures to redress disadvantages of the past experienced by people from designated groups (Finnemore, 2013). The implementation of affirmative action legislation gives previous disadvantaged groups a golden opportunity to develop their skills and through the development of their skills take part in the economic wealth of South Africa.

Business Day reported in 2013 that the Black middle class has grown from 1.7-million people in 2004 to 4.2-million people in 2013 (Shevel, 2013). That is a growth rate of over 250% within eight years. This in itself is wonderful news; however, in the larger scheme of things this figure does raise reason for concern. Statistics SA released a report in 2014 that indicated that the estimated Black African population between the ages of 20 – 60 years old is over 22-million people in South Africa. The Black middle class therefore only represents a small fraction of the economically active Black South Africa population. The concern is that affirmative action legislation has not had the desired effect with regards to the development of the skills of the large majority of previously disadvantaged people. The lack of skills in these people has meant that not a lot has changed for these people in terms of their economic status since Apartheid. The aforementioned statistics strongly suggest that affirmative action has not had the desired effect that it was initially set out to have and to the growing restlessness of people who are still stuck in poverty.

The current study harbours the concern that affirmative action in its current interpretation and implementation entails previously disadvantaged people being placed in positions that they very often are not equipped for[8]. The traditional interpretation of aggressive affirmative action benefits an already privileged few, but ultimately hurts the people it is meant to help through gradual systematic implosion of organisations due to the lack of motivated and competent employees and a loss of institutional memory (Du Toit, 2014; Esterhuyse, 2008). As previously stated, affirmative action should instead of placing previously disadvantaged people in jobs for the sake of numbers place more emphasis on development. Affirmative development places emphasis on the creation and enhancement of competence in targeted populations (Du Toit, 2014; Esterhuyse, 2008).

[8] Again it is confessed that the current study failed to find empirical scientific research evidence published in peer-reviewed accredited journals that backs up such a claim. Anecdotal evidence in the press, however, more than often make similar claims in an attempt to explain the financial problems experienced by ESKOM, SAL and the SABC.

The challenge with regards to affirmative development is for Human Resources Managers to select previously disadvantaged candidates that will benefit from affirmative development programs and transcend learnt skills into the work environment. The importance of selecting candidates that will truly benefit from these programs is emphasised by the limited resources that companies have at their disposal. The main reason for a company's existence is to generate and maximise profit and therefore companies want to allocate resources as effectively as possible. It is thus of critical importance that candidates are selected that will truly benefit from affirmative development programs.

There is a nomological network of latent variables that characterise the learner and the learning environment that determines the learning performance of the individual. It is important that human resource managers validly understand the latent variables and the manner in which they structurally combine that (directly and indirectly) influence the success of candidates on affirmative development programs. This will allow them to affect the level of competence that learners achieve on the learning competencies through flow interventions (Milkovich, Boudreau & Milkovich, 1994) aimed at non-malleable determinants and stock interventions (Milkovich et al., 1994) aimed at malleable learner and situational characteristics. An important flow intervention is the process of selecting candidates into affirmative development opportunities (rather than into a job) based on these identified learning competency potential latent variables and latent learning competencies.

To ensure effective selection of candidates a learning potential structural model that explains variance in learning performance needs to be developed. This model will indicate the predictor latent variables that should be included in a selection procedure that will help identify potential candidates which will benefit from affirmative development programs.

Effective selection procedures on its own will, however, not ensure the success of affirmative development programs. Some of the person-centred latent variables in the nomological network of latent variables that determine learning performance are not malleable. Selection therefore represents a flow intervention (Milkovich et al., 1994) that can be used to control the level of these determinants of learning performance. Recruitment represents another flow intervention (Milkovich et al., 1994). Some of the person-centred latent variables in the nomological network of latent variables characterising the learning environment, are, however, malleable. In addition to selection, an integrated set of post-selection stock interventions (Milkovich et al., 1994) aimed at enhancing levels of these malleable determinants of learning performance, should therefore also be used to attempt to increase the likelihood that those that are admitted on to the development programme will successfully complete the programme.

De Goede (2007) developed a learning potential structural model with the specific aim of identifying previously disadvantaged candidates that will truly benefit from affirmative development programs. De Goede (2007) argued that the measurement of learning potential, the core or fundamental ability that determines the level of learning performance that can be achieved if one would be granted the privilege to learn, as opposed to the measurement of crystallised abilities developed through exposure to previous learning opportunities is critically important in the South African environment when identifying disadvantaged South Africans for entry into affirmative development opportunities. It needs to be stressed though that the measurement of crystallised abilities developed through exposure to previous learning opportunities unavoidably remains important for job selection. Learning potential in and by itself is not enough to ensure job success. Learning potential needed to have had the opportunity to (indirectly) affect the extent to which crystallised job competency potential developed through its effect on the level of competence achieved on the learning competencies. The South Africa tragedy is that there are too many South Africans with high learning potential that have never been granted this opportunity. This in turn is what lies at the root of adverse impact in job selection.

De Goede (2007) explicated the internal structure of the learning potential construct as measured by the APIL test battery developed by Taylor (1989,1992,1994,1997). The APIL test battery was specifically developed for South Africa with aim of measuring an individual's hidden latent and reserve potential whilst reducing the influence of verbal abilities, cultural meanings and educational qualifications. The use of the APIL test battery in the South African context has proven to add significant value in terms of selecting candidates that will truly benefit from affirmative development programs (De Goede, 2007). The APIL test battery allows human resource managers to have a deliberate, systematic approach in terms of selecting candidates for affirmative development programs based on expected learning performance instead of having to rely on random selection.

Additional studies (Burger, 2012; Du Toit, 2014; Mahembe, 2014; Pretorius, 2015; Prinsloo, 2014; Van Heerden, 2013) have elaborated on the original learning potential structural model that was proposed by De Goede (2007). The original structural model that was proposed by De Goede (2007) focused only on the cognitive aspects of learning potential. The model argued that there are two learning competencies, *transfer of knowledge* and *automisation*, which play an influential role in learning. It could be argued that *transfer of knowledge* and *automisation* are the core competencies that constitute *classroom learning performance* as well as *learning performance during evaluation*[9]. Burger (2012) argued that focusing purely on

[9] The term *learning performance during evaluation* refers to the performance achieved in evaluations aimed at determining to what extent learning took place. The term has been coined to specifically acknowledge that, during

cognitive factors that constitute learning potential and influence learning performance is too restrictive a view to have, and that to truly understand learning potential the structural model should be elaborated to include non-cognitive factors as well. All the studies that directly or indirectly elaborated on the De Goede (2007) model acknowledged in one way or another that *classroom learning performance* and *learning performance during evaluation* in part is comprised of cognitive learning competencies and that the level of competence that is achieved is influentially determined by cognitive learning competency potential latent variables. As indicated earlier, during the empirical testing of all these elaborated learning potential structural models the cognitive competencies and the cognitive learning competency potential latent variables had to be deleted the Taylor (1989,1992,1994,1997) scaled did not provide appropriate operationalisation of the two learning competencies, *transfer of knowledge* and *automisation.* This study will argue that although the elaboration of the original De Goede (2007) learning potential structural model through the inclusion of the non-cognitive factors proposed by Burger (2012) is of definite value, it is nonetheless imperative that the cognitive competencies and the cognitive learning potential latent variables are returned to the elaborated learning potential structural model and that this extended model is then further elaborated on to more accurately reflect the intricate manner in which the cognitive part of the psychological mechanism underpinning learning performance operates. The critical problem that will have be solved though, to allow the return of the cognitive competencies and the cognitive learning competency potential latent variables to the learning potential model, is the operationalisation of these two core learning competencies.

Firstly, background will be given on the elaborations that were made by Burger (2012), which will be followed by the discussion and elaboration of the cognitive paths suggested by De Goede (2007). Both of these models will be integrated into the learning potential structural model proposed in this study.

2.2 BURGER'S (2011) ELABORATION OF THE DE GOEDE (2007) LEARNING POTENTIAL STRUCTURAL MODEL.

The basic argument put forward by Burger (2012) is that cognitive ability is not the sole determinant of learning performance and that an individual invests both intellectual and non-intellectual resources to succeed in training. It is argued that these resources probably simultaneously and interdependently contribute to learning. It is proposed that non-cognitive

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a test or assignment in which learners are confronted with a novel problem to which the solution depends on insight in the learning material covered during the development programme, the ability to successfully find a solution depends on the level of competence displayed at *transfer*.

factors that possibly influence learning performance do not do so directly through *transfer of knowledge* and *automisation*. If non-cognitive determinants like those harvested from subjective introspective insight are to affect learning performance, they most likely do so through other learning competencies than *transfer of knowledge* and *automisation* (Burger, 2011). The learning potential structural model proposed by Burger (2012) is shown in Figure 2.1. The learning competencies that constitute *classroom learning performance* in the Burger (2012) model are shown in blue as well as *learning performance during evaluation*. The original De Goede (2007) learning potential model is shown in terms of dashed paths and blue shaded latent variables.

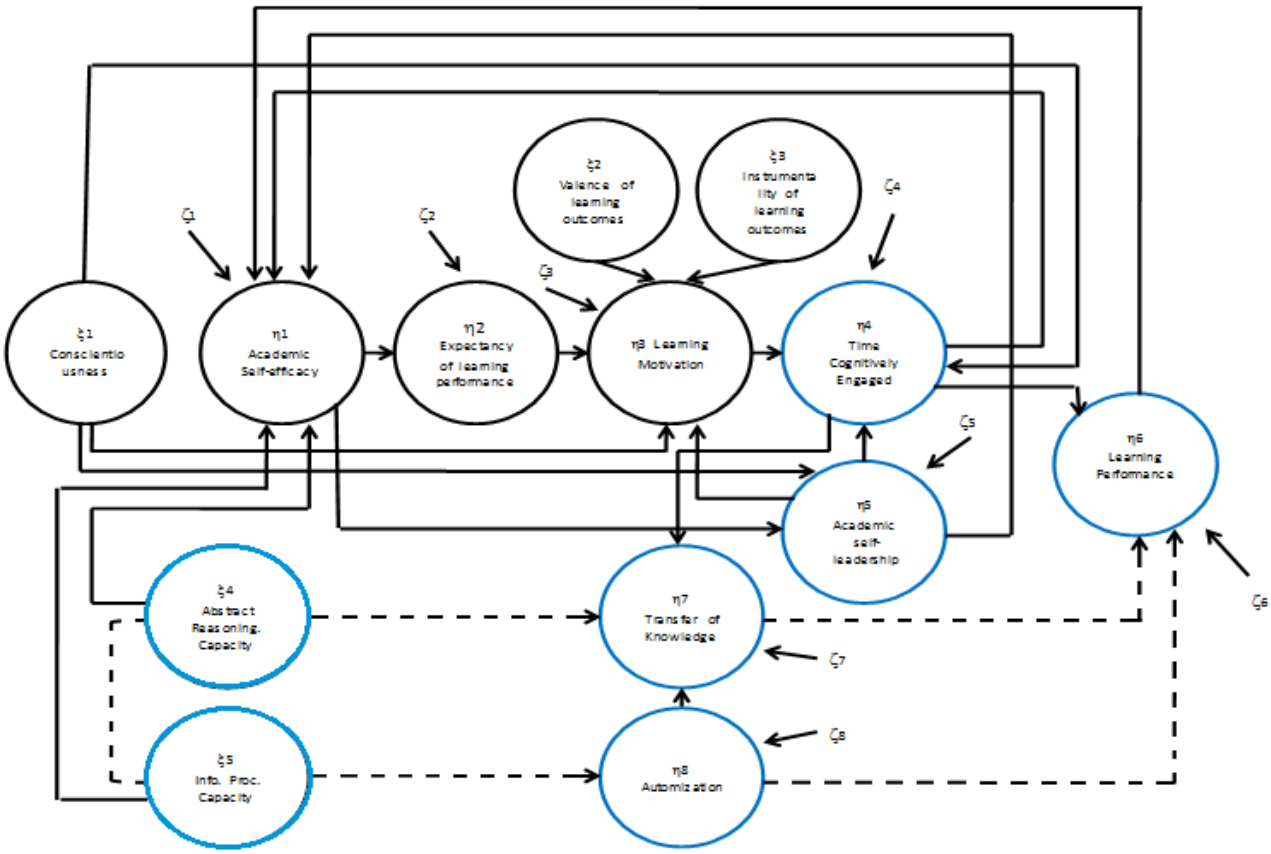


Figure 2.1: ***Burger learning potential structural model (Burger, 2012, p. 79)***

Burger (2012) did, however, not fit the full elaborated learning potential structural model shown in Figure 2.1 that she derived via theorising. Instead she fitted the reduced learning potential structural model shown in Figure 2.2.

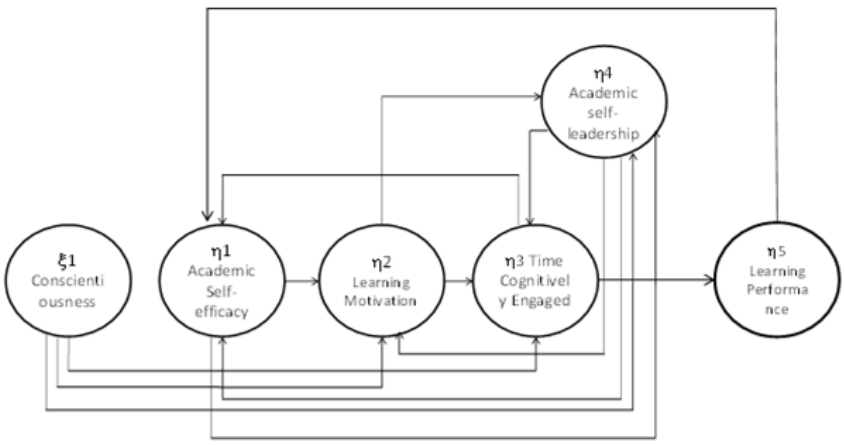


Figure 2.2: ***The reduced Burger learning potential structural model (2012, p. 82)***

The whole original De Goede (2007) model was pruned from the full elaborated learning potential structural model shown in Figure 2.1 due to problems associated with the appropriate operationalisation of the two cognitive learning competencies. The expectancy, valence and instrumentality latent variables were also deleted from the model that was fitted. This was due to the complexity of the learning potential structural model and the large sample size that would have been required, which was deemed as impractical by Burger (2012) in terms of the scope of the study. A brief argument in support of each of the hypothesised paths in the reduced Burger (2012) model is subsequently presented to evaluate the theoretical merit of each of the paths and to inform decisions on whether the path should be incorporated in the integrated and elaborated learning potential structural model proposed in the current study.

2.2.1 Time Cognitively Engaged

It was argued by Burger (2012) that student engagement is a good predictor of learning and that the more students study or practice a task, the chances increase that they learn more about the specific task. Engaged learners exhibit sustained involvement in learning activities; these learners initiate action when given the opportunity and exert intense effort and concentration in the application of learning tasks (Burger, 2012). Student engagement can therefore be seen as a student's willingness to engage in routine learning activities such as attending class. Skinner and Belmont (1993) stated that engagement includes both emotional and behavioural aspects. They stated that the cognitive criteria of engagement are the extent to which students are attending to and expending mental effort in the learning task encountered. With regards to behavioural criteria Skinner and Belmont (1993) refer to the extent to which students are making active responses to the learning tasks presented. Affective criteria refer to the level of students' investment in, and their emotional reaction to,

the learning tasks. For *transfer of knowledge* to occur the individual should create meaningful structure in the learning material by adapting existing knowledge and transferring it onto the initially meaningless learning material. Creating such meaningful structure, however, requires time and the application of continuous 'intellectual pressure' on the problem. Pintrich and Schunk (2002) as cited in Burger (2012) suggests that individuals who exert more effort and persevere longer at learning tasks increase their likelihood of learning and achieving higher levels of academic achievement. The reason for this, according to Burger (2012), is that these individuals are more likely to transfer their knowledge in order to ultimately learn. In agreement with Burger's (2012) original learning potential structural model, but contrary to her reduced model, the current study hypothesises that *time cognitively engaged* positively influences *transfer of knowledge*.

Hypothesis 2[10]: In the learning potential structural model it is hypothesised that *time cognitively engaged* positively influences *transfer of knowledge.*

2.2.2 Personality Variables

The inclusion of personality variables by Burger (2012) in her elaborated learning potential structural model is based on the fact that these variables help understand an individual's suitability for work-related activities. These variables describe an individuals' propensity to respond in a certain manner in different settings or environments. Personality measures are different to cognitive ability measures and provide information about a different but important part of the work performance criterion space than cognitive ability measures (Burger, 2012). More specifically personality tends to explain variance in contextual performance rather than task performance (Borman & Motowidlo, 1993 Borman & Motowidlo, 1997; Van Scotter & Motowidlo, 1996 Visweswaran & Ones, 2000). Contextual performance is defined as: "activities that contribute to organisational effectiveness in ways that shape the organisational, social, and psychological context and serves as the catalyst for task activities and processes" (Borman & Motowidlo, 1997, p. 100).

The rather persuasive evidence that personality does play a role in work performance, specifically contextual performance begs the question whether personality does also play a similarly influential role in learning performance.

[10] Hypothesis 1 represents the overarching substantive research hypothesis that will only emerge once all the path-specific substantive research hypotheses have been derived via theorising

2.2.2.1 Conscientiousness

Conscientiousness should be a good predictor of learning performance because it represents personal characteristics such as being persistent, planful, careful, responsible, and hardworking, which are important attributes for accomplishing work tasks in all jobs (Barrick and Mount, 1991). Goff and Ackerman (2002); Chamorro-Premuzic and Furnham (2003) as cited in Burger (2012) stated that Conscientiousness has consistently been found to positively correlate with academic performance. In Burger's elaborated learning potential structural model *conscientiousness* is defined as individuals, who are prepared, diligent, make plans and stick to them, who are thorough in their work, self-disciplined and organised.

Hypothesis 3: In the learning potential structural model it is hypothesised that *conscientiousness* positively affects *time cognitively engaged*.

2.2.2.2 Learning Motivation

Burger (2012) argues that although cognitive ability is an important determinant of performance (Schmidt & Hunter, 1992), it is insufficient to yield performance in the absence of motivation and motivation in the absence of ability is also insufficient to yield performance. *Classroom learning performance, learning performance during evaluation* and the *transfer of knowledge* will be possible only when candidates have the necessary ability and motivation to acquire and apply a new skill. *Learning motivation* is defined by Ryman and Biersner (as cited in Burger 2012) as the desire on the part of learners to learn the learning material, and is defined by Burger in this manner for the purpose of elaborating on the original learning structural model proposed by De Goede (2007). It is proposed that *learning motivation* influences the extent to which individuals exerts effort towards the learning task in an attempt to form structure and transfer existing knowledge to the current task. In agreement with Burger's (2012) original learning potential structural model, but contrary to her reduced model, the current study hypothesises that *learning motivation* positively influences *transfer of knowledge,* but that its effect on *transfer of knowledge* is mediated by *time cognitively engaged.*

Hypothesis 4: In the learning potential structural model it is hypothesised that *learning motivation* positively influences *time cognitively engaged.*

It is also proposed that *conscientiousness* positively influence *classroom learning performance*[11]. Earlier it was hypothesised that *conscientiousness* has a positive influence on *time cognitively engaged*. Burger (2012, p.48) argued in this regard:

> "Personality characteristics such as Conscientiousness are expected to influence motivation to learn and, in turn, learning itself. Individuals, who score high on Conscientiousness generally set high standards for themselves, are more likely to be willing to work hard on tasks and generally have a stronger desire to learn."

Following the rational of this argument it would make sense that candidates that are high in *conscientiousness* would have a higher *learning motivation* than learners who are less *conscientious.* In agreement with the reduced Burger (2012) model, the current study therefore hypothesises that *conscientiousness* also indirectly affects *time cognitively engaged* through its positive effect on *learning motivation.*

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

2.2.2.3 Academic Self-Leadership

Academic self-leadership is the process through which individuals influence themselves to achieve the necessary self-direction and motivation to perform well in a learning task (Houghton & Neck, 2002). This empowers individuals to be in control of their own behaviour by influencing and leading themselves through the use of specific behavioural and cognitive strategies. These behavioural and cognitive strategies according to Houghton and Neck (2002) entail; behaviour-focused strategies, natural reward strategies and constructive thought pattern strategies. Behaviour-focused strategies involve the self-regulation of behaviour which is achieved through the use of self-assessment, self-reward and self-discipline. Natural reward strategies focus on seeking out work activities that are inherently enjoyable. Constructive thought pattern strategies involve the creation and maintenance of functional patterns of habitual thinking. In agreement with Burger (2012) the current study therefore hypothesises that *academic self-leadership* will positively influence *learning motivation*.

[11] Classroom learning performance is not a single latent variable in the original Burger (2012) learning potential model but rather represents a domain of latent learning competencies (transfer, automisation, time cognitively engaged, academic self-leadership) that constitute learning in the classroom.

Hypothesis 6: In the learning potential structural model it is hypothesised that *academic self-leadership* positively influences *learning motivation*.

2.2.2.4 Academic Self-Efficacy

Bandura, Barbaranelli, Caprara and Pastorelli (2001) stated that efficacy beliefs predict occupational choices and level of mastery of educational requirements for those pursuits when variations in actual academic ability, prior level of academic achievement, scholastic aptitude and vocational interests are controlled. *Academic self-efficacy* is the belief of a learner in his/her academic capabilities. It is this belief rather than his/her actual academic performances, that tends to shape the course of his/her developmental trajectories (Bandura et al. 2001). According to Bandura (1977) and Woodruff and Cashman (1993) there are various levels of self-efficacy that are task specific. Domain efficacy refers to efficacy for performance within an entire definable domain of tasks. General self-efficacy refers to an individual's overall self- confidence for dealing with a variety of domains in life. Burger interprets *academic self-efficacy* as a domain-specific efficacy. Burger (2012) stated that when an individual experiences a sense of confidence in his/her ability to improve and develop their skills, the more likely the individual is to feel confident toward development activities, to be interested in them, to intend to participate and then to actually improve his/her skills and subsequently learn from the activity.

Self-efficacy should therefore in terms of this line of reasoning not only have a general relationship with performance and achievement but also a relationship with learning performance. According to Burger (2012) differences in self-efficacy are associated with legitimate differences in skill level and research evidence has demonstrated that self-efficacy has an influence on skill acquisition and retention in learning situations. This can possibly boost self-efficacy in a mutually enhancing process. Burger (2012) consequently proposed that *academic self-efficacy* positively influences *learning motivation*. In agreement with Burger (2007) the current study therefore hypothesises that *academic self-efficacy* positively influences *learning motivation.*

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

Burger (2012) also proposed that there is a positive relationship between *academic self-efficacy* and *academic self-leadership*. This proposed path was found to be statistically significant, but was found to be negative whereas a positive relationship was hypothesised. This unexpected negative relationship was *post hoc* explained by arguing that individuals who

believe that they are capable of succeeding in academic or learning tasks, would tend not to see the need to aggressively implement academic self-leadership strategies as the individual may feel that he/she is capable of performing successfully without the implementation of these strategies (Burger 2012). In agreement with Burger's (2007) *post hoc* interpretations of her results, the current study therefore hypothesises that *academic self-efficacy* negatively influences *academic self-leadership.*

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

2.2.2.5 Feedback Loops

Feedback loops in an explanatory structural model indicates a formal acknowledgement that the to-be-explained phenomenon is complexly determined. Feedback on learning performance is considered important in many theories of learning because it provides learners with information that allows them to verify the correctness of the actual response or solution and evaluate the achieved performance level (Burger 2012). Feedback that reports clear information about the development of learners can raise self-efficacy and subsequent performance. Self-efficacy is developed via various mechanisms with self-referenced information, such as performance accomplishment, being the largest contributors (Bandura, 1977). The lack of feedback in terms of performance accomplishment can possibly influence the self-efficacy of the individual. Bandura and Cervone (1986) demonstrated that feedback information, in the form of a discrepancy between performance and a personal standard or goal, can influence self-efficacy. Bandura indicated on the other side of the spectrum that the feedback that individuals receive by achieving difficult goals leads to an increased perception of self-efficacy and higher levels of self-efficacy which in turn leads to even higher future performance standards (Bandura 1997). Therefore, the more a student learns and the better they perform, the higher their self-efficacy becomes. When students engage in activities, they're influenced by personal influences, like goal setting, and situational influences, like feedback, which provide students with cues about how well they are learning. Burger (2012) therefore proposed that *learning performance during evaluation* will positively influence *academic self-efficacy* as a form of feedback. This is the first feedback loop proposed by Burger (2012). In agreement with Burger (2007) the current study therefore hypothesises that *learning performance during evaluation* will positively influence *academic self-efficacy*.

Hypothesis 9: In the learning potential structural model it is hypothesised that *learning performance during evaluation* positively influences *academic self-efficacy* as a form of feedback

The second feedback loop is that *time cognitively engaged* will influence *academic self-efficacy*. The most influential sources of self-efficacy information are the nature of the student's engagement during learning (Bandura 1977, 1997). Burger (2012) argued that previous studies support the inference that tasks afford students opportunities to generate internal feedback about learning and achievement and that this feedback affects *academic self-efficacy.* Burger (2012) found no support for this hypothesis with the estimated path coefficient not being statistically significant (p<.05). Despite this, and in agreement with Burger's (2012) original theorising, the current study nonetheless still hypothesises that *time cognitively engaged* will positively influence *academic self-efficacy.*

Hypothesis 10: In the learning potential structural model it is hypothesised that time *cognitively engaged* positively influences *academic self-efficacy* as a form of feedback.

2.3 BURGER (2012) EMPIRICAL FINDINGS

Burger (2012) made use of an ex post facto correlational design in which the latent variables were operationalised through two or more indicator variables. Burger (2012) made use of two indicator variables each to operationalise *time cognitively engaged*, *academic self-leadership*, *academic self-efficacy*, *learning motivation* and *conscientiousness* and made use of three indicator variables to represent *learning performance*.

The success of the operationalisation of the latent variables comprising the structural model largely depends on extent to which the factor loadings of the indicator variables on the latent variables, that they were tasked to reflect, were found to be statistically significant and (in the completely standardised solution) large. The credibility of the verdict on the success of the operationalisation of the latent variables comprising the structural model to a significant degree hinges on the fit of the measurement model. Measurement model fit refers to the fitted measurement models' ability to reproduce the observed covariance matrix. The model fits well if the reproduced covariance matrix approximates the observed covariance matrix. Burger (2012) interpreted the measurement model fit by inspecting the full spectrum of goodness of fit indices provided by LISREL. The measurement model in Burger's study did not obtain exact fit (Satorra-Bentler Scaled Chi-Square of 67.934; p = .0465), however the model did obtain close fit with the null hypothesis for close fit not being rejected (p=0.992; RMSEA = .0280). The factor loadings of all the indicator variables on the latent variables that they were tasked to reflect were found to be statistically significant (p<.05). In all but one of the composite indicator variables in excess of 70% of the variance was explained by the latent variable that they were designed to represent (Burger, 2012). Burger (2012) concluded that the operationalisation of the latent variables comprising the structural model was successful.

With the measurement model showing good fit and the indicator variables generally reflecting their designated latent variables well, the structural relationship between latent variables hypothesised by the reduced learning potential structural model proposed by (Burger, 2012) could be tested via SEM. When fitting the model to the data, the solution failed to converge. It was finally decided, based on the nature of the error message issued by LISREL, to delete one of the paths which involved the *learning motivation* latent variable in an attempt to solve the deadlock. The path that was deleted hypothesised that *learning motivation* has a positive impact on *academic self-leadership* as it was considered to be the least convincing path in the theoretical argument. It was therefore decided to delete this path and to refit the model (Burger, 2012). The model now converged with the null hypothesis for exact fit being rejected (Satorra-Bentler Scaled Chi-Square of 105.178; $p = .000$), however good model fit was obtained with the close fit null hypothesis not being rejected ($p = .664$; RMSEA = .0463)

No support was found for the hypotheses that *time cognitively engaged* positively influences *academic self-efficacy* with the estimated path coefficient not being statistically significant ($p < .05$). All other hypothesised paths were found to be statistically significant ($p<.05$), however, the direction of the effect of *academic self-efficacy* on *academic self-leadership* was in disagreement with the hypothesised direction and therefore the Burger (2012) failed to find support for her path-specific hypothesis that *academic self-efficacy* had a positive effect on *academic self-leadership*. *Post hoc* reflection and theorising by Burger (2012) indicated that a negative relationship between these two latent learning competencies made theoretical sense. Hence the current study hypothesised a negative effect of *academic self-efficacy* on *academic self-leadership* in hypothesis 9 of the current study.

The potential structural model modification indices calculated for the beta matrix in Burgers' study proposed two additional paths that would possibly improve the model fit. The first path that is proposed is a path from *learning performance* to *learning motivation*. Burger (2012) states that this proposed path makes theoretical sense, arguing that if a learner performs well on a learning task, he or she may be more motivated to learn, assuming that high *learning performance* is intrinsically rewarding. The significant feedback loop from *learning performance* to academic *self-efficacy* and the significant path from *academic self-efficacy* to *learning motivation* therefore implies a direct and a mediated feedback of *learning performance* on *learning motivation.* The results seem to suggest that the mediated feedback effect of *learning performance on learning motivation* operates via the *effort-performance expectancy* whereas the main feedback effect of *learning performance* on *learning motivation* operates via the *valence of learning performance.* The modification indices also indicated that there could be a relationship where *learning motivation* directly affects *learning performance*. Burger (2012) acknowledged that it makes sense that *learning motivation* should affect

learning performance but not directly. The theoretical argument given for the mediating effect of time cognitively engaged is that the individual's behaviour is put into motion by *learning motivation* but that it is *time cognitively engaged* that ultimately positively influences *learning performance*. In agreement with Burger's (2012) findings the current study therefore hypothesises that learning performance during evaluation will positively influence *learning motivation*.

Hypothesis 11: In the learning potential structural model it is hypothesised that learning performance positively influence *learning motivation* as a form of feedback.

2.4 BACK TO A COGNITIVE STANCE

It seems a bit ironic that it is necessary to argue the importance of focusing on the cognitive factors that influence *learning potential* rather than continuing the further elaboration of the *learning potential* structural model with environmental or personality factors, seeing that Burger (2012) made the exact opposite argument. Looking at Burgers' study it is evident that non-cognitive factors do play an influential role in *classroom learning performance* as well as *learning performance during evaluation*. This was even acknowledged by Taylor (1994). He stated that *transfer* and *automisation*, are the core learning competencies and that the ability to solve abstract problems, and the ability to commit newly developed insights to memory in a way that it can be easily retrieved, are fundamental forces behind the development of specific skills and competencies. Taylor (1994) went on to state that these competencies will not develop crystallised abilities to the optimum level that the individual is capable of attaining unless the environmental conditions are there to foster their growth.

The original learning potential structural model that was proposed by De Goede (2007) focused only on the cognitive aspects of learning potential. All the studies that directly or indirectly elaborated on the De Goede (2007) model (Burger, 2012; Du Toit, 2014; Mahembe, 2014; Pretorius, 2015; Prinsloo, 2014; Van Heerden, 2013) acknowledged that *classroom learning performance* and *learning performance during evaluation* in part is comprised of cognitive learning competencies. These studies acknowledged that the level of competence that is achieved is influentially determined by cognitive learning competency potential latent variables, however all these subsequent models nonetheless ignored these two core cognitive competencies during the empirical testing of these elaborated learning potential structural models. In the long-term this neglect (or exclusion) of the core cognitive aspects of learning potential in learning potential structural models cannot be sustained. It would only be possible to gain an insight into the richly inter-connected complex nomological network of factors that influence *learning performance* if the two cognitive learning competencies and their drivers

are returned to the model. This will, however, only be possible if the methodological problems encountered during the operationalisation of *transfer of knowledge* and *automisation* can be satisfactorily resolved.

It is widely believed that measures of cognitive ability are among the most valid predictors of job performance, training performance and educational success (Roth, Bevier, Bobko, Switzer III & Tyler, 2001). This coincides with what Taylor (1994) proposed when he referred to *abstract thinking capacity* and *information processing capacity* as the two main cognitive "engines" behind the development of competence, with their "home-base" in the core of the cognitive space which may be represented as a circle, with the fundamental learning competency potential at the centre. Taylor (1994) argued that these two cognitive competency potential variables have a close relation and even overlap in a sense and probably give birth to all sorts of specific, crystallised problem-solving and knowledge-acquisition competency potential variables in the outer reaches of the circle. This was corroborated by Snow, Kyllonen and Marshalek (1984) who applied scaling techniques to multivariate data, in which subjects did many different tests with some measuring specific skills and other measuring broader abilities. They found that the various abilities measured by the tests they administered could indeed be scaled as a wheel, with the broader, more fundamental, abilities nearer the core and specific, crystallised abilities scattered around the periphery. The outer reaches of the wheel are where the abilities and skills that are developed as a result of experience with relevant stimuli or behaviour, the crystallised abilities can be found (Taylor, 1994). The argument is made that the core of an individual's cognitive ability lies *abstract thinking capacity* and *information processing capacity* and that as the individual interacts with specific stimuli or behaviour the individual develops certain skills or abilities (crystallised abilities) through using these core cognitive abilities.

The study of Burger (2012) appears to make a strong case that the crystallised abilities, that lie on the outer reaches of the wheel, and that develop when the core cognitive abilities in the centre of the wheel succeed in creating meaningful structure in novel stimuli through transfer, and succeed in automating this insight, do not only depend on the core cognitive abilities at the core of the wheel but also on a complex net of non-cognitive factors. These non-cognitive factors, however, influence the crystallised abilities that lie on the outer reaches of the wheel by indirectly influencing the cognitive learning behaviour (i.e. *transfer* and *automisation*) that lead to the development of specific crystallised competency potential latent variables.

Seeing that previously disadvantaged Black South Africans might not have had access to stimuli that are necessary for the development of job competency potential variables, although for many of them their cognitive 'engine' would have allowed them to develop the abilities

needed to succeed in the world of work if they had access to such opportunities, the focus on fundamental cognitive competency potential variables at the centre of the wheel in affirmative development interventions appears to be of significant importance. According to Taylor (1994) the ravages of disadvantagement will be most marked in the outer part of the wheel of cognitive competence. As previously stated, it is of critical importance that the core cognitive aspects of learning potential be understood and assessed seeing that these factors appear to be less susceptible to the influence of the lack of development opportunities[12] and will be able to give insight into the learning potential of the individual in terms of whether he or she will be able to successfully perform the required affirmative development tasks at hand. Therefore, this study will reintroduce the cognitive part of the psychological mechanism that regulates the level of *classroom learning performance* and through that the level of *learning performance at evaluation* that learners on affirmative development programmes achieve. In this regard the current study will rely heavily on the original model proposed in the study by De Goede (2007) whilst trying to address possible shortcomings of the original De Goede (2007) study.

2.5 A REVIEW OF THE ORIGINAL DE GOEDE (2007) STUDY

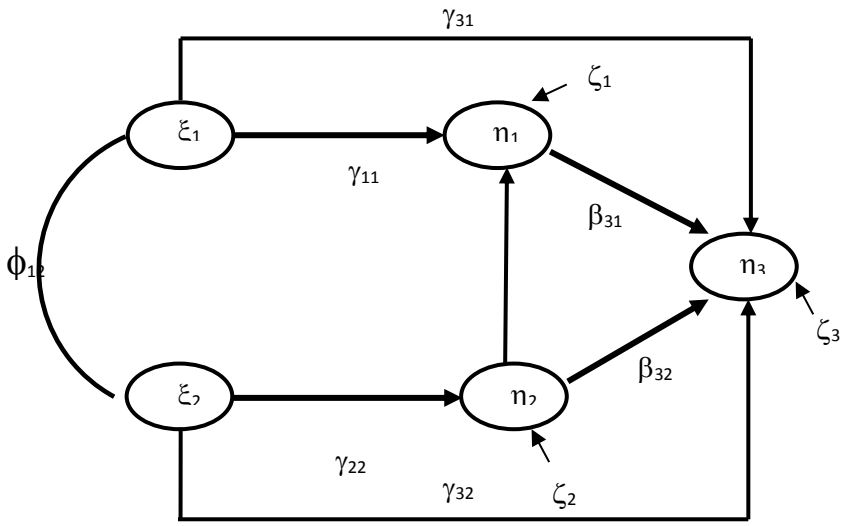
2.5.1 Aim of the Original Study

The original study by De Goede proposed to explicate and empirically test the underlying structural model on which the APIL test battery is based to explain learning performance. The De Goede learning potential structural model is depicted in Figure 2.3. De Goede (2007) in his study argued that adverse impact in job selection should be reduced if three conditions were met. Firstly, he argued that the structural model of his study needed to be proven as valid. Secondly, the APIL test battery needed to succeed in validly predicting the learning performance of previously disadvantaged South Africans on affirmative development programmes in which they have to master cognitively demanding developmental material aimed at enhancing the required knowledge, skills, and abilities needed to succeed on the job. Lastly the developmental programmes needed to succeed in reducing the differences in the criterion distributions.

[12] This represents a rather optimistic position. The claim that abstract thinking capacity and information processing capacity is to a lesser degree affected by disadvantagement than the crystallised abilities that develop through transfer of knowledge and automisation has in the past probably not been sufficiently subjected to critical examination.

2.5.2 Learning Performance

Individual are enrolled into affirmative development programmes with the aim of achieving specific learning objectives defined in terms of specific learning outcomes. These outcomes are determined by the minimum levels required on the competency potential (i.e., the crystallised abilities and knowledge) required to do the job efficiently and serve the purpose for which the job exists. Learning competencies play a crucial role in attaining the desired learning outcomes. These learning competencies are influenced by a complex nomological network of person-centred variables (De Goede, 2007) and variables characterising the learning environment. To argue the relevance of learning performance in the work environment De Goede (2007) argued that a Performance@Learning competency model could be assumed to be comparable to the Performance@Work model originally proposed by Saville and Holdsworth (2001). De Goede proposed that these models should be sequentially linked with the aim of creating a conceptual model that will explicate the relationship between the characteristics required of the learner to exhibit the learning behaviours needed to develop the qualities necessary to exhibit the work behaviours that are instrumental in achieving outcomes for which the job in question was created.



Where:
ξ_1 = Abstract thinking capacity
ξ_2 = Information processing capacity
η_3 = Learning performance
η_1 = Transfer of knowledge
η_2 = Automisation

Figure 2.3: The De Goede learning potential structural model

De Goede (2007), in line with Taylor (1994), proposed that learning performance should be defined in terms of two core learning competencies; *transfer of knowledge* and *automisation*. It was proposed that these two competencies constituted the learning behaviours required to develop the specific attainments required to succeed on a behavioural level in the job in

question. Ultimately it is the job competencies, served by the affirmative development intervention, where the primary interest lies. Affirmative training and development programmes are designed to empower employees with the job competency potential and job competencies required to deliver outputs for which the job in question exists (De Goede, 2007). Prior to affirmative development disadvantaged Black South Africans fail to achieve the required level of competence on the job competencies because of deficiencies in the job competency potential variables due to lack of developmental opportunity. The expectation of the affirmative development program would be to enable individuals to not just merely regurgitate previously transferred and automated responses to familiar stimuli but also apply newly derived knowledge to novel stimuli not explicitly covered in the affirmative development programme. It can be argued that to apply newly acquired knowledge in solving novel work-related problems involves *transfer* in the workplace which is dependent on *fluid intelligence/abstract thinking capacity* as well as the extent to which previous relevant learning (transfer) has been successfully internalised (automated) (De Goede, 2007). This corresponds with De Goede's argument that the Performance@Learning model and the Performance@Work model should be integrated. The knowledge that an individual acquires in the class room should assist the individual in solving novel problems in the workplace, otherwise it is of very little value.

Taylor (1994) refers to learning performance as the specialised skills that an individual has acquired through transfer from other, previously developed, specialised skills or abilities. Learning performance should, however, also be understood as the behavioural process that takes place when a person comes to grips with a novel learning task involving unfamiliar stimulus material by using very general transfer and skill acquisition strategies. Learning performance, like job performance, therefore should be understood in terms of competencies (or behaviours) and the outcomes served by the behaviours. Moreover, it is important to appreciate that learning is not a process that is confined to formal learning in a classroom. Learning is a never-ending, in terms of outcomes, upward-spiralling process. A distinction can in this regard be made between *classroom learning performance, learning performance during evaluation* and *action learning on the job.* These three forms of learning are sequentially structurally linked. In all three cases the distinction between the learning competencies and the learning outcomes applies. In addition, structural relations exist between the outcomes of the one form of learning and the level of competence achieved on the competencies in the subsequent form of learning.

The level of competence achieved on the competencies that constitute learning and therefore also the levels achieved on the learning outcomes depend on specific person and environmental characteristics. These collectively constitute learning potential. Learning

potential therefore refers to characteristics, that the individual currently to some degree possesses and environmental characteristics that the learning context currently to some degree satisfies, that determines the level of learning performance that the learner will achieve if provided with the opportunity to learn. An important distinction between learning performance and learning potential is made here. In terms of the manner in which Taylor defines learning performance it should be understood as crystallised learning potential (i.e. learning outcomes). In terms of the current study's expanded conceptualisation of learning performance it should be understood as the (future) behaviours that the learner will have to display in the classroom to attain the crystallised abilities, knowledge and skill demanded by the job. Therefore, learning performance under both interpretations is seen as an endogenous latent variable on which direct information is not available at the time of the selection decision. Measures of learning potential, serves as the substitute predictor (exogenous latent variable) of learning performance. To be able to explain and predict the variation in learning performance between individuals, Taylor (1994) reviewed the learning or dynamic approach to cognitive assessment, which focuses on learning and modifiability, and found *transfer of knowledge* and *automisation* to be the two dimensions of learning that (in part) constitute successful learning performance.

The structural relations hypothesised by De Goede between the two learning competency potential latent variables (*abstract thinking capacity* and *information processing capacity*) and the two learning competencies (*transfer of knowledge* and *automisation*) and eventual *learning performance during evaluation,* as depicted in Figure 2.3, are subjected to a renewed critical examination in the following paragraphs. Path-specific substantive hypotheses on the manner in which these four cognitive latent variables should be embedded in the reduced Burger (2012) learning potential model will be argued in the subsequent paragraphs (paragraphs 2.5.3, 2.5.4, 2.6 and 2.7). The need for additional latent variables to allow for the construction of a truly convincing, plausible stance on the manner in which cognitive latent variables operate in the psychological mechanism that regulates learning performance will also be considered in the subsequent paragraphs.

2.5.3 Learning Competencies

2.5.3.1 Transfer of Knowledge

Early in the life of the individual small amounts of learning takes place after which every instance of learning is a function of the already learned organisation of knowledge on the

subject. The acquisition of job competency potential can be described as a process during which new attainments have to be built on older ones (*transfer*) and these have to be integrated into existing conceptual frameworks (*automisation*) that subsequently become more general and elaborated (Taylor 1994). These *transfer* and *automisation* processes serve as the primary basis for elaboration according to Taylor (1994). The transfer process refers to the manner through which crystallised abilities develop from the interaction between *fluid intelligence/abstract thinking capacity* (Cattell, 1971), currently existing crystallised abilities and novel stimuli (Taylor, 199). In essence *transfer* refers to the influence that previously attained knowledge has on the performance of new learning tasks. Therefore, previous knowledge might make the performance of new work-related tasks or the solving of work-related novel problems easier or more difficult.

Ferguson (1954), states that *transfer* is a more general phenomenon and learning is a particular formal case. He goes on to argue that an implied condition for *transfer* to occur is that the previous task must differ in some manner from the successive task (Ferguson, 1956). Ferguson argued that if two tasks are similar, and leads to changes in the ability of an individual to perform, the specific task is assignable to repetition and not to *transfer*. After small amounts of learning early in the life of the individual every instance of learning is a function of the already learned organisation of the subject; that is all learning is influenced by *transfer*. De Goede (2007) stated that individuals who are able to show superior learning performance would be those that are able to *transfer* better. Through this line of reasoning it, in addition also, does appear that the ability to *transfer* plays a pivotal role in the successful functioning of the individual in his/her job in the sense of solving novel problems. *Transfer* therefore refers to the individual's ability to learn new skills or abilities by transferring previously gained knowledge through the use of *fluid intelligence/abstract thinking capacity*

2.5.3.2 Automisation

Automisation refers to an individual's ability to become more effective and efficient in the execution of a task. The extent to which one develops expertise in a certain domain or task depends on the ability of the individual to automate new information. If no skills or knowledge relevant to the execution of a task exist, the individual would make use of *fluid intelligence* and *abstract reasoning* to cope with the task by *transferring* existent relevant knowledge onto the solution of the novel problem. De Goede (2007) states that for an individual to become more effective and efficient in the execution of a task the individual needs to automate the operations in a task.

The *automisation* of the operations required to perform complex tasks enables the individual to perform the task with minimum mental effort (Sternberg, 1984). Sternberg (1984) proposed that controlled information processing is under the conscious direction of the individual and that it is hierarchical in nature. Sternberg (1984) distinguishes between non-executive processes and executive processes, which direct non-executive processes. Executive processes are processes that are used to plan, monitor and revise strategies of information processing and non-executive processes are processes that are used to carry out the strategies that have been selected, monitored and revised by the executive processes. Sternberg (1984) also proposes that when information is being processed from old domains that are entrenched by nature, the individual will rely primarily on automatic, local processing. De Goede (2007) argued that control is passed onto an already local system once an executive process has identified a given situation as one for which a local system might be relevant. The local system would then act upon the given problem as a production system with a set of readily available productions.

The various functions in the production systems are executive and non-executive in nature and integrated into a single non-hierarchical system (Sternberg, 1984). When none of the productions in a system is able to satisfy a given present condition, control is passed back to the single non-hierarchical system (global processing system) (Sternberg, 1984). According to De Goede (2007) *transfer* can play an influential role here as the expression of an individual's *fluid intelligence/abstract reasoning capacity*, which operates on the content of a local processing system in solving novel problems. An individual would establish whether or not he/she possesses the necessary skills, knowledge and abilities to address the situation or problem at hand. Problems that have been automated from previous experiences would enable the individual to use a learned response to deal with the new problem in a similar manner. The lack of the necessary skills, knowledge or abilities to address a novel problem would require the individual to make use of *fluid intelligence* or *abstract reasoning capacity* to cope with a specific problem or situation. *Abstract reasoning capacity* or *fluid intelligence* would allow the individual to *transfer* existing relevant, but not directly applicable skills, knowledge and abilities onto a solution of the novel problem (De Goede, 2007). The critical requirement here though to allow the existing relevant, but not directly applicable skills, knowledge and abilities to be transferred is that the existing, crystallised abilities should have been successfully *automated*. The insight previously derived through *transfer* should have been successfully written to a knowledge station in a manner where it can easily be retrieved for future problem-solving via *transfer*. This happens through *automisation* (Taylor, 1994). De Goede (2007) argues that once a task is mastered an individual can add his/her new skills, knowledge or abilities to his/her already existing pool of skills, knowledge and abilities, thus

elaborating it. In order to respond to unfamiliar stimuli or situations the individual would have to make use of already automated responses and *transfer* relevant knowledge from the automated responses, through the use of *fluid intelligence*, to respond to the unfamiliar stimuli or situation. To successfully *automate* this newly attained skill or ability (response) the individual would need to repeat this skill or ability and spend time cognitively engaged in this process of repetition.

2.5.4 Learning Competency Potential

2.5.4.1 Abstract Thinking Capacity (Fluid Intelligence)

The capacity to form abstract concepts and the capacity to be efficient at information processing, which refers to the characteristics that learners have or possess, are integral elements of cognitive ability or intelligence. These two facets of intelligence constitute the nucleus of the learning cognitive competency potential that drives the two learning competencies that constitute learning (*transfer* and *automisation*) (Taylor, 1992). Fluid intelligence refers to an individual's inherent capacity ability to learn new things, and apply that knowledge to problem-solve new situations.

There are two general paradigms in psychology regarding intelligence. The first is that of Sir Francis Galton who proposed that a unitary general cognitive ability underlies all learning, problem solving and other cognitive processing. Binet on the other hand proposed that intelligence is the average of a number of independent or semi-independent abilities (De Goede, 2007). Spearman (1904, 1927) proposed that the base of human intelligence lies in unitary, general intelligence factor, which was branded the *g-factor*, which overlaps with the original proposition of Sir Francis Galton. De Goede (2007) explains that Binet's theory of separate abilities also adds value as evidence has shown that in addition to general intelligence (*g*), there are a number of group factors/ primary abilities independent of *g* and explains a certain amount of the total variance in cognitive testing. It is however evident that *g* carries a greater weight in determining the cognitive ability of an individual.

Cattell (1971) acknowledges that general intelligence is not a unitary factor but consists of fluid- (*Gf*) and crystallised (*Gc*) intelligence. *Gf* is very similar to general intelligence (*g*) proposed by Spearman (1904, 1927) while *Gc* is the same as group factors or primary abilities. De Goede (2007) identified the two-factor model of fluid- and crystallised intelligence as proposed by Cattell (1971) in conjunction with the learning competency of *transfer* as a persuasive explanation of why differences in abilities between individuals exists. Cattell (1971) identifies *Gf* as a fundamental, innate intelligence that is related to all kinds of problem-solving.

Gf is related to how well an individual perceives complex relations, forms concepts and engages in abstract reasoning. It is the fundamental abstract reasoning and concept formation capacity or ability that an individual applies to novel problems (De Goede, 2007). *Gf* is therefore applied in the acquisition of new knowledge and skills. It is important to keep in mind that *Gf* is formless and appears independent of experience and education but not necessarily independent of stimulation and nurturing (Bhattacharjee, 2015). *Gc* refers to an individual's acquired crystallised abilities and knowledge. This refers to the acquired abilities and knowledge which arise from schooling, becoming competent with one's culture and mastering one's specific circumstances (De Goede, 2007). Acquired abilities such as verbal and numerical abilities could be categorised under *Gc* relating it to scholastic and cultural foundations. De Goede (2007) proposes that the learning competency of *transfer* acts as a link between *Gf* and *Gc*, with *transfer* being *Gf* in action in the solution of novel problems. He goes on to suggest that existing *Gc* is elaborated via *transfer* by *Gf* utilising existing *Gc.* It is therefore proposed that an individual's level of *fluid intelligence/abstract reasoning capacity* either contribute or inhibit the individual's capacity to make sense of the learning task allowing the learning and acquisition of new knowledge, skills and abilities (via *transfer*) (De Goede, 2007).

2.5.4.2 Information Processing Capacity

The inclusion of *information processing capacity* by De Goede in his learning potential structural model necessitates the careful conceptualisation of the construct so as to avoid any conceptual confusion with the already proposed constructs of *transfer*, *automisation* and *abstract thinking capacity*. Information processing refers to how individuals apprehend, discriminate, select, and attend to certain aspects of the vast welter of stimuli that impinge on the sensorium to form internal representations that can be mentally manipulated, transformed, stored in memory and later retrieved to govern a person's decisions and behaviour in a particular situation (Jensen, 1998).“Information” is defined by Jensen (1998) as any stimulus that reduces uncertainty in a given situation and uses the term “information processing” to describe the hypothetical processes that depend on the structural and physiological properties of the brain that are activated whenever uncertainty is perceived and the individual works to reduce it. Taylor (1994) acknowledges that information processing makes up one of the constituent parts of cognitive ability. This is also acknowledged by Hunt (1980); however, he also acknowledges that the search for a “true” single information-processing function underlying intelligence is likely to be as successful as the search for the Holy Grail.

In learning and work situations individuals are faced with novel tasks that could lead to the individual experiencing a lot of uncertainty, which he or she would naturally try to reduce. To reduce uncertainty, the individual has to make use of executive processes (Sternberg, 1984) to process the bits of information or stimuli provided in the task and select a strategy to follow and secondly, use non-executive processes (Sternberg, 1984) to ensure that the strategy is carried out. According to De Goede (2007) the processing of information and stimuli through cognitive processes, which are activated in an uncertain situation in order to reduce the amount of uncertainty, could be termed information processing. Taylor (1992) states that an individual in more complex behaviours has to string together a large number of processes in order to make sense of the proposed problem. He goes on to explain that the individual becomes more adept with experience, as he/she develops new and more efficient ways of assembling and employing the processes. The strategy chosen by the individual to solve a given problem either contributes or impinges the capacity to solve the problem (Hunt, 1980; Underwood, 1978). There are however other proposed factors that places a boundary on an individual's capacity to process information.

These factors are explained by Underwood (1978, p.2):

> "Our limitations in solving problems, given any one strategy, will be a composite of the speed of comprehension and assimilation of the information comprising the problem, of the storage limits of working memory, of the forgetting characteristics of the memory systems used, of the efficiency of the access code for retrieving information stored in permanent memory and which may be relevant to the problem, and of the speed and efficiency of any other system used in the total activity".

Taylor (1994) identifies three broad *information processing capacity* parameters namely; processing speed, processing accuracy and cognitive flexibility. Processing speed refers to the speed or quickness with which information of a moderate difficulty level is processed. Taylor (1997) argues that individuals who are slow information processors might fall behind in learning situations, because they might not have enough time to investigate the reasonable solution options to problems. Processing accuracy refers to the accuracy with which information of a moderate difficulty level is processed. A lack of processing accuracy can be associated with lapses in concentration accompanied by a failure to monitor processing performance (De Goede, 2007). Cognitive flexibility refers to selecting the appropriate problem-solving approach to the problem. De Goede (2007), states that individuals who follow an inappropriate strategy would be regarded as having a lesser capacity to process information.

The *capacity to process information* is also, like *abstract reasoning ability*, argued to be awarded according to genetic factors (Taylor, 1994). Taylor (1994) argues that just as abstract reasoning capacity, an individual's *capacity to process information* is mostly genetically endowed, implying that an individual's *capacity to process information* is fairly free from the influence of culture and opportunities, but also that a certain capacity sets an upper limit to performance.

In order to automate the "aha" that is acquired through *transfer* a learner would have to spend the necessary time cognitively engaged and make us of the appropriate information processing systems. The learner would have to string together a large number of processes which will enable him/her to make sense of the proposed problem. As explained by Taylor (1994) the individual becomes more adept with experience, as he/she develops new and more efficient ways of assembling and employing the processes. However, to gain this type of experience the individual would have to constantly spend time engaged cognitively with the newly acquired insights of the proposed problem. It is proposed that this process will enable the individual to effectively automate the newly attained knowledge and attribute to the individual's ability to become more effective and efficient in the execution of a task. It is therefore proposed that *information processing capacity* and *time cognitively engaged* form an interaction effect that positively influences *automisation*.

Hypothesis 12: In the learning potential structural model it is hypothesised that the interaction effect between *time cognitively engaged* and *information processing capacity* positively effects *automisation* of newly transferred insight that occurs as part of the *classroom learning.*

2.6 PRIOR KNOWLEDGE

The argument by Taylor (1994) that the *fluid intelligence* of people influences their ability to develop solutions to novel problems through the *transfer of knowledge* makes theoretical sense. Furthermore, De Goede's (2007) argument that individuals who are able to show superior learning performance would be those who are able to *transfer* better, makes theoretical sense. Both Taylor's (1994) and De Goede's (2007) positions, however, appear to be lacking in terms of providing a holistic picture of the various factors that influence the process of *transfer* onto novel stimuli.

Affirmative training and development programmes are designed to empower employees with the job competency potential and job competencies required to deliver outputs for which the job in question exists (De Goede, 2007). This statement indicates that job competencies and

job competency potential are unique to outcomes required in a specific job. An individual's unsatisfactory ability to use transfer to address novel problems in a specific job with certain unique outcomes would according to De Goede indicate that an individual does not possess the required job competency potential at a level (or to a degree of *automisation*) that would allow his/her *fluid intelligence* to successfully *transfer* it onto the novel job problems. This deficiency is what the affirmative development programme attempts to correct. But the same logic also applies to the *transfer* that needs to occur in the classroom. Despite an adequate level of *abstract thinking capacity,* a learner can nonetheless still fail to make sense of the learning material presented in the programme because of insufficient crystallised *prior knowledge*. An example of this would be if an (intelligent) Industrial Psychology student is unable to make meaningful sense of learning material presented in an advanced module in Biochemistry because he/she is unable to *transfer knowledge* onto the novel Biochemistry learning problems. This inability to transfer is not because of the student's low level of *abstract thinking capacity*, but because of the student's lack of *prior knowledge* in Biochemistry.

Fluid intelligence cannot operate in a vacuum. *Transfer of knowledge* cannot occur in the absence of *prior knowledge*. In the literature there are various indications that certain knowledge or skills that should precede the acquirement of new knowledge. Taylor (1994) acknowledges that already acquired skills or knowledge serves as a building block for acquiring new knowledge and the acquisition of job competency potential. The acquisition of job competency potential can be described as a process during which new attainments have to be built on older ones and these have to be integrated into conceptual frameworks that subsequently become more general and elaborated (Taylor 1994). After small amounts of learning early in the life of the individual every instance of learning is a function of the already learned organisation of knowledge on the subject (De Goede, 2007). In the discussion of the De Goede (2007) study in De Goede and Theron (2010) it is evident that there is certain required knowledge that precedes the transfer process and this should be formally acknowledged by the learning potential structural model. The question is how? The preceding argument suggested that *abstract thinking capacity* will positively influence the extent to which *transfer of knowledge* occurs provided that the requisite level of *prior knowledge* is available. De Goede himself acknowledges that certain relevant *prior knowledge* needs to be present which *fluid intelligence* (*abstract thinking* capacity) transfers onto the solution of the novel problem. *Abstract reasoning capacity* or *fluid intelligence* would allow the individual to *transfer* existing relevant, but not directly applicable skills, knowledge and abilities onto a solution of the novel problem (De Goede, 2007). De Goede (2007), however, failed to reflect this line of reasoning in his proposed learning potential structural model. The De Goede (2007) learning potential structural model failed to formally model *prior learning*.

This line of reasoning suggests that *prior learning* moderates the positive effect of *abstract thinking capacity* on *transfer of knowledge.*

Hypothesis 13: In the learning potential structural model it is hypothesised that the ordinal interaction between *prior knowledge* and *abstract thinking capacity* positively influences *transfer of knowledge.*

For transfer to occur the learner needs to actively wrestle with the learning material and spend the necessary time being cognitively engaged with the specific learning material. As previously argued individuals who are engaged show sustained involvement in learning activities; they initiate action when given the opportunity and exert intense effort and concentration in the implementation of learning tasks (Burger, 2012). It could be argued the time that a learner would require to achieve the necessary "aha" that would enable him/her to transfer the acquired knowledge would depend on Gf (*fluid intelligence/abstract thinking capacity*). A *Gf* (*fluid intelligence/abstract thinking capacity*)*TCE (*time cognitively engaged*) interaction effect on *transfer of knowledge* is therefore hypothesised. Stated differently, in contrast to the hypothesis held by De Goede (2007) that *abstract thinking capacity* on *transfer of knowledge* is moderated by *time cognitively engaged.* A learner with a lower *abstract thinking capacity* would have to spend more *time cognitively engaged* than a learner with a higher *fluid intelligence* to find meaningful structure in the same novel learning material (assuming similar *prior learning*).

Hypothesis 14: In the learning potential structural model it is hypothesised that the interaction effect between *abstract thinking capacity* and *time cognitively engaged* positively influences *transfer of knowledge.*

2.7 POST KNOWLEDGE

Newly attained knowledge, obtained through the *transfer* at time 1 from *prior knowledge* onto a novel problem and the subsequent *automisation* of that insight, can be termed *post knowledge.* That *post knowledge* will however again serve as *prior knowledge* at time 2 that will interact with *fluid intelligence* to determine whether the next novel problem is successfully solved through *transfer*. The individual's *prior knowledge* therefore becomes more and more elaborated. New attainments have to be built on older ones and these have to be integrated into conceptual frameworks that subsequently become more general and elaborated (Taylor 1994). De Goede (2007) argues that once a task is mastered an individual can add his/her new skills, knowledge or abilities to the *prior knowledge*. It thus appears that the forming of *post knowledge* (new knowledge) and using this knowledge again as *prior knowledge* to solve

new novel problems forms a spiral process[13] where the basis of *prior knowledge* is repeatedly elaborated. It is therefore hypothesised that *automisation* positively influences the *post knowledge* of learners. De Goede (2007) put forward the hypothesis that *automisation* (along with *transfer*) directly affects *learning performance during evaluation*. The latter in essence represents *transfer* of *post knowledge.* The De Goede (2007) learning potential structural model failed to formally model *post knowledge*.

Hypothesis 15: In the learning potential structural model it is hypothesised that *transfer* positively influences *automisation*.

Hypothesis 16: In the learning potential structural model it is hypothesised that *automisation* positively influences *post knowledge.*

In the context of an affirmative development program it can be hypothesised that the *transfer* that will occur as part of the *classroom learning performance* will be determined by the level of *Gf* and the interaction between *Gf* and *prior knowledge*. This *transfer* will allow *automisation* to occur, provided sufficient time is spent on committing the newly developed insight to memory. How much *time cognitively engaged* will be required will depend in turn on the level of *information processing capacity*. It can moreover be hypothesised that the *post knowledge*, which emerges from successful *automisation,* together with *abstract thinking capacity* forms an interaction effect that positively influences *transfer* that occurs as part of the learning during evaluation.

Hypothesis 17: In the learning potential structural model it is hypothesised that *post knowledge* positively influences *learning performance during evaluation*.

Hypothesis 18: In the learning potential structural model it is hypothesised that the interaction effect between *post knowledge and abstract thinking capacity* positively effects *transfer* that occurs as part of the *learning during evaluation* (i.e. *learning performance*).

2.8 THE PROPOSED LEARNING POTENTIAL STRUCTURAL MODEL DEPICTED AS A STRUCTURAL MODEL

The research initiating question in this study is why variance occurs in learning performance amongst previously disadvantaged individuals who participate in an affirmative development programme? More specifically the research initiating question is how the original proposed De

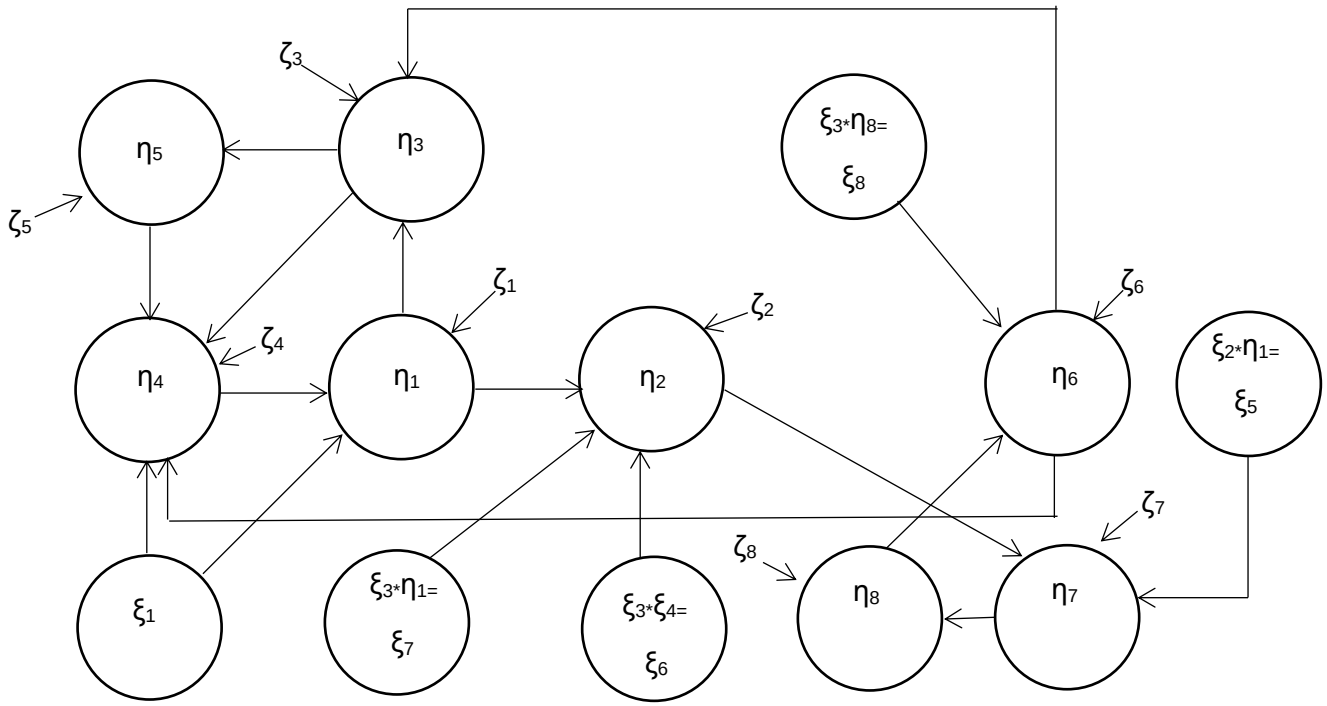
[13] This line of reasoning suggests that future research on the cognitive center of learning potential might benefit from longitudinal structural equation modelling.

Goede (2007) model should be expanded and combined with the reduced Burger (2012) model to more closely approximate the psychological processes that determine the level of learning performance achieved by previously disadvantaged trainees in affirmative development programmes. As can be seen in the proposed sampling strategy (section 3.7) it is assumed that the psychological processes underpinning learning performance in affirmative development programmes are to a large extent similar to the psychological processes underpinning other teaching and training contexts. It is assumed that the same complex nomological network of latent variables that determine learning performance in affirmative development programmes is to a large extent the same latent variables that determine learning performance of engineering students. The latent variables will most probably differ in level across different teaching and training contexts as well as across previously and non-previously disadvantaged backgrounds[14].

A theoretical argument was presented in the literature study with the aim of deriving a convincing answer to the research initiating question. Through the process of theorising, in the literature study, a theoretical position was developed in response to the research initiating question that can be summarised in the form of a structural model and depicted in the form of a path diagram. The expanded and combined learning potential structural model is shown in Figure 2.4 and in essence represents the over-arching substantive research hypothesis. The overarching substantive research hypothesis states that the structural model depicted in Figure 2.4 provides a valid description of the psychological mechanism that regulates the differences in learning performance of learners on an affirmative development programme.

The overarching substantive research hypothesis is represented in the form of a matrix equation in Equation 1.

[14] It is acknowledged that this claim needs to subjected to empirical evaluation. The argument presented here claims that a multi-group configural invariance structural model will fit closely but that lack of alpha invariance and/or equivalence will be obtained (Theron & Spangenberg, 2016)



ξ_1 = *Conscientiousness*

ξ_2 = *Information processing capacity*

ξ_3 = *Abstract thinking capacity*

ξ_4 = *Prior knowledge*

$\xi_5 = \xi_2 * \eta_1$

$\xi_6 = \xi_3 * \xi_4$

$\xi_7 = \xi_3 * \eta_1$

$\xi_8 = \xi_3 * \eta_8$

η_1 = *Time cognitively engaged*

η_2 = *Transfer of knowledge*

η_3 = *Academic self-efficacy*

η_4 = *Learning motivation*

η_5 = *Academic self-leadership*

η_6 = *Learning performance*

η_7 = *Automisation*

η_8 = *Post knowledge*

Figure 2.4: ***The hypothesised expanded and combined learning potential structural model***.

$$\begin{pmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \\ \eta_6 \\ \eta_7 \\ \eta_8 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & \beta_{14} & 0 & 0 & 0 & 0 \\ \beta_{21} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \beta_{31} & 0 & 0 & 0 & 0 & \beta_{36} & 0 & 0 \\ 0 & 0 & \beta_{43} & 0 & \beta_{45} & \beta_{46} & 0 & 0 \\ 0 & 0 & \beta_{53} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_{68} \\ 0 & \beta_{72} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \beta_{87} & 0 \end{pmatrix} \begin{pmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \\ \eta_6 \\ \eta_7 \\ \eta_8 \end{pmatrix} + \begin{pmatrix} \gamma_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \gamma_{26} & \gamma_{27} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_{41} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \gamma_{68} \\ 0 & 0 & 0 & 0 & \gamma_{75} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \\ \xi_5 \\ \xi_6 \\ \xi_7 \\ \xi_8 \end{pmatrix} + \begin{pmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \\ \zeta_4 \\ \zeta_5 \\ \zeta_6 \\ \zeta_7 \\ \zeta_8 \end{pmatrix} \quad \ldots\ldots\ldots\ldots [1]$$

The $\boldsymbol{\Psi}$ and $\boldsymbol{\Phi}$ matrices need to be defined in order for equation 1 to fully capture the theoretical position that has been developed through theorising in response to the research initiating question. It is assumed that the 8 x 8 variance-covariance matrix $\boldsymbol{\Psi}$, which reflects the variance in and covariance between structural error terms (ζ_i), is a diagonal matrix. The structural error variances ψ_{ii} are therefore freed to be estimated but the off-diagonal covariance terms ψ_{ij} are fixed to zero. Therefore, the structural error terms are assumed to be uncorrelated. It is assumed that the 8 x 8 variance-covariance matrix $\boldsymbol{\Phi}$, which reflects the variance in and the covariance between the exogenous latent variables (ξ_i), is a symmetrical matrix in which all off-diagonal covariance ϕ_{ij} terms are freed to be estimated. It is therefore assumed that the exogenous latent variables are correlated. An assumption is made that the completely standardised solutions will be more meaningful to interpret and thus the 8 exogenous variance terms are fixed to 1 given the fact that the latent variables are standardised. Equation 1 can be reduced to equation 2.

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \quad [2]$$

Where:

$\boldsymbol{\eta}$ is an 8 x 1 column vector of endogenous latent variables;

$\mathbf{B}$ is an 8 x 8 matrix of regression/ path coefficients (β) describing the strength of the regression of η_i on η_i in the structural model;

$\boldsymbol{\xi}$ is an 8x1 column vector of exogenous latent variables;

$\boldsymbol{\Gamma}$ is an 8x8 matrix of path/regression coefficients (γ) describing the strength of the regression of η_i on ξ_i in the structural model;

$\boldsymbol{\zeta}$ is an 8 x 1 column vector of residual error terms.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 INTRODUCTION

In the literature study various arguments were presented with the aim of integrating the learning potential structural model that was proposed by De Goede (2007) and the reduced model that was proposed and tested by Burger (2012). The value of the non-cognitive factors that were proposed by Burger (2012) were acknowledged, however, with the aim of obtaining a more holistic understanding of learning potential, and acknowledging the critical importance of cognition in learning potential, it was argued that the cognitive mechanism that was proposed by De Goede (2007) should be elaborated on and integrated with the reduced potential structural model that was proposed by Burger (2012). This culminated into a basic learning potential structural model. The proposed learning potential structural model includes latent variables that were proposed by Burger (2012) and De Goede (2007) to have an influence on learning potential. The model also includes additional latent variables, *prior knowledge* and *post knowledge,* which were included with the aim of correcting the too simplistic explanation of the manner in which *transfer* and *automisation* as learning competencies comprising *classroom learning performance* influence *learning performance during evaluation* provided by the original De Goede (2007) model.

In the previous chapter it was acknowledged that *learning performance* is influenced by a nomological network of factors that comprise both cognitive - and non-cognitive factors. It was argued in the previous chapter that despite *learning performance* being influenced by both cognitive and non-cognitive factors that the former has been ignored in most of the learning potential structural models that were proposed and empirically tested in response to the De Goede model (2007). The cognitive learning competencies and learning competency potential variables are of critical importance and could not be neglected in future explanatory learning potential structural models any longer. It was argued that obtaining a rich and fruitful insight into *learning performance* would only be possible if the two core learning competencies namely*, transfer* and *automisation*, were to be returned to the proposed structural model of *learning potential*.

The methodology used to arrive at a verdict on the validity of the proposed learning potential structural model will determine the extent to which the claim of the study to have come to the correct verdict on the fit of the structural model is accurate. The purpose of the methodology in research is to serve the epistemic ideal of science. Two characteristics of scientific

methodology serves the epistemic ideal of science, namely the objectivity and rationality of science (Babbie & Mouton, 2001). Science is objective in the sense that it is explicitly, and purposefully focused on the reduction/minimisation of error through the making of considered methodological choices. Science is rational in the sense that it insists that the methodological choices made by researchers should be subjected to critical examination by knowledgeable peers to identify possible methodological flaws and shortcomings. This can, however, only occur if the methodological choices that were made have been described sufficiently comprehensively. If the methodology that was used is ambiguous and the methodological choices that were made have not made explicit, the evaluation of the merits of the conclusions that were reached will be jeopardised, which will mean that the verdict that was reached will have to be accepted purely on face value. This is problematic because the verdict might be inappropriate due to the fact that an inappropriate procedure was used to investigate the merits of the structural model. The rationality of science is therefore jeopardised and ultimately the epistemic ideal of science (Babbie & Mouton, 2001). The following section therefore gives a detailed description of the research methodology that was used to test the validity of the overarching and path-specific substantive hypotheses with the aim of serving the epistemic ideal of science.

3.2 LEARNING POTENTIAL STRUCTURAL MODEL

The reduced learning potential structural model that was proposed by Burger (2012) was combined with the proposed cognitive learning competency latent variables that have been argued as influential in the literature study in explaining learning performance during evaluation. The resultant learning potential structural model is shown in Figure 2.4. The learning potential structural model shown in Figure 2.4 is expressed as a matrix equation in Equation 1.

3.3 SUBSTANTIVE RESEARCH HYPOTHESES

The objective of this study is to refocus previous elaborations made (Burger, 2012; Du Toit, 2014; Mahembe, 2014; Pretorius, 2015; Prinsloo, 2014; Van Heerden, 2013) to the original De Goede (2007) learning potential structural model and to thereby reemphasise the importance of the influence of cognitive factors in *learning potential.* Through the process of theorising the inclusion of previous non-cognitive learning competency latent variables, introduced by Burger (2012), have been combined with the latent cognitive learning competencies and learning competency potential latent variables that were proposed by De

Goede (2007) along with additional cognitive learning competency potential latent variables. This was done with the aim of providing a more comprehensive and balanced picture of the nomological network of variables that constitute *learning potential.*

The structural model (see Figure 2.4) is a combination of the reduced Burger (2012) (see Figure 2.2) model and the cognitive learning competency latent variables that were reintroduced. The over-arching substantive hypothesis of this study (hypothesis 1) is that the structural model illustrated in Figure 2.4 provides a valid representation of the nomological network of latent variables that determine the level of learning achieved by trainees in an affirmative development programme. The overarching substantive research hypothesis can be sub divided into the following more detailed, path-specific direct-effect substantive research hypotheses:

Hypothesis 2: In the learning potential structural model it is hypothesised that *time cognitively engaged* positively influences *transfer of knowledge*[15].

Hypothesis 3: In the learning potential structural model it is hypothesised that *conscientiousness* positively affects *time cognitively engaged*.

Hypothesis 4: In the learning potential structural model it is hypothesised that *learning motivation* positively influences *time cognitively engaged*.

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

Hypothesis 6: In the learning potential structural model it is hypothesised that *academic self-leadership* positively influences *learning motivation*.

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

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

Hypothesis 9: In the learning potential structural model it is hypothesised that *learning performance during evaluation* positively influences *academic self-efficacy* as a form of feedback.

[15] The phrase *in the learning potential structural model* has been used on purpose to acknowledge the fact that the hypotheses do not unconditionally claim that a specific exogenous or endogenous latent variable produces variance in a specific endogenous latent variable. Rather the phrase has been used to acknowledge that the hypotheses claim that a specific exogenous or endogenous latent variable produces variance in a specific endogenous latent variable when controlling for the other latent variables that were structurally linked to the endogenous latent variable in question.

Hypothesis 10: In the learning potential structural model it is hypothesised that *time cognitively engaged* positively influences *academic self-efficacy* as a form of feedback.

Hypothesis 11: In the learning potential structural model it is hypothesised *that learning performance during evaluation* positively influences *learning motivation* as a form of feedback.

Hypothesis 12: In the learning potential structural model it is hypothesised that the interaction effect between *information processing capacity* and *time cognitively engaged* positively influences automisation.

Hypothesis 13: In the learning potential structural model it is hypothesised that the ordinal interaction between *prior knowledge* and *abstract thinking capacity* positively influences transfer of knowledge.

Hypothesis 14: In the learning potential structural model it is hypothesised that the interaction effect between *abstract thinking capacity* and *time cognitively engaged* positively influences *transfer of knowledge*.

Hypothesis 15: In the learning potential structural model it is hypothesised that *transfer of knowledge* positively influences *automisation*.

Hypothesis 16: In the learning potential structural model it is hypothesised that *automisation* positively influences *post knowledge*.

Hypothesis 17: In the learning potential structural model it is hypothesised that *post knowledge* positively influences *learning performance during evaluation*.

Hypothesis 18: In the learning potential structural model it is hypothesised that the interaction effect between *post knowledge* and *abstract thinking capacity* positively effects *transfer* that occurs as part of the *learning performance during evaluation*.

3.4 RESEARCH DESIGN

In order to investigate the overarching substantive hypothesis empirically, as well as the various path-specific direct-effect substantive research hypotheses, a strategy is required that will provide unambiguous, empirical evidence in terms of which to evaluate the validity of the stated hypotheses. The research design provides a plan and structure of the investigation which is set up to firstly, procure answers to the research question and secondly, to control variance (Kerlinger, 1973). The ability of the research design to maximise systematic variance, minimise error variance and control extraneous variance (Kerlinger, 1973; Kerlinger & Lee, 2000) will ultimately determine the unambiguousness of the empirical evidence.

Ex post facto research entails the systematic empirical inquiry in which a researcher does not have direct control of independent variables as their manifestations have already occurred or because the independent variables inherently cannot be manipulated (Kerlinger & Lee, 2000). Therefore, the experimental manipulation and random assignment of treatments are not possible in *ex post facto* research. Inferences about the hypothesised relation existing between the latent variables ξ_j and η_i are made from concomitant variation in independent and dependent variables (Kerlinger & Lee, 2000). The *ex post facto* nature of the research design, however, inhibits the drawing of casual inferences from significant path coefficients as correlations or covariances do not imply causation. The objective of this study was to determine the existence of specific causal linkages between specific cognitive and non-cognitive learning competency potential latent variables, the learning competencies that constitute *classroom learning performance* and *learning performance during evaluation* as proposed by the expanded learning potential structural model. The *ex post facto* nature of the research design, however, precluded the drawing of causal inferences from significant path coefficients.

With regards to the logic of the *ex post facto* correlation design (rather than *ex post facto* quasi-experimental design) used in the current study, measures of the observed variables are obtained and the observed covariance matrix is calculated. Diamantopoulos and Siguaw (2000) state that estimates for the freed structural and measurement model parameters are obtained in an iterative fashion with the objective of reproducing the observed covariance matrix as closely as possible.

The inability of the fitted model to accurately reproduce the observed covariance matrix means that the fitted model does not provide an acceptable explanation for the observed covariance matrix (Diamantopoulos & Siguaw, 2000; Kelloway, 1998). If that is the case in this study it would mean that the proposed learning potential structural model does not give a satisfactory explanation of the variance in *learning performance during evaluation*.

The opposite is, however, not true. In the instance where the covariance matrix, which is derived from the estimated model parameters, closely corresponds to the observed covariance matrix it would not imply that the processes postulated by the structural model necessarily must have produced the observed covariance matrix. It would also not imply that the psychological learning mechanism designed via the literature study presented in Chapter 2 must be the one operating in reality. A high degree of fit between the observed and estimated covariance matrices would only imply that the processes portrayed in the structural model provide one plausible (or valid (i.e. permissible)) explanation for the observed covariance

matrix. The structural model could, under such an outcome, be considered corroborated in the sense that it survived an opportunity to be refuted (Popper, 1972).

3.5 STATISTICAL HYPOTHESES

The proposed overarching and path-specific substantive research hypotheses will be represented in the form of statistical hypotheses in this section. These hypotheses represent the proposed casual paths that were postulated between the exogenous and endogenous latent variables, and between the endogenous latent variables in the structural model (see Figure 2.4.). These hypotheses will be analysed through the use of structural equation modelling, which allows the possibility of testing the proposed structural model as an integrated, complex hypothesis. The explanation as to why learners vary in the level of learning performance they achieve is not located to any specific point in the structural model but rather is contained in the whole network of relationships between the latent variables. The estimation of the hypothesised model's fit enables researchers to determine the extent to which the model is consistent with obtained empirical data. In order to investigate a hypothesised model's fit, an exact fit null hypothesis and a close fit null hypothesis will be tested (Diamantopoulos & Siguaw, 2000).

Hypothesis 1a:

The overarching substantive hypothesis (Hypothesis 1), states that the learning potential structural model provides a valid account of the psychological mechanism determining the level of *learning performance during evaluation*. Should this hypothesis be interpreted to mean that the hypothesised structural model provides a perfect account of this psychological mechanism at work then the structural model expressed as Equation 1 should fit the data in the parameter exactly. There is therefore no discrepancy between the reproduced covariance matrix implied by the model and the observed population covariance matrix.

$$H_{0107a}^{16}: \text{RMSEA}=0$$

$$H_{a107a}: \text{RMSEA}>0$$

Hypothesis 1b:

The likelihood that the hypothesised structural model provides a perfect account of the psychological mechanism that determines the level of *learning performance during evaluation* is small. At best it is more likely that the hypothesised structural model only approximates the psychological mechanism determining the levels of *learning performance during evaluation* achieved by affirmative development learners. If the overarching substantive hypothesis is

[16] H_{01a} and H_{01b} have been reserved for the fit of the measurement model.

interpreted to mean that the structural model only provides an approximate account of the psychological mechanism underpinning levels of *learning performance during evaluation* the structural model expressed as Equation 1 should fit the data in the parameter closely. The reproduced covariance matrix implied by the model closely approximates the observed population covariance matrix.

$$H_{0,107b}: RMSEA \leq .05$$

$$H_{a,107b}: RMSEA > .05$$

Hypothesis 2:

Time cognitively engaged (η_1) has a statistically significant positive effect on *transfer of knowledge* (η_2).

$$H_{0,108}: \beta_{21} = 0^{17}$$

$$H_{a,108}: \beta_{21} > 0$$

Hypothesis 3:

Conscientiousness (ξ_1) has a statistically significant positive effect on *time cognitively engaged* (η_1).

$$H_{0,109}: \gamma_{11} = 0$$

$$H_{a,109}: \gamma_{11} > 0$$

Hypothesis 4:

Learning motivation (η_4) has a statistically significant positive effect on *time cognitively engaged* (η_1).

$$H_{0,110}: \beta_{14} = 0$$

$$H_{a,110}: \beta_{14} > 0$$

Hypothesis 5:

Conscientiousness (ξ_1) has a statistically significant positive effect on *learning motivation* (η_4).

$$H_{0,111}: \gamma_{41} = 0$$

$$H_{a,111}: \gamma_{41} > 0$$

Hypothesis 6:

[17] Strictly speaking the statistical hypotheses should be formulated in a manner that explicitly acknowledges that the γ_{ij} and β_{ij} parameters are partial regression coefficients that reflect the slope of η_i on ξ_j and the slope of η_i on η_j when statistically controlling for the effects of the other endogenous and exogenous latent variables that been hypothesised to affect η_i. In the case of hypothesis 2 a more accurate formulation of the statistical hypothesis would have been: H_{02}: $\beta_{21} = 0|\gamma_{26} \neq 0; \gamma_{27} \neq 0$ and H_{a2}: $\beta_{21} > 0|\gamma_{26} \neq 0; \gamma_{27} \neq 0$.

Academic self-leadership (η_5) has a statistically significant positive effect on *academic self-efficacy* (η_3).

$$H_{0,112}: \beta_{35} = 0$$

$$H_{a,112}: \beta_{35} > 0$$

Hypothesis 7:

Academic self-efficacy (η_3) has a statistically significant positive effect on *learning motivation* (η_4).

$$H_{0,113}: \beta_{43} = 0$$

$$H_{a,113}: \beta_{43} > 0$$

Hypothesis 8:

Academic self-efficacy (η_3) has a statistically significant negative effect on *Academic self-leadership* (η_5).

$$H_{0,114}: \beta_{53} = 0$$

$$H_{a,114}: \beta_{53} > 0$$

Hypothesis 9:

Learning performance during evaluation (η_6) has a statistically significant positive effect on *Academic self-efficacy* (η_3).

$$H_{0,115}: \beta_{36} = 0$$

$$H_{a,115}: \beta_{36} > 0$$

Hypothesis 10:

Time cognitively engaged (η_1) has a statistically significant positive effect on *Academic self-efficacy* (η_3).

$$H_{0,116}: \beta_{31} = 0$$

$$H_{a,116}: \beta_{31} > 0$$

Hypothesis 11:

Learning performance during evaluation (η_6) has a statistically significant positively effect on *learning motivation* (η_4).

$$H_{0,117}: \beta_{46} = 0$$

$$H_{a,117}: \beta_{46} > 0$$

Hypothesis 12:

The proposed interaction effect between *information processing capacity* (ξ_2) and *time cognitively engaged* (η_1) ($\xi_2 * \eta_1 = \xi_5$), has a statistically positive effect on *automisation* (η_7).

$$H_{0,118}: \gamma_{75} = 0$$

$$H_{a,118}: \gamma_{75} > 0$$

Hypothesis 13:

The ordinal interaction between *prior knowledge* (ξ_4) and *abstract reasoning capacity* (ξ_3) (ξ_4* ξ_3 = ξ_6), has a statistically significant positive effect on *transfer of knowledge* (η_2).

$$H_{0,119}: \gamma_{26} = 0$$

$$H_{a,119}: \gamma_{26} > 0$$

Hypothesis 14:

The interaction effect between *fluid intelligence*(ξ_3) and *time cognitively engaged* (η_1) (ξ_{3*} η_1 = ξ_7) statistically positively influences *transfer of knowledge* (η_2).

$$H_{0,120}: \gamma_{27} = 0$$

$$H_{a,120}: \gamma_{27} > 0$$

Hypothesis 15:

Transfer of knowledge (η_2) has a statistically significant positive effect on *automisation* (η_7).

$$H_{0,15}: \beta_{72} = 0$$

$$H_{a,15}: \beta_{72} > 0$$

Hypothesis 16:

Automisation (η_7) has a statistically significant positive effect on *post knowledge* (η_8).

$$H_{0,121}: \beta_{87} = 0$$

$$H_{a,121}: \beta_{87} > 0$$

Hypothesis 17:

Post knowledge (η_8) has a statistically significant positive effect on *learning performance during evaluation*(η_6).

$$H_{0,122}: \beta_{68} = 0$$

$$H_{a,122}: \beta_{68} > 0$$

Hypothesis 18:

The ordinal interaction effect between *post knowledge* (η_8) *and abstract thinking capacity* (ξ_3) (η_{8*} $\xi_{3 =}$ ξ_8) positively effects *transfer* of knowledge (η_2).

$$H_{0,123}: \gamma_{28} = 0$$

$$H_{a,123}: \gamma_{28} > 0$$

3.6 MEASUREMENT INSTRUMENTS

Measures of the learning competency potential latent variables and the learning competency latent variables comprising the hypothesised model depicted as Equation 1 are required to evaluate the fit of the learning potential structural model. These measures enable the gathering of empirical evidence, which will provide possible corroborating evidence that the relationships postulated by the proposed learning potential structural model offer a plausible explanation for differences observed in learning performance. These measures are representative of the various exogenous and endogenous latent variables that comprise the learning potential structural model.

3.6.1 Non-Cognitive Latent Variable Operationalisation

The same instruments that were used by Burger (2012) to empirically evaluate her model were used in the current study to measure the non-cognitive learning competencies and non-cognitive learning competency potential latent variables taken over from the Burger (2012) model. View Burger (2012) for a discussion of the operationalisation of the non-cognitive latent variables that were proposed by Burger (2012).

The measurement instruments used by Burger (2012) to measure the non-cognitive latent variables of her proposed learning potential model were as follow:

- an adapted version of the Academic Engagement Scale for Grade School Students (AES-GS) was used to measure *time cognitively engaged*,
- Burger (2012)'s adapted version of the *conscientiousness* scale that was retrieved from the NEO IPIP was used to measure *conscientiousness*,
- the adapted version of section B (motivation to learn) of the motivation to learn questionnaire (MLQ) was used to measure *learning motivation*.
- *academic self-leadership* was measured through and adapted version of the Revised Self-Leadership Questionnaire,
- *academic self-efficacy* was measured by taking and adapting items from the Morgan-Jinks Student Efficacy Scale, (MJSES), the Self-Efficacy for Learning Form (SELF) questionnaire as well as the scale developed by Vick and Packard (2008).

3.6.2 Information Processing Capacity

De Goede (2007) proposed to measure *information processing capacity* (ξ_2) through the use the Flexibility-Accuracy-Speed-Tests, which make up four sub-tests within the APIL test battery. The Flexibility-Accuracy-Speed-Tests provide measures of the dimensions of speed, accuracy and the cognitive flexibility of information processing (Taylor, 2006). The dimension scores obtained on these four subsets will be used as operational measures for *information processing capacity* to fit the model through structural equation modelling.

Taylor (2006), calculated the processing speed by adding the total number of items attempted over the first three sub-tests (the forth sub-test requires the testee to work with all three problem types presented in the first three subtests) (Taylor, 2006). To determine the reliability of the information processing speed Taylor (2006) inspected the correlations between the three components (series number attempted, mirror number attempted, transformation number attempted) that are added together to determine the speed score. The correlation coefficients between these three sub-test scores range between .45 and .72, with a mean of .61 and were obtained across six samples (Taylor, 2006).

The accuracy score is a logarithmically transformed and inverted score of error rate. The formula that was used to calculate the accuracy score is as follows (Taylor, 2006):

Accuracy = $100\text{-}30_{\log 10}$[(Number of Errors/Number Attempted) x 200]

The reliability of the accuracy score was estimated by combining sub-tests 1 and 3 and also sub-tests 2 and 4, with reliability coefficients ranging between .70 and .86 and scores being obtained across six samples (Taylor, 2006).

Flexibility score is a function of the amount of work correctly done in the first three sub-tests in comparison with the amount of work correctly done in the final sub-test (Taylor, 2006). Formula:

Flexibility = $(\text{correct output in sub-test 4})^2$/(correct output in sub-test 1,2 & 3)

Taylor (2006) argues that reliability of the Flexibility scores cannot be calculated due to the fact that the learning effect would corrupt the scores, unless the test-retest exercise is conducted many months apart. Taylor (2006) does however state that flexibility score typically has large variance, which is a prerequisite (but no guarantee) for good reliability.

3.6.3 Abstract Thinking Capacity

The concept formation test of the APIL test battery was used to measure *abstract thinking capacity* $\xi_{3,}$ which is a sub-test of the test-battery. The concept formation test measures the ability of the individual to form abstract concepts, reason hypothetically, theorise, build scenarios and trace causes (Taylor, 1997). This test consists of a classificatory task where sets of geometrical diagrams are presented to testees and testees have to identify a diagram, which does not share a characteristic that all the others share (Taylor, 2006).

Kuder-Richardson-type estimates were used to calculate the reliability of the concept formation test scores. The concept formation test obtained KR-20 coefficients that ranged between .78 and .87 (Taylor, 2006).

3.6.4 Transfer of Knowledge

The knowledge transfer test, which is a sub-test of the APIL test battery, was used by De Goede (2007) to measure *transfer of knowledge*. This test measures transfer by exposing the testees to a number of related but increasingly complex problems presented in the form of abstract geometric figures. Answers and feedback are given to individuals on example problems after he or she has completed each problem (Taylor, 2006). De Goede and Theron (2010), however, subsequently recognised that the knowledge transfer test does not provide an appropriate and valid measure of the extent to which transfer of knowledge occurs with regards to the novel learning material that is presented in the classroom. It is the extent to which transfer of knowledge occurs with regards to the novel learning material that is presented in the classroom that determines the level of post learning knowledge that is used to solve novel learning problems via transfer in the subsequent learning during evaluation. De Goede and Theron (2010) moreover recognised that developing a measure similar to the knowledge transfer test for the specific content of a specific affirmative development programme would have too little utility to justify the investment that would be required to develop such an instrument. Such an approach would require unique transfer of knowledge tests for each specific development programme.

Psychological constructs or latent variables are measured indirectly through observable behaviour in which the construct visibly expresses itself. An individual's standing on a latent variable is therefore indirectly assessed by requesting the individual to respond to a set of stimuli to which the responses depend on the level of the individual's standing on the latent variable. A distinction can be made between two distinct approaches here. In the first approach the stimuli and the accompanying instructions result in live behavioural denotations

of the testees standing on the latent variable. The knowledge transfer test of the APIL (Taylor, 2006) provides an example of this approach. In the second approach the stimuli and the accompanying instructions result in the recall from memory of historical behavioural denotations of the testees standing on the latent variable. The 16 PF personality test (Cattell, Eber, & Tatsuoka, 1970) provides an example of this approach. In the first approach the stimuli in a test or questionnaire elicits a behavioural response that is a behavioural denotation of the latent variable of interest from the testee, which is then measured. The second approach relies on the testee giving a historical recollection of his or her behaviour/pattern of thinking/ emotions in a specific situation. The second approach could for example cite critical behavioural incidents that reflect a high or low standing on the latent variable of interest. These critical behaviour serves as test stimuli to which the testee needs to respond. The testee recollects to what extent he/she displayed such behaviour in the past in a specific situation and indicates that by selecting a specific response option on a scale.

The latter approach was used to operationalise *transfer of knowledge* as it occurs with regards to the novel learning material that is presented in the classroom during a specific development programme. It is argued that the extent to which *transfer of knowledge* successfully combines and transfers *prior knowledge* to create meaningful structure in the novel learning material that is encountered in the classroom expresses itself in behaviours and cognitive, affective and conative experiences.

The psychometric properties of this test were determined as part of the current research study.

3.6.5 Automisation

The learning competency of *automisation*, in which individuals internalise their understanding of new knowledge attained or become more efficient in a new task, can be expressed as a learning curve. The steeper the learning curve, the more rapid the process of automisation (Taylor, 1992). To assess automisation the curve of learning test, a sub-test of the APIL test battery, was used by De Goede (2007). The curve of learning test looks at the increase of work output over four sessions (Taylor, 2006). Two operational measurement scores that is used for automisation is a total output score and a memory and understanding score. De Goede and Theron (2010), however, subsequently recognised that the curve of learning test also does not provide an appropriate and valid measure of the extent to which *automisation* of the insight derived through *transfer* occurs with regards to the novel learning material that is presented in the classroom. The problem was again the same as with the transfer of knowledge test. The APIL purposefully uses abstract learning material that nobody is familiar with. When using the post-development training evaluation measures as a measure of

learning performance during evaluation that performance depends on the extent to which *transfer* of *prior knowledge* on the actual novel learning material occurred and on the extent to which that insight attained during the development programme was *automated*.

Automisation was therefore in the current study also measured via its psychological denotations.

The psychometric properties of this newly developed *automisation* test were determined as part of the current research study.

3.6.6 Prior Knowledge

The initial aim was to develop a test that would measure domain specific knowledge that a student should be able to display based on prior academic studies. It was however decided to rather use previous academic marks as a measurement of prior knowledge. This decision was made due to the survey that was already long.

Prior knowledge for first year engineers was determined by requesting access to their grade 12 mathematics mark. Prior knowledge for second, third- and fourth-year engineering students was determined by requesting access to their previous years academic average. These marks were used as an indication of the knowledge that these students obtained in their Grade 12-year, first year of university studies, second year of university studies or third year of university studies. A limitation of this measure was that it was not possible to subject the various test papers and assignments, which make up the student's average mark, to psychometric analysis to determine the psychometric properties of the instrument.

3.6.7 Post Knowledge

It was initially decided to develop a test that will determine engineering students' general automated knowledge of the engineering mathematics (for first year students) or the general automated engineering principles (for second, third- or fourth-year students) that were covered during the first semester. This test would not have assessed the application (or transfer) of new knowledge that have been obtained by students, but rather engineering students ability to retrieve (automated) knowledge about mathematics or engineering that had been gained during the first semester and that would be necessary (according to the logic of the hypothesised learning potential structural model) to successfully solve novel problems in end-of-semester tests set at the end of first semester engineering modules. The measurement of *post knowledge* had to focus on whether the knowledge that the student obtained during the

semester became part of the student's long-term memory in the sense that he/she would not only be able to remember and apply the material that was covered during the semester in a test or an assignment, but after a period of time has lapsed since the material was covered as well. The knowledge domain would have been dissected in engineering knowledge facets. Appropriate items would have been developed to measure the level of post knowledge with regards to each facet.

However, in the process of designing the research data collection questionnaire used to collect data the researchers were a bit negligent and allowed the construct post knowledge to slip of the radar. No data was therefore collected for this construct. It is moreover acknowledged that if the development of measures to assess this construct had not slipped off the radar it would have set daunting practical challenges to the researchers in terms of developing the items for these scales.

The necessity to adjust the proposed learning potential structural model by removing *post knowledge* (η_8) as a latent variable (see Figure 4.5 in Chapter 4) was an unfortunate consequence of the omission of the operationalisation of the *post knowledge* construct[18]. The interaction between *post knowledge* and *abstract thinking capacity* (ξ_8) therefore also had to be removed from the structural model. Hypotheses 17 and 18 could therefore not be tested since the paths β_{68} and γ_{68} had to be deleted from the original model .

3.6.8 Learning Performance

The mark that first year engineering students obtained on their first semester engineering maths module in the programme was used as a measure of *learning performance*. The academic average for the first semester was used for second-, third- and fourth year engineering students. A limitation of this measure was that it was not possible to subject the test papers and assignments, that make up the average mark of the engineering students, to psychometric analysis to determine the psychometric properties of the instrument.

[18] It serves to point out that the researchers could have chosen not to confess to this omission and could have simply revised the hypothesised structural model by writing out Post Knowledge from the theorising. Such a practice of deciding at the writing-up stage what to report and what not to is, however, an extremely dangerous practice that can set the researcher on the slippery slope of hypothesising after results are known (HARKing) (Murphy & Aguinis, 2019). Although the neglect of the researchers in omitting this scale from the composite research questionnaire should not be condoned, the researchers do deserve some recognition for taking this principled stance of accurately and transparently reporting events, problems, decisions and results as they historically unfolded.

3.6.9 Indicator terms for the latent interaction effects

In order to create orthogonalised indicators for the latent interaction constructs in the learning potential structural model, each possible product term from two sets of indicators for two latent constructs involved in the interaction were formed (Little, Boviard & Widaman, 2006). The product term from the two sets of indicators for two latent constructs involved in the interaction were formed for each of the latent interaction terms in the proposed model. After the uncentered product terms were calculated they were individually regressed onto the first-order effect indicators of the constructs involved in the interaction term. The resulting unstandardised residuals for these regressions were saved and used as indicators of the interaction constructs.

There are three latent interaction effects in the revised proposed learning potential structural model. The above-mentioned procedure was followed for each of the interaction effects in the proposed model. The three latent interaction effects are; *information processing capacity* (ξ_2) * and *time cognitively engaged* (η_1) ($\xi_{2*}\eta_1 = \xi_5$), *prior knowledge* (ξ_4) * and *abstract reasoning capacity* (ξ_3) ($\xi_4 * \xi_3 = \xi_6$), and *Gf* (*fluid intelligence/ abstract thinking capacity* (ξ_3))* and *TCE* (*time cognitively engaged* (η_1)) ($\xi_{3*}\ \eta_1 = \xi_7$). The calculated unstandardised residuals for each of these interaction effects were saved and used as indicators of the interaction constructs.

The interaction term *post knowledge* (η_8)**abstract thinking capacity* (ξ_3) ($\eta_{8*}\xi_3 = \xi_8$) had to be removed due to the latent variable *post knowledge* being removed from the proposed learning potential structural model (see Fig 4.5 in Chapter 4).

3.7 SAMPLING

The target population in sampling refers to the theoretical totality of elements that is implied by the research initiating question. The target population in the current study was all South Africans that qualify for an affirmative development opportunity. The ideal would have been to include all the elements of the target population in the research investigation, but this had certain practical limitations which made the investigation of the target population not feasible. An alternative to investigating the target population was investigating a representative sample of the target population. The sampling population refers to the population of elements from which a sample of elements is actually selected (Babbie & Mouton, 2001). It was initially decided to use the first-year cohort registered for the degree BCom (Accounting) at Stellenbosch University in 2017 as the sampling population for this study. The use of grade 12 accounting marks as a measurement of prior knowledge, however, limited this cohort as a

viable option seeing that not all first-year accounting students had accounting at school. To address this, it was decided to make use of first year engineering students. The reasoning behind this was that all first-year engineering students had mathematics in grade 12 as well as engineering maths in their first year of studying. These two marks were argued to represent *prior knowledge* and *learning performance during evaluation*. The gap between the target- and sampling population should ideally be kept to a minimum as far as possible. In the case of the current study a large non-ignorable gap existed between the target and sampling populations[19].

The motivation for this study was to develop a structural model that explains the determinants of learning performance from an affirmative development perspective. The importance of such a model has been argued from an affirmative development perspective, but this model will also add value to other forms of development, training and teaching. This is based on the argument made by Prinsloo (2013) that the psychological dynamics underlying learning performance in affirmative development programmes do not differ significantly from that governing learning performance in other learning contexts. Therefore, it is proposed that the same complex nomological network of latent variables that determine learning performance in affirmative development programmes will also determine learning performance in undergraduate engineering students. An aspect that should differ across different teaching contexts are the levels of specific latent variables that characterise the learners that has been affected by disadvantagement[20].

By adopting this line of reasoning the testing of the hypothesised learning potential structural model on a sample not entirely representative of previously disadvantaged learners would be warranted. Based on this conclusion, and the argument put forth by Prinsloo (2013), this study empirically evaluated the structural model on a sample of previously disadvantaged learners in addition to not previously disadvantaged learners who have enrolled for a teaching/training programme that cannot be classified as an affirmative development programme.

There are two issues that are of relevance when considering the selection of the sample. The first issue pertains to the representativeness of the study sample of the target population, as a function of the method of sampling and the magnitude of the sampling gap between the target population and the sampling population. The second issue pertains to the statistical

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[19] An alternative possibility that had been considered was to define the sampling population in the current study as Grade 11 and 12 High School learners from Cloetesville High School. The majority of these learners form part of the cohort of previously disadvantaged cohort, but are not representative of all race groups that are acknowledged as previously disadvantaged.

[20] It is again acknowledged that such claims should be subjected to an empirical test. Multi-group structural equation modelling constitutes the appropriate technique to examine the configural invariance as well as the alpha invariance and equivalence of the multi-group learning potential structural model.

power of the subsequent statistical analyses [1-β =P(Reject H_0|H_0 false)] as a function of sample size (Babbie & Mouton, 2001). The representativeness of the sample is determined by the extent to which the characteristics of the target population are accurately portrayed by the sample.

A distinction exists between two types of sampling procedures namely probability sampling - and non-probability sampling procedures. In a probability sampling procedure, each element in a sampling population has a known positive, but not necessarily equal, probability of being selected into the sample. In a non-probability sampling procedure, the probability of selection is unknown for each element of the sampling population (Babbie & Mouton, 2001). The current study was forced to utilise a non-probability sample since it could only invite members of the sampling population to participate in the research. Learners had the right to voluntarily decide whether they wished to accept the invitation to participate or not.

For the purpose of this study, the question of sample size was primarily considered from the perspective of structural equation modelling (SEM). SEM is very much a large sample technique which bases tests of model fit on the assumption of large samples (Kelloway, 1998). According to Kelloway (1998) the number of observations that are deemed as satisfactory for most SEM applications are 200 observations or more. There are three issues that were considered when deciding on the appropriate sample size. Firstly, the ratio of sample size to the number of parameters to be estimated was considered. In the case where more freed model parameters would need to be estimated than the number of observations in the sample, it would not be regarded as acceptable. Elaborate measurement and structural models which contain more variables and have more freed parameters that have to be estimated, necessitate larger sample sizes (Burger, 2012). Bentler and Chou (1987) proposed that the ratio of sample size to number of parameter estimated should be between 5:1 and 10:1. According to the Bentler and Chou (1987) guideline the proposed structural model (Figure 2.4) and the proposed procedure for operationalising the latent variables (see paragraph 3.7) would require a sample of 533 - 1070 research participants to provide a convincing test of the proposed learning potential structural model (107 freed parameters).

A second consideration was 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 > 0.05). Statistical power in the context of SEM refers to the probability of rejecting the null hypothesis of close fit (H_0: RMSEA ≤ 0.05) when in fact it should be rejected (i.e., the model fit actually is mediocre, H_a: RMSEA > 0.05) (Burger, 2012). Exceptionally high statistical power would lead to any attempt made to formally empirically corroborate the validity of the model being futile. If this is the case even a small deviation from close fit would result in a rejection

of the close fit null hypothesis. Exceptionally low power would mean that even if the model fails to fit closely, the close fit null hypothesis would still not be rejected. When close fit is not rejected under conditions of low power evidence provided on the validity of the model will not be very convincing. Syntax that was developed by Preacher and Coffman (2006) in R was used to derive sample size estimates for the test of close fit, given the effect size assumed above, a significance level (α) of .05, a power level of .80 and degrees of freedom (v) of (½[(p+q][p+q+1]-t)=595-95 = 500. The Preacher and Coffman (2006) software indicated that a sample of 69 observations would be required to ensure statistical power of .80 in testing the null hypothesis of close fit for the proposed learning potential structural model.

A third consideration when deciding on the appropriate sample size was practical and logistical considerations. This includes aspects like cost, availability of suitable respondents and the willingness of the employer (Stellenbosch University) to commit large numbers of respondents (i.e. first year engineering students) to the research. Taking all three the above considerations into account it was suggested that a sample of 500 – 550 research participants should be selected for the purpose of testing the proposed learning potential structural model.

The third consideration of practicality and logistical consideration was a factor that had a significant impact on the members of the sampling population that actually completed the survey that was sent out. After a month of data collection only 19 of 900 first year engineering students completed the survey. The composite research questionnaire took *circa* 1 hour 30 minutes to complete. Moreover, the APIL subtests that were incorporated in the composite research questionnaire were cognitively demanding. Completing the composite research questionnaire therefore required a substantial investment both in terms of time and effort from respondents. In a desperate attempt to increase the number of respondents the sampling population was increased from first year engineering students to first year, non-final year[21] and final year engineering students. After four months of data collection a total of 123 responses were obtained of which 9 responses were incomplete. It was decided to conclude the data collection due to the poor prognosis of soliciting more responses from the expanded sampling population given the magnitude of the investment required from respondents combined with the fact that the number of observations that were obtained (114) were at least more than the number of freed parameters (107) in the reduced structural model.

[21] Non-final year students are students that have passed at least one first-year module but have not earned enough credits be to be able to graduate in the specific year of registration.

3.8 STATISTICAL ANALYSIS

3.8.1 Missing Values

Missing values provide a potential problem that needed to be solved before the composite indicator variables could be calculated and data could be analysed. Not addressing the problem of missing values before calculating the composite indicator variables could have resulted in seemingly adequate, but in reality, deficient, indicator variables.

The three solutions available to address the problem of missing values are Imputation by Matching (IM), Multiple Imputation (MI) and Information Maximum Likelihood (FIML), which is available in LISREL 8.8 (Jöreskrog & Sörbrom, 2003).

The Full Information Maximum Likelihood (FIML) is the more efficient estimation procedure of the three procedures (De Goede, 2007), however, no separate data set is created by this procedure which would prevent the item and dimensionality analyses as well as the formation of item parcels (Du Toit & Du Toit, 2001; Mels, 2003), which is a requirement in this study. The Full Information Maximum Likelihood (FIML) procedure is also not used because of the fact that FIML assumes that the values are missing at random and that the observed variables are continuous and follow a multivariate normal distribution (Du Toit & Du Toit, 2001).

It was therefore decided to use the multiple imputation procedure. The biggest advantage of both the two multiple imputation procedures available in LISREL 8.8 is that estimates of missing values are derived for all cases in the initial sample (i.e., no cases with missing values are deleted like in the case of IM) and the full data set is available for subsequent item and dimensionality analyses, and the formation of item parcels (De Goede, 2007). A possible problem is the fact that the multiple imputation procedures available in LISREL 8.8, assume that the values are missing at random and that the observed variables are continuous and follow a multivariate normal distribution (De Goede, 2007). Mels (2003) however, contends that the use of MI is warranted when the univariate indicator variables are not excessively skewed and less than 30% of the possible observations have missing values.

3.8.2 Item Analysis

Various scales were used and developed to measure the various latent variables that compromise the structural model depicted in Figure 2.4. Items were developed with the aim of providing stimuli to which respondents would react with observable behaviour that would be a relatively uncontaminated expression of the specific underlying latent variable. The

objective of item analysis was to identify poor items that did not successfully reflect the intended latent variable. Items that failed to discriminate between different levels of the latent variable that they are designed to reflect (Burger, 2012) were also considered poor items. A variety of item statistics were used as psychometric evidence to identify poor items and the basket of evidence obtained from a variety of item statistics was used to determine whether items should be deleted from the scale or not. The reliability procedure in SPSS 25 was used to perform the item analysis (SPSS, 2018).

3.8.3 Exploratory Factor Analysis

The architecture of each of the scales or subscales used to operationalise the latent variables comprising the elaborated learning potential structural model reflected the intention to construct essentially one-dimensional sets of items. The aim of these items was to operate as stimulus sets to which test takers responded with behaviour that was primarily an expression of a specific uni-dimensional underlying latent variable. The behavioural response to each item was, however, never only dependent on the latent variable of interest but also influenced by a number of other non-relevant latent variables and random error influences (Guion, 1998). It was however assumed that only the relevant latent variable was a common source of variance across all the items comprising a subscale (Smuts, 2011). The assumption was therefore that if the latent variable of interest would be statistically controlled that the partial correlation between items would approach zero (Hulin, Drasgow & Parson, 1983). The implication of this argument was the existence of a single underlying common factor.

To explore this assumption exploratory factor analysis (EFA) was conducted through the use of the exploratory factor analysis procedure in SPSS 25 (SPSS, 2018). Principal axis factor analysis was performed on the inter-item correlation matrix of each scale or subscale. Oblique rotation was used in the case of factor fission.

If the EFA corroborated the uni-dimensionality assumption for a specific scale or subscale the question in addition arose whether the scale or subscale provided relatively uncontaminated measures of the specific underlying latent variable via the items comprising the scale. This was evaluated by inspecting the magnitude of the factor loadings. Factor loadings were considered satisfactory if $\lambda_{ij} \geq .50$.

3.8.4 Structural Equation Modelling

3.8.4.1 Variable Type

The measurement level on which the indicator variables were measured determined the appropriate moment matrix to analyse and the appropriate estimation technique to use to estimate freed model parameters. As paragraph 3.6 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 structural model. By reducing the number of freed model parameters that have to be estimated and thereby the required sample size, by creating linear composite indicator variables for each latent variable the additional advantage of creating more reliable indicator variables was obtained (Nunnally, 1978). It is acknowledged though that the use of larger numbers of indicator variables to represent latent variables tends to produce more satisfactory SEM solutions (Marsh, Hau, Balla and Grayson, 1998). If individual items would have been used as indicator variables an extremely complex comprehensive LISREL model would have resulted in the current study (Burger, 2012). By using individual items as indicator variables an extremely large sample would have been required to ensure credible parameter estimates. Consequently, it was decided to use composite indicator variables. The assumption was made that the indicator variables were continuous variables, measured on an interval level (Jöreskog & Sörbom, 1996a; 1996b; Mels, 2003). The observed covariance matrix (rather than the polychoric correlation matrix) was consequently analised. The decision whether to use maximum likelihood estimation or robust maximum likelihood (Du Toit & du Toit, 2001; Mels, 2003) was based on the outcome of the test for multivariate normality.

3.8.4.2 Multivariate Normality

The maximum likelihood estimation technique assumes that the indicator variables follow a multivariate normal distribution (Smuts, 2011). The null hypothesis that this assumption is satisfied was consequently formally tested in PRELIS. Given that the null hypothesis of multivariate normality was rejected, an attempt was made to normalise the data (Jöreskog & Sörbom, 1996a). The extent to which this attempt was successful in normalising the data was evaluated by testing the null hypothesis that the normalised indicator variable distribution follows a multivariate normal distribution. Given that the null hypothesis of multivariate normality was again rejected, robust maximum likelihood estimation was used to fit the measurement and comprehensive models (Burger, 2012).

3.8.4.3 Confirmatory Factor Analysis

Structural model fit indices can only be interpreted unambiguously for or against the fitted structural model if it can 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 (Smuts, 2011). This first required that the fit of the measurement model that was used to operationalise the structural model had to be evaluated first before fitting the comprehensive LISREL model. If the measurement model fits at least closely, the estimated factor loadings are all statistically significant ($p<.05$), the completely standardised factor loadings are large (i.e. $\lambda_{ij}\geq.71$)[22] and the measurement error variances are statistically significant ($p<.05$) but small (i.e. $\Theta_{\delta}\leq.75$) it could be concluded that the operationalisation of latent variables was successful.

If the overarching measurement hypothesis would be interpreted to mean that the measurement model provides a perfect account of the manner in which the latent variables manifest themselves in the indicator variables, the measurement hypothesis translated into the following exact fit null hypothesis:

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

$$H_{01a}: RMSEA>0$$

If the measurement hypothesis would be interpreted to mean that the measurement model only provides an approximate account of the dynamics that produced the observed covariance matrix, the measurement hypothesis translated into the following close fit null hypothesis:

$$H_{01b}: RMSEA\leq.05$$

$$H_{01b}: RMSEA>.05$$

If exact and/or close model fit was obtained (i.e. H_{01a} and/or H_{01b} was not rejected), or if the measurement model at least demonstrated reasonable fit, the following 25[23]null hypotheses on the slope of the regression of item j on latent personality dimension k were tested:

$$H_{0i}: \lambda_{jk}=0;\ i=2, 3, \ldots, 26;\ j=1, 2, \ldots, 25;\ k=1, 2, \ldots, 11$$

$$H_{ai}: \lambda_{jk}\neq0;\ i=2, 3, \ldots, 26;\ j=1, 2, \ldots, 25;\ k=1, 2, \ldots, 11$$

[22] A more stringent critical factor loading of .71 was chosen in accordance with Hair et al. (1995) so that a composite indicator was considered a valid indicator of the latent variable it was designated to reflect only if the latent variable explained at least 25% of the variance in the item (i.e. $\lambda^2_{ij}\geq.25$).

[23] The formulation of the measurement model statistical hypotheses reflect the fact that no post knowledge measures have been obtained and that the interaction effects in which post knowledge had been involved had to be deleted from the model that was empirically tested

If exact and/or close model fit was obtained (i.e. H_{01a} and/or H_{01b} was not rejected), or if the measurement model at least demonstrated reasonable fit, the following 25 null hypotheses were tested with regards to the freed elements in the variance-co-variance matrix Θ_δ:

$$H_{0i}: \Theta_{\delta jj} = 0;\ i = 27, 28, \ldots, 51;\ j = 1, 2 \ldots 25$$

$$H_{ai}: \Theta_{\delta jj} > 0;\ i = 27, 28, \ldots, 51;\ j = 1, 2 \ldots 25$$

If exact and/or close model fit was obtained (i.e. H_{01a} and/or H_{01b} was not rejected), or if the measurement model at least demonstrated reasonable fit, the following 55 null hypotheses will be tested with regards to the freed elements in the variance-co-variance matrix ϕ:

$$H_{0i}: \phi_{jk} = 0;\ i = 52, 53, \ldots, 106;\ j = 1, 2 \ldots 11;\ k = 1, 2 \ldots 11;\ j \neq k$$

$$H_{ai}: \phi_{jk} > 0;\ i = 52, 53, \ldots, 106;\ j = 1, 2 \ldots 11;\ k = 1, 2 \ldots 11;\ j \neq k$$

If at least close measurement model fit was obtained, the freed factor loadings in the unstandardised Λ^x were statistically significant [p<.05], the freed factor loadings in the completely standardised Λ^x were large [λ_{ij} >.50], the measurement error variances in the unstandardised Θ_δ were statistically significant [p<.05], the measurement error variances in the completely standardised Θ_δ were small [θ_δ<.50] and the R^2 for indicator variables were large [R^2>.50] the operationalisation of the latent variables in the structural model was considered successful.

3.8.4.4 Interpretation of the Measurement Model Fit

To deduce valid and credible conclusions on the ability of the proposed learning potential structural model to explain variance in learning performance, evidence needed to be obtained which supported the position that the manifest indicator variables were indeed valid and reliable representations of the latent variables they are linked to. Diamantopoulos and Siguaw (2000), state that unless the quality of measures can be trusted the assessment of the substantive relations of interest will be problematic. Therefore, an evaluation of the measurement part of the model should precede the detailed evaluation of the structural part of the model.

The measurement model fit was interpreted by investigating the full array of fit indices provided by LISREL (Diamantopoulos & Siguaw, 2000). An additional factor that was taken into consideration was the magnitude and distribution of the standardised residuals as well as the magnitude of model modification indices calculated for Λx and Θ_δ. Modification index values

that are large indicate measurement model parameters that, if set free, would improve the fit of the model. Large numbers of large and significant modification index values comment negatively on the fit of the model in that it suggests that various possibilities exist to improve the fit of the model proposed by the researcher. Investigating the model modification indices for the previously mentioned matrices served the sole purpose of commenting on the model fit.

3.8.4.5 Interpretation of the Measurement Model Parameter Estimates

The measurement model parameter estimates were interpreted by testing H_{02} – $H_{0,106}$. The magnitude of statistically significant parameter estimates ($p < .05$) were interpreted by inspecting the completely standardised solution for Λx, $\Theta\delta$ and Φ.

3.8.4.6 Fitting of the Comprehensive LISREL Model

If reasonable measurement model fit was obtained and if the completely standardised factor loadings were considered to be satisfactory, H_{0107a} and H_{0107b} were tested by fitting the comprehensive LISREL model. The comprehensive LISREL model was fitted by analysing the covariance matrix. Robust maximum likelihood estimation was used since the multivariate normality assumption was not satisfied and the attempt at normalisation failed to achieve multivariate normality in the observed data. LISREL 8.8 (Du Toit & Du Toit, 2001) was used to perform the structural equation analysis.

3.8.4.7 Interpretation of Structural Model Fit and Parameter Estimates

Structural model fit was interpreted by investigating the full array of fit indices provided by LISREL (Diamantopoulos & Siguaw, 2000). Additional considerations were also given to the magnitude and distribution of the standardised residuals as well as the magnitude of model modification indices calculated for Γ, B and Ψ. Large modification index values indicate structural model parameters that, if set free, would improve the fit of the model. Large numbers of large and significant modification index values comment negatively on the fit of the model in that it suggests that a number of possibilities exist to improve the fit of the model proposed by the researcher. The investigation of the model modification indices for the previously mentioned matrices here primarily served the purpose of commenting on the model fit. Inspection of the model modification calculated for the Γ and B matrices were, however, also

used to explore possible modifications to the current structural model if such modifications make substantive theoretical sense.

If the comprehensive LISREL model obtains close fit or even reasonable fit, H_{02} – H_{18} were tested. The significance and magnitude of the indirect and total effect of ξ_j on η_i and the indirect and total effect of η_j on η_i were also examined. The proportion of variance in each of the endogenous latent variables that was explained by the model was also interpreted.

The psychological model proposed in Figure 2.4 as an explanation of learning performance can be seen as satisfactory to the extent that the comprehensive model fitted the data well (given that the measurement model fitted the data well), the path coefficients for the hypothesised structural relations were significant and the model explained a substantial proportion of the variance in each of the endogenous latent variables, especially the learning competency latent variables.

3.8.4.8 Considering Possible Structural Model Modifications

The modification indices and completely standardised expected change values (Diamantopoulos & Siguaw, 2000) calculated for the $\boldsymbol{\Gamma}$ and $\mathbf{B}$ matrices were investigated to establish whether or not any additional meaningful possibilities exist to improve the fit of the comprehensive model through the addition of additional paths. Modification of the model was, however, only be considered if the proposed structural changes can be theoretically substantiated (Diamantopoulos & Siguaw, 2000; Henning, Theron & Spangenberg, 2004). The modification indices calculated for $\boldsymbol{\Gamma}$ and $\mathbf{B}$ were used to derive data-driven suggestions for future research. These data-driven suggestions for model modification are discussed in Chapter 5 in the paragraph on suggestions for future research.

3.9 EVALUATION OF RESEARCH ETHICS

Potential ethical risks associated with the proposed research as outlined in this proposal were reflected on with the purpose of protecting the dignity, rights, safety and well-being of the research participants involved in this study. Empirical behavioural research requires the active or passive involvement of people, which may lead to the dignity, rights, safety and well-being of research participants being compromised to some degree. The critical question that needed to be asked by the researcher was whether this compromise is justifiable in terms of the purpose of the research. The argument that was put forth in the introduction of this study convincingly argues that the envisaged research in this study has a benevolent purpose. The

critical question was therefore whether the costs that research participants have to incur balances with the benefits that accrue to society (Standard Operating Procedure, 2012).

The research participant had to have freedom of choice when he/she decided whether or not to accept an invitation to participate in the research. For the participant to make an informed decision on whether or not he/she wanted to participate in the research, the objectives and purpose of the study needed to be made clear to participants as well as; what participation in the research would involve, how the research results would be disseminated and used, who the researchers are, what their affiliation is, where and how they can make further inquiries about the research if they wish to do so, what their rights as participants are and where they can obtain more information on their research rights (Standard Operating Procedure, 2012).

The information provided to potential research participants needed to be provided in a vernacular that is accessible to the age and educational level of the participants (Standard Operating Procedure, 2012).

In Annexure 12 of the Ethical Rules of Conduct for Practitioners Registered under the Health Professions Act (Act no. 56 of 1974) (Republic of South Africa, 2006) it is required of a psychologist doing research to enter into an agreement with participants on the nature of the research, the participants" responsibilities as well as those of the researcher. The agreement in terms of which the research participant provides informed consent should meet the following requirements according to Annexure 12 (Republic of South Africa, 2006, p.42):

> 89. (1) A psychologist shall use language that is reasonably understandable to the research participant concerned in obtaining his or her informed consent.
>
> (2) Informed consent referred to in sub rule (1) shall be appropriately documented, and in obtaining such consent the psychologist shall –
>
> (a) inform the participant of the nature of the research;
>
> (b) inform the participant that he or she is free to participate or decline to participate in or to withdraw from the research;
>
> (c) explain the foreseeable consequences of declining or withdrawing;
>
> (d) inform the participant of significant factors that may be expected to influence his or her willingness to participate (such as risks, discomfort, adverse effects or exceptions to the requirement of confidentiality);
>
> (e) explain any other matters about which the participant enquires;

(f) when conducting research with a research participant such as a student or subordinate, take special care to protect such participant from the adverse consequences of declining or withdrawing from participation;

(g) when research participation is a course requirement or opportunity for extra credit, give a participant the choice of equitable alternative activities; and

(h) in the case of a person who is legally incapable of giving informed consent, nevertheless –

(i) provide an appropriate explanation;

(ii) obtain the participants assent; and

(iii) obtain appropriate permission from a person legally authorized to give such permission.

The participant consent formulation that was used in the current study is shown in Appendix A.

Annexure 12 of the Ethical Rules of Conduct for Practitioners Registered under the Health Professions Act (Act no. 56 of 1974) (Republic of South Africa, 2006, p.41) requires psychological researchers to obtain institutional permission from the organisation from which research participants will be solicited:

A psychologist shall –

(a) obtain written approval from the host institution or organisation concerned prior to conducting research;

(b) provide the host institution or organisation with accurate information about his or her research proposals; and

(c) conduct the research in accordance with the research protocol approved by the institution or organisation concerned.

Informed institutional permission was obtained from the Division of Institutional Research and Planning of Stellenbosch University and from the Faculty of Engineering that were involved in the research. A copy of the research proposal accompanied the application for institutional permission addressed to the Division of Institutional Research and Planning of Stellenbosch University. The student numbers of participating students had to be collected and recorded so as to allow the various measures obtained at different points in time to be collated. The reason why the student numbers of participating students needed to collected was explained in the informed consent formulation.

Prior knowledge was determined by using the Grade 12 marks of first year engineering students. This was used as an indication of the knowledge that these students obtained in their Grade 12 year with regards to mathematics. For non-final year and final year engineering students the mathematics mark obtained in the previous year of study was used. As a measure of *learning performance during evaluation* the first semester performance mark for engineering mathematics was used (first year engineering respondents) whilst the academic average for the first semester was used for second-, third- and fourth year engineering students. The information gathered on Grade 12 mathematics marks or semester marks was not anonymous information. This was acknowledged in the informed consent formulation

The collected data was treated as confidential. The emphasis in the study was not on describing the level of learners on the various latent variables but rather on the relationships hypothesised between the various latent variables.

The study did not involve the assessment of critical latent variables where the possibility of unusually high or low scores could signal serious threats to the well-being of research participants. Annexure 12 of the Ethical Rules of Conduct for Practitioners Registered under the Health Professions Act (Act no. 56 of 1974) (Republic of South Africa, 2006, p.41) requires psychological researchers to disclose confidential information under the following circumstances:

A psychologist may disclose confidential information –

> (a) only with the permission of the client concerned;
>
> (b) when permitted by law to do so for a legitimate purpose, such as providing a client with the professional services required;
>
> (c) to appropriate professionals and then for strictly professional purposes only;
>
> (d) to protect a client or other persons from harm; or
>
> (e) to obtain payment for a psychological service, in which instance disclosure is limited to the minimum necessary to achieve that purpose.

In the absence of *prima facie* arguments that necessitated (d) no reference was made of this in the informed consent and assent formulations. No specific steps were therefore taken to make arrangements for contingency support. The principal outlined in Annexure 12 would nonetheless have been honoured if results would have indicated that the well-being of any research participant is threatened.

The data was collected under the guidance and supervision of Dr Billy Boonzaier, in the Department of Industrial Psychology at Stellenbosch University, who is registered with the HPCSA as a psychologist. An application for ethical clearance of the proposed research study

had been submitted to the Research Ethics Committee Human Research (Humanities) of Stellenbosch University.

CHAPTER 4

RESEARCH RESULTS

4.1 INTRODUCTION

In this chapter the statistical results of the various analyses, which were performed on the collected data, are presented and discussed. The extent to which the data was plagued by missing values is described first followed by a discussion of the manner in which the current study responded to the problem. The results obtained on the item analysis performed on each sub-scale are subsequently discussed in-order to determine the extent to which the items of each sub-scale represent the various latent dimensions with psychometric integrity. The results of the dimensionality analysis performed on each sub-scale are then reported and discussed. This is done in-order to determine whether the items that were proposed to represent latent variables or latent dimensions of a multidimensional construct that were conceptualised as unidimensional latent variables succeeded in doing so. Or if more than one factor had to be extracted to adequately explain the observed inter-item correlations. This is followed by an evaluation of the extent to which the data satisfied the statistical data assumptions relevant to the data analysis techniques utilised. Lastly, the results obtained on the fit and parameter estimates of the measurement model and the fit of the structural model are discussed. The structural model was to be considered on the condition of acceptable measurement model fit.

4.2 SAMPLE

The target population in the current study was all South Africans that qualify for consideration for an affirmative development opportunity. The sampling population referred to the population of elements from which a sample of elements was actually selected (Babbie & Mouton, 2001). It was initially decided to use the first-year cohort registered for Engineering at Stellenbosch University in 2017 as the sampling population for this study. The gap between the target- and sampling population should ideally be kept to a minimum as far as possible. In the case of the current study a large non-ignorable gap is acknowledged to exist between the target and sampling populations.

The motivation for this study argued the need to develop a structural model that explains the determinants of learning performance from an affirmative development perspective. Despite this the model will also add value to other forms of development, training and teaching. This

position is based on the argument put forward by Prinsloo (2013) that the psychological dynamics underlying learning performance in affirmative development programmes do not differ significantly from that governing learning performance in other learning contexts. Therefore, it was argued that the same complex nomological network of latent variables that determine learning performance in affirmative development programmes will also determine learning performance in first year Engineering students. An aspect that should differ across different teaching contexts are the levels of specific latent variables that characterise the learners that has been affected by disadvantagement.

This line of reasoning warranted the testing of the hypothesised learning potential structural model on a sample not entirely representative of previously disadvantaged learners. Based on this conclusion, and the argument put forth by Prinsloo (2013), this study empirically evaluated the structural model on a sample of previously disadvantaged learners in addition to not previously disadvantaged learners who have enrolled for a degree programme that cannot be classified as an affirmative development programme.

A very small number of first year students responded to the invitation sent out via email to all first-year students that registered for an Engineering degree at Stellenbosch University in 2017. The length, difficulty level and consequently the time (*circa* 1 hour 30 minutes) it took to complete the questionnaire most likely dissuaded many students that were invited to accept the invitation despite the reasonably attractive prize that they could win in a lucky draw if they completed the questionnaire. A reminder emailed to all first-year Engineering students did not substantially improve the situation. It was consequently then decided to extend the sampling population to all undergraduate Engineering students registered at Stellenbosch University in 2017[24]. This introduced further methodological limitations to the study. The Matric Mathematics mark served as the prior knowledge measure for first year students and their first year first semester mark for Engineering Mathematics as a measure of learning performance. For the senior students, however, the first-year previous year's average for all their Engineering modules served as a measure of prior learning and their average Engineering mark for the first semester as measure of learning performance. The extension of the sampling population did not bring a satisfactory solution to the problem of obtaining a sufficiently large sample size. Despite further attempts to entice students to complete the questionnaire in the end the researcher had to concede defeat. The final sample only comprised of 114 completed questionnaires. The extremely small sample size, although exceeding the number of freed parameters in the structural model, is acknowledged as a serious limitation.

[24] The change in research methodology was submitted to the Departmental Ethics Screening Committee for approval.

No demographic information was collected from respondents because of the already long questionnaire. This is acknowledged as a further limitation to the study.

4.3 MISSING VALUES

The extent to which missing values occurred on the items comprising the sub-scales of the Learning Potential Questionnaire were calculated using PRELIS. As can be seen in Table 4.1, shown in Appendix C, which depicts the distribution of missing values across items, the maximum number of respondents who failed to respond to any individual item was 109 (95.61%). The reason for this high number of missing values on certain items is due to the nature of sub-tests of the APIL-B assessment battery that was used in the survey. Both the FAST and the CFT sub-tests were time bound assessments. The FAST consisted of four sub-tests of, which each needed to be completed within a certain amount of time. The CFT sub-test consisted of thirty questions that also needed to be completed within a certain time period. As soon as the time was finished on each of these assessments the survey automatically moved on to the next section in the survey. Therefore, the reason for the high number of missing values was because most of the respondents were unable to complete all the questions for each sub-test within the specific allocated time. As can be seen in Table 4.1 in Appendix C there were no missing values reported on the items that measure the behavioural components of learning potential due to the fact that this part of the survey did not have any time restrictions.

In order to minimise the impact of missing values on the composite indicator variables calculated from the individual items, it was decided to impute missing values. A consideration that played an important role in the decision on how to respond to the missing value problem was the small number of participants that agreed to complete the questionnaire and therefore it was deemed necessary to salvage as much of the data as possible.

The method that was used to impute missing values was the multiple imputation method. The multiple imputation method is based on the assumption that the data that is missing, is missing at random and that the observed data follows an underlying multivariate normal distribution (Du Toit & Du Toit, 2001). Multiple imputation was considered permissible given the recommendation of Mels (2003) that this imputation technique may be used if the observed variables are measured on a scale comprising five or more scale values, if the item distributions are not excessively skewed (even if the null hypothesis of multivariate normality had been rejected) and if less than 30% of the data constitutes missing values. The missing values constituted 23.03% of the data in this study. Multiple imputations were conducted for

each missing value. Each of these imputations created a completed data set, which could be analysed separately in order to obtain multiple estimates of the parameters of the model (Burger, 2012). PRELIS calculated the average of the values imputed in each of the data sets and then these averages were used to substitute the missing values for each case. The use of this method allowed for plausible values to be delivered whilst the uncertainty in the estimates are also reflected. Moreover, multiple imputation imputed missing values for all observations in the data set unlike imputation by matching where the risk exists that observations may be deleted from the imputed data set (Du Toit & Du Toit, 2001).

4.4 ITEM ANALYSIS

Item analysis was conducted via SPSS 25 (SPSS, 2018) to evaluate the validity and reliability of each item that was designated to reflect a specific latent dimension of a construct or a unidimensional construct. Item analysis via the SPSS reliability procedure allowed the identification of items that were not contributing to a valid and reliable description of the latent dimension in question, and then to remove or to reflect these items. Item analysis allowed the detection of bad items in a sub-scale, which can be removed to improve the reliability and validity of the sub-scale. Bad items were items that are not reflective of the latent dimension which they were tasked to reflect or items that were not sensitive to relatively small differences on the latent dimension they were tasked to reflect. Items that were not reflective of the latent dimension that they were tasked to reflect revealed themselves by not responding in unison with other items assigned to a specific subscale (Burger, 2012).

Each of the latent variables included in the reduced learning potential structural was measured through the scales and subscales that were included in the Learning Potential Questionnaire (LPQ). Each of the scales that measured a unidimensional latent variable and each of the subscales that measure a unidimensional latent dimension of a multidimensional latent variable in the proposed learning structural model were subjected to item analysis. This was done to investigate: (i) the reliability of indicators of each latent variable, (ii) homogeneity of each sub-scale and (iii) screen items prior to their inclusion in composite item parcels representing the latent variables.

Item analysis was performed on the imputed data set via the Reliability procedure of SPSS 25 (SPSS, 2018). The items comprising the various sub-scales can be seen in Appendix A attached at the end of the thesis[25]. Sub-scales were deemed satisfactory if the sub-scale

[25] Those subscales that are not available in the public domain but, that are the intellectual property of a test publisher were not included in Appendix A.

returned a Cronbach-alpha value higher than .70. Ideally though an Cronbach alpha value of .80 or higher was preferred. Although alpha values of .70 can be seen as lenient with regards to determining internal consistency it is generally accepted as satisfactory in research studies (Nunnally, 1978).

Items were considered for possible deletion from the scale or subscale based on the results of the classical measurement theory item analysis. The decision was, however, never mechanically based on any single item statistic result but rather on the whole basket of item statistic results. Moreover, the magnitude of the current internal consistency was taken into account, the magnitude of the increase in the Cronbach alpha and the length of the original scale or subscale.

4.4.1 Time Cognitively Engaged

Time cognitively engaged was conceptualised as a unidimensional latent variable. A single item analysis was therefore performed on all the items comprising this scale. The results for the item analysis of the various items comprising the *time cognitively engaged* sub-scale are depicted in Table 4.2. The scale comprised 17 items and obtained a highly satisfactory Cronbach's alpha of .920. The analysis did not indicate any extreme means and small standard deviations, thus indicating the absence of insensitive items. The item means shown in the in the item statistics section of Table 4.2 fell in a range from 4.39 to 5.33 (on a 7-point scale) and the standard deviations from 1.118 to 1.592. Extreme small or large means would imply truncated item distributions and hence range restriction. Items with outlier standard deviations to the lower end of the standard deviation distribution would indicate insensitive items that failed to reflect relatively small differences on the *time cognitively engaged* latent variable.

Table 4.2

Time Cognitively Engaged item analysis results

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.920	.921	17

Item Statistics

	Mean	Std. Deviation	N
TCE_1	4.73	1.359	114
TCE_2	4.84	1.314	114
TCE_3	4.46	1.483	114
TCE_4	5.03	1.347	114
TCE_5	4.71	1.394	114
TCE_6	4.55	1.234	114

TCE_7	4.70	1.282	114
TCE_8	5.33	1.118	114
TCE_9	4.94	1.123	114
TCE_10	4.50	1.592	114
TCE_11	4.45	1.529	114
TCE_12	4.55	1.512	114
TCE_13	4.85	1.422	114
TCE_14	4.39	1.701	114
TCE_15	5.22	1.143	114
TCE_16	5.13	1.164	114
TCE_17	4.77	1.458	114

Inter-Item Correlation Matrix

	TCE_1	TCE_2	TCE_3	TCE_4	TCE_5	TCE_6	TCE_7	TCE_8	TCE_9	TCE_10	TCE_11	TCE_12	TCE_13	TCE_14	TCE_15	TCE_16	TCE_17
TCE_1	1.000	.774	.450	.347	.407	.423	.542	.363	.238	.714	.489	.436	.469	.264	.449	.336	.259
TCE_2	.774	1.000	.565	.437	.511	.436	.502	.421	.203	.668	.520	.521	.527	.269	.495	.477	.337
TCE_3	.450	.565	1.000	.747	.747	.327	.288	.338	.150	.474	.606	.702	.717	.293	.498	.369	.492
TCE_4	.347	.437	.747	1.000	.806	.241	.143	.300	.054	.378	.467	.793	.709	.328	.324	.291	.616
TCE_5	.407	.511	.747	.806	1.000	.330	.258	.363	.147	.477	.576	.774	.715	.350	.390	.340	.568
TCE_6	.423	.436	.327	.241	.330	1.000	.474	.256	.050	.434	.266	.309	.299	.083	.290	.294	.169
TCE_7	.542	.502	.288	.143	.258	.474	1.000	.471	.294	.581	.362	.273	.383	.013	.419	.412	.195
TCE_8	.363	.421	.338	.300	.363	.256	.471	1.000	.439	.442	.523	.424	.466	.271	.566	.612	.183
TCE_9	.238	.203	.150	.054	.147	.050	.294	.439	1.000	.141	.207	.192	.221	.050	.486	.453	.154
TCE_10	.714	.668	.474	.378	.477	.434	.581	.442	.141	1.000	.507	.381	.436	.225	.338	.275	.271
TCE_11	.489	.520	.606	.467	.576	.266	.362	.523	.207	.507	1.000	.627	.629	.399	.394	.365	.483
TCE_12	.436	.521	.702	.793	.774	.309	.273	.424	.192	.381	.627	1.000	.813	.364	.452	.421	.608
TCE_13	.469	.527	.717	.709	.715	.299	.383	.466	.221	.436	.629	.813	1.000	.222	.467	.418	.598
TCE_14	.264	.269	.293	.328	.350	.083	.013	.271	.050	.225	.399	.364	.222	1.000	.266	.269	.164
TCE_15	.449	.495	.498	.324	.390	.290	.419	.566	.486	.338	.394	.452	.467	.266	1.000	.657	.285
TCE_16	.336	.477	.369	.291	.340	.294	.412	.612	.453	.275	.365	.421	.418	.269	.657	1.000	.300
TCE_17	.259	.337	.492	.616	.568	.169	.195	.183	.154	.271	.483	.608	.598	.164	.285	.300	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TCE_1	76.43	211.221	.657	.717	.914
TCE_2	76.32	209.599	.728	.709	.912
TCE_3	76.69	205.100	.747	.744	.911
TCE_4	76.13	210.699	.678	.806	.914
TCE_5	76.45	206.922	.752	.751	.911
TCE_6	76.61	221.639	.431	.334	.920
TCE_7	76.46	218.091	.509	.544	.918
TCE_8	75.82	218.164	.593	.628	.916
TCE_9	76.22	227.518	.302	.366	.922
TCE_10	76.66	207.466	.633	.671	.915
TCE_11	76.71	205.500	.711	.647	.912
TCE_12	76.61	203.126	.780	.801	.910
TCE_13	76.31	205.347	.777	.757	.911
TCE_14	76.77	218.284	.355	.318	.924
TCE_15	75.94	216.748	.623	.605	.915
TCE_16	76.03	217.990	.573	.593	.916
TCE_17	76.39	213.938	.538	.527	.917

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum/ Minimum	Variance	N of Items
Item Means	4.774	4.386	5.333	.947	1.216	.080	17
Item Variances	1.886	1.251	2.894	1.643	2.314	.226	17
Inter-Item Correlations	.405	.013	.813	.800	64.164	.030	17

Note:TCE_1 – TCE_17 represent the 17 items from the *Time Cognitively Engaged* scale

Item TCE_9 and item TCE_14 showed themselves to consistently correlate somewhat lower with the remaining items. In the distribution of item-total correlations and the distribution of squared multiple correlations itemTCE_9 and TCE_14 showed themselves as outliers to the lower end of the distributions. The squared multiple correlation reflects the square of the multiple correlation obtained when regressing each item on a weighted linear composite of the remaining variables. The corrected item-total correlation reflects the correlation between each item and the unweighted sum of the remaining items. Outliers towards the lower end of these two distributions would therefore indicate items that do not tap into the same source of systematic variance than the other items. This is also reflected in the inter-item correlation finding that these two items tended to respond somewhat out of step with the remaining items. The item-total statistics indicated that there would be a slight (.007) increase in the Cronbach's alpha if Items TCE_9 and TCE_14 were deleted. It was nonetheless decided, based on the basket of evidence) to delete these two items and run the analysis again. After items TCE_9 and TCE_14 were deleted the Cronbach's alpha improved from .920 to .927. No additional items subsequently came to the fore as problematic.

4.4.2 Academic Self-leadership

Academic self-leadership was measured using an adapted version of the Revised Self-Leadership Questionnaire (RSLQ) developed by Houghton and Neck (2002). The RSLQ conceptualised academic self-leadership in terms of nine factors, namely, self-goal setting, self-reward, self-punishment, self-observation, self-cueing, natural rewards, visualising successful performance, self-talk and evaluating beliefs and assumptions (Houghton & Neck, 2002). Norris (2008) reports that the RSLQ items load on three second-order factors, namely, behaviour focused self-leadership strategies, natural reward self-leadership strategies and constructive thought self-leadership strategies. The original scale consists of 35 items. The manner in which the original 35 items load on the nine first-order self-leadership factors and three second-order self-leadership factors are shown in Table 4.3. Burger (2012) however, deleted 12 items from the scale. The current study adapted the Burger (2012) items to make them applicable to engineering students. The manner in which the 23 items measuring academic self-leadership in the current LP questionnaire load on the nine first-order self-

leadership factors and three second-order self-leadership factors are shown in Table 4.3. Separate item analyses should ideally be performed on the first-order factor level. The number of items allocated to each of the first-order self-leadership factors in the LP questionnaire were, however, too few to have meaningfully conducted item analysis on this level. Item analysis was therefore performed on the level of the three second-order factors. This is acknowledged as a methodological limitation as the items were written as indicators of the first-order self-leadership factors.

Table 4.3

Mapping of the Academic self-leadership scale items onto the original Houghton and Neck (2002) factor structure

Second-order ASL factors	First-order ASL factors	Original RSLQ item numbers	Item numbers in LP questionnaire
Behaviour-focussed strategies	Self-goal setting	2, 11, 20, 28, 34	5, 23
	Self-reward	4, 13, 22	8, 9,
	Self-punishment	6, 15, 24, 30	12, 13, 14
	Self-observation	7, 16, 25, 31	16, 17 15
	Self-cuing	9, 18	4, 22,
Natural reward strategies	Focusing thoughts on natural rewards	8, 17, 26, 32, 35	18, 19, 20, 21
Constructive thought pattern strategies	Visualising successful performance	1, 10, 19, 27, 33	1, 2, 3
	Self-talk	3, 12, 21	6, 7,
	Evaluating beliefs and assumptions	5, 14, 23, 29	10, 11,

The results for item analysis of the various items comprising the *Behavioural focussed self-leadership strategies* sub-scale are depicted in Table 4.4. The scale is comprised of 11 items and obtained a somewhat disappointing Cronbach's alpha of .769. It, however, needs to be acknowledged that the assumption made by Cronbach's alpha that the subscale satisfies the uni-dimensionality assumption had not been satisfied. Hence the somewhat disappointing internal consistency reliability is not altogether a surprise. The analysis did not indicate any extreme means and small standard deviations, thus indicating the absence of insensitive items. The means in the item statistics fell in a range from 3.17 to 5.12 (on a 7-point scale) and the standard deviations from 1.277 to 1.764. No items showed themselves as outliers in the standard deviation distribution. No items normatively presented themselves as insensitive items.

Table 4.4

Academic Self-leadership item analysis results for the Behavioural focussed self-leadership strategies

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.769	.776	12

Item Statistics

	Mean	Std. Deviation	N
ASL_5	4.08	1.541	114
ASL_23	4.58	1.739	114
ASL_8	4.30	1.734	114
ASL_9	4.38	1.610	114
ASL_12	4.99	1.436	114
ASL_13	4.76	1.410	114
ASL_14	5.02	1.540	114
ASL_15	4.56	1.511	114
ASL_16	5.12	1.277	114
ASL_17	4.71	1.329	114
ASL_4	3.17	1.651	114
ASL_22	4.66	1.764	114

Inter-Item Correlation Matrix

	ASL_5	ASL_23	ASL_8	ASL_9	ASL_12	ASL_13	ASL_14	ASL_15	ASL_16	ASL_17	ASL_4	ASL_22
ASL_5	1.000	.178	.167	.245	.216	.257	.171	.319	.022	.189	.461	.163
ASL_23	.178	1.000	-.028	-.025	.186	.125	.095	.151	.051	.142	.327	.780
ASL_8	.167	-.028	1.000	.844	.101	.228	.207	.162	.119	.076	.171	-.016
ASL_9	.245	-.025	.844	1.000	.047	.211	.183	.069	.012	.014	.246	-.045
ASL_12	.216	.186	.101	.047	1.000	.720	.608	.280	.198	.189	.135	.118
ASL_13	.257	.125	.228	.211	.720	1.000	.748	.354	.257	.237	.146	.070
ASL_14	.171	.095	.207	.183	.608	.748	1.000	.292	.296	.176	.131	.015
ASL_15	.319	.151	.162	.069	.280	.354	.292	1.000	.569	.725	.196	.205
ASL_16	.022	.051	.119	.012	.198	.257	.296	.569	1.000	.647	.049	.035
ASL_17	.189	.142	.076	.014	.189	.237	.176	.725	.647	1.000	.147	.169
ASL_4	.461	.327	.171	.246	.135	.146	.131	.196	.049	.147	1.000	.278
ASL_22	.163	.780	-.016	-.045	.118	.070	.015	.205	.035	.169	.278	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ASL_5	50.25	84.169	.407	.332	.753
ASL_23	49.75	83.997	.346	.636	.761
ASL_8	50.03	84.291	.338	.737	.762
ASL_9	49.95	86.103	.314	.750	.763
ASL_12	49.33	83.888	.460	.555	.748
ASL_13	49.56	81.753	.562	.694	.737
ASL_14	49.31	82.427	.474	.595	.746
ASL_15	49.76	81.050	.541	.618	.738
ASL_16	49.20	87.968	.353	.503	.759
ASL_17	49.61	85.584	.436	.621	.751
ASL_4	51.16	83.391	.396	.305	.754
ASL_22	49.67	84.932	.308	.631	.766

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	4.527	3.167	5.123	1.956	1.618	.277	12
Item Variances	2.411	1.631	3.112	1.481	1.908	.246	12
Inter-Item Correlations	.224	-.045	.844	.888	-18.948	.043	12

Note: ASL_i represent the 12 items from the *Behavioural focussed self-leadership* subscale

No item consistently correlated lower with the remaining items. The inter-item correlation matrix did, however, point to patterns of higher and lower correlation between each item and the remaining items which are indicative of factor fission. This was, however, no real surprise as Table 4.3 indicates that 5 first-order self-leadership factors load on the second-order Behaviour-focussed self-leadership factor. None of the items showed themselves as outliers in the distribution of corrected item-total correlations or in the distribution of squared multiple correlations. As can be seen in Table 4.5. no items squared multiple correlation was smaller than .30. Additionally, the item-total statistics indicates that there would be no significant increase in the Cronbach's alpha if any of the items were deleted. None of the items were therefore flagged as problematic and no items were deleted from the subscale.

The results for item analysis of the various items comprising the *Natural reward self-leadership strategies* sub-scale are depicted in Table 4.5. The scale is comprised of 4 items and obtained a rather disappointing Cronbach's alpha of .697. The analysis did not indicate any extreme means and small standard deviations, thus indicating the absence of poor items when viewed from the perspective of item discrimination. The item means in the item statistics section of Table 4.5 fell in a range from 4.39 to 4.77 (on a 7-point scale) and the standard deviations from 1.268 to 1.434. No items showed themselves as outliers in the standard deviation distribution. No items normatively presented themselves as insensitive items.

Table 4.5

Academic Self-leadership item analysis results for the Natural rewards self-leadership strategies

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.697	.699	4

Item Statistics

	Mean	Std. Deviation	N
ASL_18	4.39	1.361	114
ASL_19	4.49	1.434	114
ASL_20	4.66	1.268	114
ASL_21	4.77	1.317	114

Inter-Item Correlation Matrix

	ASL_18	ASL_19	ASL_20	ASL_21
ASL_18	1.000	.340	.330	.416
ASL_19	.340	1.000	.288	.360
ASL_20	.330	.288	1.000	.472
ASL_21	.416	.360	.472	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ASL_18	13.92	9.383	.475	.230	.637
ASL_19	13.82	9.403	.424	.183	.671
ASL_20	13.66	9.820	.474	.254	.638
ASL_21	13.54	9.029	.559	.326	.584

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	4.579	4.395	4.772	.377	1.086	.028	4
Item Variances	1.813	1.608	2.057	.450	1.280	.037	4
Inter-Item Correlations	.368	.288	.472	.184	1.640	.004	4

Note: ASL_i represent the 8 items from the *Natural rewards self-leadership* subscale

No item consistently correlated lower with the remaining items. None of the items showed themselves as outliers in the distribution of corrected item-total correlations or in the distribution of squared multiple correlations. Additionally, the item-total statistics indicates that there would be no significant increase in the Cronbach's alpha if any of the items were deleted. None of the items were therefore flagged as problematic and no items were deleted from the subscale.

The results for item analysis of the various items comprising the *Constructive thoughts pattern self-leadership strategies* sub-scale are depicted in table 4.6. The scale is comprised of 7 items and also obtained a more satisfying Cronbach's alpha of .739. The analysis did not indicate any extreme means and small standard deviations, thus indicating the absence of poor items when viewed from the perspective of item discrimination. The item means in the item statistics section of Table 4. 6 fell in a range from 3.78 to 4.69 (on a 7-point scale) and the standard deviations from 1.286 to 1.624. No items showed themselves as outliers in the standard deviation distribution. No items normatively presented themselves as insensitive items.

Table 4.6

Academic Self-leadership item analysis results for the Constructive thoughts pattern self-leadership strategies

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.739	.739	7

Item Statistics

	Mean	Std. Deviation	N
ASL_1	3.82	1.489	114
ASL_2	3.78	1.309	114
ASL_3	4.05	1.419	114
ASL_6	4.65	1.624	114
ASL_7	4.69	1.603	114
ASL_10	4.57	1.382	114
ASL_11	4.68	1.286	114

Inter-Item Correlation Matrix

	ASL_1	ASL_2	ASL_3	ASL_6	ASL_7	ASL_10	ASL_11
ASL_1	1.000	.807	.658	.201	.133	.187	.086
ASL_2	.807	1.000	.597	.218	.183	.236	.115
ASL_3	.658	.597	1.000	.154	.097	.183	.068
ASL_6	.201	.218	.154	1.000	.757	.275	.089
ASL_7	.133	.183	.097	.757	1.000	.335	.136
ASL_10	.187	.236	.183	.275	.335	1.000	.543
ASL_11	.086	.115	.068	.089	.136	.543	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ASL_1	26.42	29.290	.535	.701	.688
ASL_2	26.46	30.127	.577	.668	.682
ASL_3	26.19	31.007	.450	.449	.708
ASL_6	25.60	29.340	.464	.585	.706
ASL_7	25.55	29.736	.448	.595	.710
ASL_10	25.68	31.230	.453	.386	.708
ASL_11	25.57	34.654	.253	.300	.748

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	4.321	3.781	4.693	.912	1.241	.174	7
Item Variances	2.102	1.655	2.637	.982	1.593	.152	7
Inter-Item Correlations	.288	.068	.807	.739	11.935	.054	7

Note: ASL_i represent the 7 items from the *Constructive thoughts pattern self-leadership* subscale

No item consistently correlated lower with the remaining items. The inter-item correlation matrix did, however point to patterns of higher and lower correlation between each item and the remaining items which are indicative of factor fission. This was, however, no real surprise as Table 4.3 indicates that 3 first-order self-leadership factors load on the second-order

Constructive thought patterns self-leadership factor. This fundamentally also lies at the root of the disappointing Cronbach alpha values. Item ASL_11 showed itself as a marginal outlier in the distribution of corrected item-total correlations and in the distribution of squared multiple correlations. Additionally, the item-total statistics indicates that in the case of Item ASL_11 there would be a marginal increase in the Cronbach's alpha (from .739 to .748) if item ASL_11 would be deleted. The evidence against item ASL_11 was, however, not considered sufficiently strong given the limited number of items representing each first-order self-leadership factor to delete the item from the subscale.

4.4.3 Academic Self-efficacy

Academic self-efficacy was conceptualised as a unidimensional latent variable. A single item analysis was therefore performed on all the items comprising this scale. The results for the item analysis of the various items comprising the *academic self-efficacy* sub-scale are depicted in Table 4.7. The scale comprised 12 items and obtained a satisfactory Cronbach's alpha of .872. The item means in the item statistics section of Table 4.7 fell in a range from 4.21 to 5.69 (on a 7-point scale) and the standard deviations from 1.097 to 1.345. No items showed themselves as outliers in the standard deviation distribution. No items normatively presented themselves as insensitive items.

Table 4.7

Academic Self-efficacy item analysis results

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.872	.875	12

Item Statistics

	Mean	Std. Deviation	N
ASE_1	5.10	1.097	114
ASE_2	5.69	1.138	114
ASE_3	4.21	1.340	114
ASE_4	4.89	1.326	114
ASE_5	5.01	1.279	114
ASE_6	5.63	1.243	114
ASE_7	5.27	1.192	114
ASE_8	5.00	1.304	114
ASE_9	4.54	1.345	114
ASE_10	4.75	1.322	114
ASE_11	4.91	1.266	114
ASE_12	5.54	1.345	114

Inter-Item Correlation Matrix

	ASE_1	ASE_2	ASE_3	ASE_4	ASE_5	ASE_6	ASE_7	ASE_8	ASE_9	ASE_10	ASE_11	ASE_12
ASE_1	1.000	.527	-.237	.500	.523	.539	.372	.334	.480	.475	.510	.367
ASE_2	.527	1.000	-.224	.471	.342	.714	.421	.298	.226	.318	.399	.461
ASE_3	-.237	-.224	1.000	-.251	-.202	-.261	-.164	-.218	-.241	-.254	-.192	-.107
ASE_4	.500	.471	-.251	1.000	.762	.529	.600	.374	.375	.368	.437	.394
ASE_5	.523	.342	-.202	.762	1.000	.486	.596	.493	.553	.462	.503	.450
ASE_6	.539	.714	-.261	.529	.486	1.000	.474	.448	.433	.449	.536	.516
ASE_7	.372	.421	-.164	.600	.596	.474	1.000	.530	.431	.516	.550	.411
ASE_8	.334	.298	-.218	.374	.493	.448	.530	1.000	.661	.662	.601	.500
ASE_9	.480	.226	-.241	.375	.553	.433	.431	.661	1.000	.770	.548	.410
ASE_10	.475	.318	-.254	.368	.462	.449	.516	.662	.770	1.000	.621	.445
ASE_11	.510	.399	-.192	.437	.503	.536	.550	.601	.548	.621	1.000	.464
ASE_12	.367	.461	-.107	.394	.450	.516	.411	.500	.410	.445	.464	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ASE_1	55.45	82.727	.613	.508	.859
ASE_2	54.85	83.562	.544	.604	.863
ASE_3	56.33	102.295	-.292	.127	.912
ASE_4	55.65	79.398	.635	.666	.857
ASE_5	55.54	78.516	.706	.699	.852
ASE_6	54.91	79.514	.681	.634	.854
ASE_7	55.27	80.394	.671	.539	.855
ASE_8	55.54	79.011	.667	.595	.855
ASE_9	56.00	78.637	.659	.695	.855
ASE_10	55.80	78.339	.687	.688	.853
ASE_11	55.63	78.695	.706	.551	.852
ASE_12	55.01	79.849	.603	.408	.859

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	5.045	4.211	5.693	1.482	1.352	.194	12
Item Variances	1.610	1.203	1.808	.605	1.503	.043	12
Inter-Item Correlations	.368	-.261	.770	1.031	-2.949	.078	12

Note: ASE_1 – ASE_12 represent the 12 items from the *Academic Self-efficacy* scale

The inter-item correlation matrix indicated that ASE_3 consistently correlated below .30 (and at times negatively) with all of the other items. The corrected item-total correlation indicated that ASE_3 is a poor item obtaining a low negative correlation of -.292. This is low compared with other item correlations which ranged from .544 to 706. To support this the squared multiple correlations suggested that item ASE_3 was a poor item as it obtained a value of .127 compared to the rest of the items which returned values ranging from .408 to .699. The responses to item ASE_3 therefore were underpinned by a different source of systematic variance than that underpinning the remaining items of the scale. The item-total statistics also

indicated that the deletion of ASE_3 would improve the Cronbach's alpha to .912, whereas the deletion of any other item didn't indicate an increase in the Cronbach's alpha.

It was decided to delete ASE_3 and the analysis was run again and the Cronbach's alpha improved from .872 to .912. The inter-item correlation matrix indicated that none of the items consistently correlated low with the remaining items. Moreover, the findings for the reduced scale indicated that the Cronbach's alpha wouldn't be improved if any of the remaining items were deleted.

4.4.4 Conscientiousness

Conscientiousness was conceptualised as a unidimensional latent variable. A single item analysis was therefore performed on all the items comprising this scale. The results for the item analysis of the various items comprising the *conscientiousness* sub-scale are depicted in Table 4.8. The scale comprised 12 items and obtained a satisfactory Cronbach's alpha of .847. The item means shown in the item statistics section of Table 4.8 fell in a range from 2.48 to 4.49 (on a 7-point scale) and the standard deviations from 1.233 to 1.809. No items returned extreme means that resulted in truncated item distributions. No items showed themselves as outliers in the standard deviation distribution.

Table 4.8

Conscientiousness item analysis results

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.847	.855	12

Item Statistics

	Mean	Std. Deviation	N
CON_1	4.30	1.233	114
CON_2	4.80	1.235	114
CON_3	2.48	1.603	114
CON_4	4.60	1.203	114
CON_5	4.61	1.266	114
CON_6	4.55	1.263	114
CON_7	4.24	1.609	114
CON_8	4.68	1.379	114
CON_9	5.49	1.409	114
CON_10	3.82	1.897	114
CON_11	3.62	1.737	114
CON_12	4.02	1.809	114

Inter-Item Correlation Matrix

	CON_1	CON_2	CON_3	CON_4	CON_5	CON_6	CON_7	CON_8	CON_9	CON_10	CON_11	CON_12
CON_1	1.000	.574	-.096	.625	.539	.490	.401	.552	.282	.242	.313	.176
CON_2	.574	1.000	-.143	.398	.454	.424	.314	.631	.220	.185	.195	.089
CON_3	-.096	-.143	1.000	-.196	-.178	-.098	.038	-.181	-.149	.206	.149	.107
CON_4	.625	.398	-.196	1.000	.717	.585	.283	.577	.483	.120	.249	.243
CON_5	.539	.454	-.178	.717	1.000	.722	.271	.678	.435	.148	.360	.289
CON_6	.490	.424	-.098	.585	.722	1.000	.336	.556	.473	.144	.447	.317
CON_7	.401	.314	.038	.283	.271	.336	1.000	.406	.233	.669	.558	.582
CON_8	.552	.631	-.181	.577	.678	.556	.406	1.000	.474	.252	.281	.304
CON_9	.282	.220	-.149	.483	.435	.473	.233	.474	1.000	.185	.232	.278
CON_10	.242	.185	.206	.120	.148	.144	.669	.252	.185	1.000	.665	.764
CON_11	.313	.195	.149	.249	.360	.447	.558	.281	.232	.665	1.000	.824
CON_12	.176	.089	.107	.243	.289	.317	.582	.304	.278	.764	.824	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
CON_1	46.91	103.373	.564	.586	.833
CON_2	46.41	106.138	.447	.521	.840
CON_3	48.73	117.863	-.040	.142	.876
CON_4	46.61	104.062	.551	.649	.834
CON_5	46.60	101.924	.607	.713	.830
CON_6	46.66	101.820	.613	.635	.830
CON_7	46.97	96.398	.634	.554	.826
CON_8	46.54	99.862	.626	.667	.828
CON_9	45.72	104.664	.429	.364	.841
CON_10	47.39	94.221	.576	.722	.831
CON_11	47.59	93.271	.678	.764	.822
CON_12	47.19	93.378	.640	.813	.825

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	4.268	2.482	5.491	3.009	2.212	.556	12
Item Variances	2.219	1.446	3.597	2.151	2.487	.582	12
Inter-Item Correlations	.329	-.196	.824	1.021	-4.197	.061	12

Note: CON_1 – CON_12 represent the 12 items from the *Conscientiousness* scale

The inter-item correlation matrix indicated that the majority of the items in the *Conscientiousness* sub-scale correlates with one or more of the other items above .50. Item CON_3 however consistently correlated below .20 with all of the other items. The corrected item-total correlation indicated that CON_3 is an extreme outlier in the corrected item-total correlation distribution obtaining a low negative correlation of -.040. This is low compared with other item correlations which ranged from .429 to 813. To support this item CON_3 showed itself as an extreme outlier in the squared multiple correlations distribution suggested that item CON_3 was a poor item as it obtained a value of .142 compared to the rest of the items which

returned values ranging from .364 to .813. The item-total statistics also indicated that the deletion of CON_3 would improve the Cronbach's alpha to .876, the deletion of any other item didn't indicate an increase in the Cronbach's alpha. The response to item CON_3 was therefore determined by a different source of variance than the responses to the remaining items.

It was decided to delete CON_3 and the analysis was run again and the Cronbach's alpha improved from .847 to .876. The inter-item correlation matrix indicated that none of the remaining items consistently correlated lower with the other items in the subscale. The item-total statistics indicated that the Cronbach's alpha wouldn't be improved if any of the other items were deleted. The *conscientiousness* sub-scale was reduced from 12 items to 11 items.

4.4.5 Learning Motivation

Learning motivation was conceptualised as a unidimensional latent variable. A single item analysis was therefore performed on all the items comprising this scale. The results for item analysis of the various items comprising the *Learning Motivation* sub-scale are depicted in Table 4.9. The scale comprised 6 items and obtained a satisfactory Cronbach's alpha of .874. The analysis did not indicate any extreme means and small standard deviations, thus indicating the absence of insensitive items. The means in the item statistics fell in a range from 5.07 to 5.70 (on a 7-point scale) and the standard deviations from 1.113 to 1.387. None of the item distributions were truncated and no item presented itself as an outlier in the standard deviation distribution. None of the items therefore failed to reflect differences on the *learning motivation* latent variable where the other items did detect differences.

Table 4.9

Learning Motivation item analysis results

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.874	.875	6

Item Statistics

	Mean	Std. Deviation	N
LMOT_1	5.70	1.113	114
LMOT_2	5.07	1.387	114
LMOT_3	5.11	1.279	114
LMOT_4	5.23	1.212	114
LMOT_5	5.12	1.364	114
LMOT_6	5.47	1.221	114

Inter-Item Correlation Matrix

	LMOT_1	LMOT_2	LMOT_3	LMOT_4	LMOT_5	LMOT_6
LMOT_1	1.000	.432	.564	.576	.409	.379
LMOT_2	.432	1.000	.734	.580	.449	.388
LMOT_3	.564	.734	1.000	.692	.617	.540
LMOT_4	.576	.580	.692	1.000	.620	.566
LMOT_5	.409	.449	.617	.620	1.000	.523
LMOT_6	.379	.388	.540	.566	.523	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
LMOT_1	26.00	27.398	.581	.384	.868
LMOT_2	26.63	24.571	.647	.552	.859
LMOT_3	26.60	23.570	.821	.706	.827
LMOT_4	26.47	24.552	.780	.613	.835
LMOT_5	26.58	24.653	.656	.475	.857
LMOT_6	26.23	26.461	.593	.390	.866

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	5.284	5.070	5.702	.632	1.125	.063	6
Item Variances	1.603	1.238	1.924	.687	1.555	.067	6
Inter-Item Correlations	.538	.379	.734	.356	1.939	.011	6

Note: LMOT_1 – LMOT_6 represent the 6 items from the *Learning Motivation* scale

The inter-item correlation matrix indicated that none of the items in the *learning motivation* sub-scale consistently correlated lower with the other items in the sub-scale. The items therefore all responded in relative unison to the same source of systematic variance (although not necessarily unidimensional source of systematic variance and not necessarily the intended source of variance). In the distribution of squared multiple correlation none of the items showed themselves as outliers. As can be seen in Table 4.9 no item's squared multiple correlation was smaller than .30 with the squared multiple correlations ranging from .384 to .390. A similar trend existed with regards to the corrected item-total correlation distribution. This suggests that all items were underpinned by a common source of systematic variance. Additionally, the item-total statistics indicates that there would be no significant increase in the Cronbach's alpha if any of the items were deleted. All 6 items were therefore retained.

4.4.6 Transfer of Knowledge

Transfer of knowledge was conceptualised as a unidimensional latent variable. A single item analysis was therefore performed on all the items comprising this scale. The results for item analysis of the various items comprising the *transfer of knowledge* sub-scale are depicted in Table 4.10. The scale comprised 27 items and obtained a satisfactory Cronbach's alpha of .761. The item means in the item statistics section of Table 4.10 fell in a range from 3.11 to 5.30 (on a 7-point scale) and the standard deviations from 1.004 to 1.582. None of the item distributions were truncated due to extreme means and no item presented itself as an outlier in the distribution of item standard deviations. None of the items therefore showed itself as an insensitive item that failed to discriminate between individuals based on their standing on the *transfer of knowledge* latent variable where the other items did detect differences.

Table 4.10

Transfer of Knowledge item analysis results

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.761	.788	27

Item Statistics

	Mean	Std. Deviation	N
TK_1	4.13	1.171	114
TK_2	4.94	1.170	114
TK_3	4.82	1.250	114
TK_4	5.30	1.463	114
TK_5	5.30	1.152	114
TK_6	4.93	1.173	114
TK_7	4.95	1.143	114
TK_8	3.99	1.442	114
TK_9	4.15	1.428	114
TK_10	3.85	1.512	114
TK_11	4.78	1.173	114
TK_12	4.79	1.201	114
TK_13	4.90	1.004	114
TK_14	4.95	1.038	114
TK_15	5.24	1.058	114
TK_16	4.96	1.170	114
TK_17	5.17	1.144	114
TK_18	3.11	1.582	114
TK_19	3.52	1.495	114
TK_20	3.12	1.535	114
TK_21	5.05	1.275	114
TK_22	5.04	1.170	114
TK_23	3.94	1.365	114
TK_24	3.16	1.473	114
TK_25	3.18	1.428	114
TK_26	5.02	1.197	114
TK_27	4.51	1.345	114

Table 4.10 (Continued)

Transfer of Knowledge item analysis results

	TK_1	TK_2	TK_3	TK_4	TK_5	TK_6	TK_7	TK_8	TK_9	TK_10	TK_11	TK_12	TK_13	TK_14	TK_15	TK_16	TK_17	TK_18	TK_19	TK_20	TK_21	TK_22	TK_23	TK_24	TK_25	TK_26	TK_27
TK_1	1.000	-.156	-.552	-.302	-.259	-.335	-.358	.504	.427	.386	.041	-.471	-.410	-.366	-.268	-.344	-.373	.441	.547	.404	-.242	-.269	.387	.208	.393	-.235	-.335
TK_2	-.156	1.000	.326	.461	.467	.390	.335	-.037	-.063	-.010	.461	.262	.334	.355	.355	.321	.458	-.341	-.280	-.104	.329	.345	-.047	-.164	-.142	.437	.144
TK_3	-.552	.326	1.000	.552	.387	.511	.557	-.276	-.213	-.234	.185	.636	.565	.627	.547	.485	.584	-.291	-.482	-.265	.445	.453	-.390	-.119	-.320	.463	.469
TK_4	-.302	.461	.552	1.000	.477	.404	.491	-.313	-.199	-.200	.410	.484	.460	.506	.485	.411	.583	-.312	-.476	-.347	.295	.457	-.310	-.137	-.364	.608	.331
TK_5	-.259	.467	.387	.477	1.000	.566	.429	-.270	-.232	-.035	.258	.411	.507	.502	.450	.522	.587	-.328	-.286	-.191	.441	.470	-.101	-.185	-.344	.484	.370
TK_6	-.335	.390	.511	.404	.566	1.000	.591	-.231	-.284	-.091	.143	.423	.625	.571	.477	.507	.523	-.430	-.338	-.108	.316	.492	-.240	-.111	-.288	.492	.421
TK_7	-.358	.335	.557	.491	.429	.591	1.000	-.365	-.391	-.230	.084	.520	.720	.602	.500	.474	.541	-.330	-.279	-.072	.312	.485	-.184	-.074	-.244	.557	.426
TK_8	.504	-.037	-.276	-.313	-.270	-.231	-.365	1.000	.800	.527	.192	-.282	-.331	-.355	-.202	-.352	-.310	.505	.524	.444	-.202	-.215	.472	.309	.542	-.287	-.235
TK_9	.427	-.063	-.213	-.199	-.232	-.284	-.391	.800	1.000	.547	.236	-.234	-.379	-.377	-.205	-.293	-.237	.530	.436	.306	-.140	-.168	.409	.351	.456	-.307	-.243
TK_10	.386	-.010	-.234	-.200	-.035	-.091	-.230	.527	.547	1.000	.355	-.134	-.278	-.174	-.188	-.154	-.144	.369	.547	.454	-.285	-.221	.450	.388	.340	-.111	-.149
TK_11	.041	.461	.185	.410	.258	.143	.084	.192	.236	.355	1.000	.281	.080	.136	.220	.148	.278	.013	.085	.153	.102	.181	.218	.246	.060	.293	.189
TK_12	-.471	.262	.636	.484	.411	.423	.520	-.282	-.234	-.134	.281	1.000	.563	.566	.576	.434	.573	-.221	-.387	-.283	.366	.340	-.343	-.141	-.438	.341	.407
TK_13	-.410	.334	.565	.460	.507	.625	.720	-.331	-.379	-.278	.080	.563	1.000	.691	.580	.471	.623	-.345	-.456	-.274	.384	.508	-.276	-.151	-.371	.531	.449
TK_14	-.366	.355	.627	.506	.502	.571	.602	-.355	-.377	-.174	.136	.566	.691	1.000	.648	.647	.671	-.396	-.496	-.251	.510	.476	-.333	-.215	-.316	.528	.476
TK_15	-.268	.355	.547	.485	.450	.477	.500	-.202	-.205	-.188	.220	.576	.580	.648	1.000	.651	.691	-.274	-.414	-.301	.482	.449	-.333	-.291	-.315	.430	.393
TK_16	-.344	.321	.485	.411	.522	.507	.474	-.352	-.293	-.154	.148	.434	.471	.647	.651	1.000	.667	-.337	-.336	-.189	.512	.505	-.279	-.109	-.165	.405	.385
TK_17	-.373	.458	.584	.583	.587	.523	.541	-.310	-.237	-.144	.278	.573	.623	.671	.691	.667	1.000	-.313	-.434	-.254	.492	.530	-.277	-.210	-.381	.502	.445
TK_18	.441	-.341	-.291	-.312	-.328	-.430	-.330	.505	.530	.369	.013	-.221	-.345	-.396	-.274	-.337	-.313	1.000	.613	.447	-.165	-.361	.433	.384	.474	-.426	-.396
TK_19	.547	-.280	-.482	-.476	-.286	-.338	-.279	.524	.436	.547	.085	-.387	-.456	-.496	-.414	-.336	-.434	.613	1.000	.774	-.298	-.322	.679	.529	.604	-.346	-.361
TK_20	.404	-.104	-.265	-.347	-.191	-.108	-.072	.444	.306	.454	.153	-.283	-.274	-.251	-.301	-.189	-.254	.447	.774	1.000	-.184	-.092	.650	.535	.620	-.136	-.215
TK_21	-.242	.329	.445	.295	.441	.316	.312	-.202	-.140	-.285	.102	.366	.384	.510	.482	.512	.492	-.165	-.298	-.184	1.000	.485	-.186	-.287	-.107	.225	.304
TK_22	-.269	.345	.453	.457	.470	.492	.485	-.215	-.168	-.221	.181	.340	.508	.476	.449	.505	.530	-.361	-.322	-.092	.485	1.000	-.164	-.076	-.222	.473	.430
TK_23	.387	-.047	-.390	-.310	-.101	-.240	-.184	.472	.409	.450	.218	-.343	-.276	-.333	-.333	-.279	-.277	.433	.679	.650	-.186	-.164	1.000	.515	.641	-.167	-.253
TK_24	.208	-.164	-.119	-.137	-.185	-.111	-.074	.309	.351	.388	.246	-.141	-.151	-.215	-.291	-.109	-.210	.384	.529	.535	-.287	-.076	.515	1.000	.525	-.102	-.121
TK_25	.393	-.142	-.320	-.364	-.344	-.288	-.244	.542	.456	.340	.060	-.438	-.371	-.316	-.315	-.165	-.381	.474	.604	.620	-.107	-.222	.641	.525	1.000	-.266	-.273
TK_26	-.235	.437	.463	.608	.484	.492	.557	-.287	-.307	-.111	.293	.341	.531	.528	.430	.405	.502	-.426	-.346	-.136	.225	.473	-.167	-.102	-.266	1.000	.363
TK_27	-.335	.144	.469	.331	.370	.421	.426	-.235	-.243	-.149	.189	.407	.449	.476	.393	.385	.445	-.396	-.361	-.215	.304	.430	-.253	-.121	-.273	.363	1.000

Table 4.10 (Continued)

Transfer of Knowledge item analysis results

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TK_1	116.65	168.920	-.057	.552	.772
TK_2	115.84	155.816	.390	.547	.749
TK_3	115.96	155.228	.378	.682	.749
TK_4	115.48	153.739	.350	.668	.750
TK_5	115.48	154.712	.437	.603	.747
TK_6	115.85	154.942	.419	.598	.747
TK_7	115.83	154.990	.431	.695	.747
TK_8	116.79	161.123	.146	.768	.763
TK_9	116.63	161.350	.143	.759	.763
TK_10	116.93	157.039	.244	.607	.757
TK_11	116.00	151.965	.526	.591	.742
TK_12	115.99	156.823	.342	.631	.751
TK_13	115.88	157.702	.391	.734	.750
TK_14	115.83	156.317	.430	.732	.748
TK_15	115.54	156.073	.430	.673	.748
TK_16	115.82	155.031	.417	.690	.748
TK_17	115.61	153.266	.494	.709	.744
TK_18	117.68	166.717	-.016	.626	.775
TK_19	117.26	164.585	.045	.816	.770
TK_20	117.66	157.147	.235	.741	.758
TK_21	115.73	156.802	.317	.577	.753
TK_22	115.74	154.727	.428	.542	.747
TK_23	116.84	160.081	.192	.666	.760
TK_24	117.62	158.113	.224	.573	.759
TK_25	117.61	162.666	.106	.704	.766
TK_26	115.76	155.244	.398	.577	.748
TK_27	116.27	157.899	.262	.431	.756

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	4.473	3.105	5.298	2.193	1.706	.544	27
Item Variances	1.665	1.008	2.502	1.494	2.481	.191	27
Inter-Item Correlations	.121	-.552	.800	1.352	-1.448	.138	27

Note: TK_1 – TK_27 represent the 27 items from the *Knowledge Transfer* scale.

The inter-item correlation matrix shown in Table 4.10 indicated that TK_1, TK_8, TK_9, TK_10, TK_18, TK_19, TK_20, TK_23, TK_24 and TK_25 correlated on par with the other items in the *transfer of knowledge* sub-scale, however all of these items consistently correlated negatively with the remaining items. These items appeared in the LPQ as follows:

- TK_1: When I encountered unfamiliar learning material in my first semester engineering modules, I struggled to make sense of the learning material.
- TK_8: I required assistance when I was introduced to new engineering course material, in-order to make sense of the material.

- TK_9: I required assistance when I was faced with a new problem in my first semester modules, in-order to solve the problem.
- TK_10: I found that instructions/information needed to be repeated multiple times when I was working through unfamiliar first semester engineering material in-order for it to make sense.
- TK_18: I memorised my first semester engineering module's learning material without really understanding what it is all about.
- TK_19: I struggled to make sense of what was said in class.
- TK_20: I did not understand the lecturer.
- TK_23: I had to reflect for a very long time before I attained aha (truly understood) on the work that was covered in class.
- TK_24: I found it difficult to understand how I would use the first semester engineering learning material covered in class.
- TK_25: Even after going over the work covered in class it still did not really make sense to me.

All these items describe manifestations of the inability to successfully transfer whereas the remaining items describe denotations of competence at transfer of knowledge. To address the negative correlations of these items, the items were reflected and the analysis was re-run. The Cronbach's alpha increased significantly from .761 to a highly satisfactory .932 (see Table 4.11). The item means in the item statistics section of Table 4.11 fell in a range from 3.8509 to 5.2982 (on a 7-point scale) and the standard deviations from 1.00414 to 1.58180. None of the item distributions were truncated due to extreme means and no item presented itself as an outlier in the distribution of item standard deviations.

Table 4.11

Transfer of Knowledge reflected items, item analysis results

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.932	.935	27

Item Statistics

	Mean	Std. Deviation	N
TK_2	4.9386	1.16956	114
TK_3	4.8246	1.24975	114
TK_4	5.2982	1.46299	114
TK_5	5.2982	1.15160	114
TK_6	4.9298	1.17284	114
TK_7	4.9474	1.14321	114
TK_11	4.7807	1.17314	114
TK_12	4.7895	1.20084	114
TK_13	4.9035	1.00414	114
TK_14	4.9474	1.03771	114

TK_15	5.2368	1.05849	114
TK_16	4.9561	1.17036	114
TK_17	5.1667	1.14379	114
TK_21	5.0526	1.27496	114
TK_22	5.0439	1.17036	114
TK_26	5.0175	1.19721	114
TK_27	4.5088	1.34523	114
TK_1R	3.8684	1.17129	114
TK_8R	4.0088	1.44207	114
TK_9R	3.8509	1.42812	114
TK_10R	4.1491	1.51238	114
TK_18R	4.8947	1.58180	114
TK_19R	4.4825	1.49472	114
TK_20R	4.8772	1.53508	114
TK_23R	4.0614	1.36508	114
TK_24R	4.8421	1.47294	114
TK_25R	4.8246	1.42820	114

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TK_2	123.5614	418.089	.430	.547	.932
TK_3	123.6754	404.434	.677	.682	.928
TK_4	123.2018	400.198	.644	.668	.929
TK_5	123.2018	411.366	.585	.603	.930
TK_6	123.5702	409.893	.606	.598	.929
TK_7	123.5526	409.966	.621	.695	.929
TK_11	123.7193	434.363	.088	.591	.936
TK_12	123.7105	408.314	.624	.631	.929
TK_13	123.5965	410.331	.705	.734	.929
TK_14	123.5526	408.214	.733	.732	.928
TK_15	123.2632	410.497	.663	.673	.929
TK_16	123.5439	409.365	.619	.690	.929
TK_17	123.3333	405.499	.721	.709	.928
TK_21	123.4474	412.851	.493	.577	.931
TK_22	123.4561	411.949	.562	.542	.930
TK_26	123.4825	410.181	.586	.577	.930
TK_27	123.9912	409.407	.529	.431	.930
TK_1R	124.6316	411.385	.574	.552	.930
TK_8R	124.4912	404.872	.570	.768	.930
TK_9R	124.6491	407.947	.521	.759	.931
TK_10R	124.3509	412.124	.417	.607	.932
TK_18R	123.6053	398.949	.611	.626	.929
TK_19R	124.0175	394.265	.734	.816	.927
TK_20R	123.6228	405.830	.515	.741	.931
TK_23R	124.4386	407.824	.551	.666	.930
TK_24R	123.6579	414.032	.398	.573	.933
TK_25R	123.6754	403.814	.596	.704	.929

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	4.759	3.851	5.298	1.447	1.376	.178	27
Item Variances	1.665	1.008	2.502	1.494	2.481	.191	27
Inter-Item Correlations	.349	-.355	.800	1.155	-2.250	.031	27

Table 4.11 (continued)

Transfer of Knowledge reflected items, item analysis results

Inter-Item Correlation Matrix

	TK_2	TK_4	TK_11	TK_26	TK_16	TK_21	TK_15	TK_14	TK_17	TK_3	TK_22	TK_20R	TK_19R	TK_23R	TK_24R	TK_25R	TK_18R	TK_8R	TK_9R
TK_2	1.000	.461	.461	.437	.321	.329	.355	.355	.458	.326	.345	.104	.280	.047	.164	.142	.341	.037	.063
TK_4	.461	1.000	.410	.608	.411	.295	.485	.506	.583	.552	.457	.347	.476	.310	.137	.364	.312	.313	.199
TK_11	.461	.410	1.000	.293	.148	.102	.220	.136	.278	.185	.181	-.153	-.085	-.218	-.246	-.060	-.013	-.192	-.236
TK_26	.437	.608	.293	1.000	.405	.225	.430	.528	.502	.463	.473	.136	.346	.167	.102	.266	.426	.287	.307
TK_16	.321	.411	.148	.405	1.000	.512	.651	.647	.667	.485	.505	.189	.336	.279	.109	.165	.337	.352	.293
TK_21	.329	.295	.102	.225	.512	1.000	.482	.510	.492	.445	.485	.184	.298	.186	.287	.107	.165	.202	.140
TK_15	.355	.485	.220	.430	.651	.482	1.000	.648	.691	.547	.449	.301	.414	.333	.291	.315	.274	.202	.205
TK_14	.355	.506	.136	.528	.647	.510	.648	1.000	.671	.627	.476	.251	.496	.333	.215	.316	.396	.355	.377
TK_17	.458	.583	.278	.502	.667	.492	.691	.671	1.000	.584	.530	.254	.434	.277	.210	.381	.313	.310	.237
TK_3	.326	.552	.185	.463	.485	.445	.547	.627	.584	1.000	.453	.265	.482	.390	.119	.320	.291	.276	.213
TK_22	.345	.457	.181	.473	.505	.485	.449	.476	.530	.453	1.000	.092	.322	.164	.076	.222	.361	.215	.168
TK_20R	.104	.347	-.153	.136	.189	.184	.301	.251	.254	.265	.092	1.000	.774	.650	.535	.620	.447	.444	.306
TK_19R	.280	.476	-.085	.346	.336	.298	.414	.496	.434	.482	.322	.774	1.000	.679	.529	.604	.613	.524	.436
TK_23R	.047	.310	-.218	.167	.279	.186	.333	.333	.277	.390	.164	.650	.679	1.000	.515	.641	.433	.472	.409
TK_24R	.164	.137	-.246	.102	.109	.287	.291	.215	.210	.119	.076	.535	.529	.515	1.000	.525	.384	.309	.351
TK_25R	.142	.364	-.060	.266	.165	.107	.315	.316	.381	.320	.222	.620	.604	.641	.525	1.000	.474	.542	.456
TK_18R	.341	.312	-.013	.426	.337	.165	.274	.396	.313	.291	.361	.447	.613	.433	.384	.474	1.000	.505	.530
TK_8R	.037	.313	-.192	.287	.352	.202	.202	.355	.310	.276	.215	.444	.524	.472	.309	.542	.505	1.000	.800
TK_9R	.063	.199	-.236	.307	.293	.140	.205	.377	.237	.213	.168	.306	.436	.409	.351	.456	.530	.800	1.000

Note: TK_2 – TK_7, TK_11 – TK_17, TK_21- TK_22, TK_26, TK_27 represent the 17 items from the *Knowledge Transfer* scale that were not reflected and TK_1R, TK_8R - TK_10R, TK_18R -TK_20R, TK_23R – TK_25R represent the 10 items from the *Knowledge Transfer* scale that were reflected.

The inter item correlation-matrix shown in Table 4.11 indicated that none of the items in the *transfer of knowledge* sub-scale consistently correlated low with the other items in the sub-scale except TK_11 which showed itself to respond somewhat out of step with the remaining items. All the items were therefore underpinned by the same systematic source of variance except TK_11. In the distribution of corrected item-total correlations item TK_11 also showed itself as a clear outlier to the lower end of the distribution. TK_24R also showed itself as somewhat of an outlier in the corrected-item total correlation distribution albeit to a substantially lesser degree. These trends were surprisingly less evident in the distribution of squared multiple correlations with the squared multiple correlations ranging from .431 to .816. The item-total statistics indicates that there would be a .003 increase in the internal consistency reliability if item TK_11 would be deleted and only a .001 increase in the Cronbach's alpha if TK_24R were deleted. It was consequently decided to not delete these two items because of the small increase it would lead to on the Cronbach's alpha taken in conjunction with the highly satisfactory internal consistency reliability of the scale after the reflection of the negatively worded items.

4.4.7 Automisation

Automisation was conceptualised as a unidimensional latent variable. A single item analysis was therefore performed on all the items comprising this scale. The results for item analysis of the various items comprising the *automisation* sub-scale are depicted in Table 4.12.

. The scale comprised 18 items and obtained a disappointing Cronbach's alpha of .667. The item means in the item statistics section of Table 4.12 fell in a range from 2.68 to 4.05 (on a 7-point scale) and the standard deviations from .622 to 1.151. None of the item distributions were truncated do to extreme high or low means. Items. AUTO_1 and AUTO_6, however, showed themselves as outliers in the distribution of item standard deviations. The ability of these two items to discriminate between relatively small differences in standing on the *automisation* latent variable therefore became a source of concern.

Table 4.12

Automisation item analysis results

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.667	.741	18

Item Statistics

	Mean	Std. Deviation	N
AUTO_1	4.02	.652	114
AUTO_2	3.23	1.031	114

AUTO_3	3.89	.849	114
AUTO_4	4.03	.734	114
AUTO_5	3.19	1.151	114
AUTO_6	4.05	.622	114
AUTO_7	3.96	.703	114
AUTO_8	3.33	.879	114
AUTO_9	3.20	.997	114
AUTO_10	2.84	1.118	114
AUTO_11	3.61	.804	114
AUTO_12	3.29	1.062	114
AUTO_13	3.68	.876	114
AUTO_14	3.64	.811	114
AUTO_15	2.95	1.003	114
AUTO_16	2.89	1.062	114
AUTO_17	2.68	1.147	114
AUTO_18	3.22	1.002	114

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
AUTO_1	57.69	38.958	.345	.400	.648
AUTO_2	58.48	36.641	.359	.299	.640
AUTO_3	57.82	36.022	.534	.550	.623
AUTO_4	57.68	36.926	.529	.509	.628
AUTO_5	58.52	42.836	-.131	.306	.708
AUTO_6	57.66	37.608	.550	.505	.632
AUTO_7	57.75	36.793	.575	.591	.626
AUTO_8	58.38	35.405	.575	.592	.617
AUTO_9	58.51	35.827	.450	.548	.629
AUTO_10	58.87	45.655	-.312	.467	.728
AUTO_11	58.10	36.353	.535	.501	.625
AUTO_12	58.42	35.237	.462	.610	.625
AUTO_13	58.03	36.026	.513	.615	.624
AUTO_14	58.07	36.774	.484	.443	.630
AUTO_15	58.76	42.501	-.101	.434	.697
AUTO_16	58.82	36.588	.348	.512	.642
AUTO_17	59.03	48.132	-.456	.566	.747
AUTO_18	58.49	36.376	.398	.396	.636

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.428	2.684	4.053	1.368	1.510	.199	18
Item Variances	.868	.387	1.325	.939	3.428	.094	18
Inter-Item Correlations	.137	-.622	.616	1.238	-.991	.094	18

Table 4.12 (continued)

Automisation item analysis results

Inter-Item Correlation Matrix

	AUTO_1	AUTO_2	AUTO_3	AUTO_4	AUTO_5	AUTO_6	AUTO_7	AUTO_8	AUTO_9	AUTO_10	AUTO_11	AUTO_12	AUTO_13	AUTO_14	AUTO_15	AUTO_16	AUTO_17	AUTO_18
AUTO_1	1.000	.205	.419	.332	.031	.413	.446	.237	.117	-.154	.199	.159	.165	.230	-.026	-.010	-.194	.184
AUTO_2	.205	1.000	.343	.121	.022	.188	.231	.179	.205	-.091	.203	.198	.198	.057	.191	.258	-.126	.182
AUTO_3	.419	.343	1.000	.572	-.231	.347	.482	.383	.215	-.150	.298	.410	.368	.364	.034	.280	-.383	.300
AUTO_4	.332	.121	.572	1.000	-.111	.482	.516	.370	.210	-.038	.242	.263	.343	.388	.014	.208	-.200	.269
AUTO_5	.031	.022	-.231	-.111	1.000	-.027	-.166	-.055	-.127	.251	-.024	-.227	-.264	-.219	.193	-.300	.341	-.190
AUTO_6	.413	.188	.347	.482	-.027	1.000	.470	.372	.311	-.103	.466	.218	.405	.407	-.166	.264	-.200	.265
AUTO_7	.446	.231	.482	.516	-.166	.470	1.000	.434	.376	-.097	.414	.429	.514	.335	-.053	.101	-.365	.275
AUTO_8	.237	.179	.383	.370	-.055	.372	.434	1.000	.589	-.360	.522	.616	.506	.381	-.311	.486	-.500	.368
AUTO_9	.117	.205	.215	.210	-.127	.311	.376	.589	1.000	-.432	.518	.521	.489	.331	-.352	.481	-.485	.451
AUTO_10	-.154	-.091	-.150	-.038	.251	-.103	-.097	-.360	-.432	1.000	-.246	-.386	-.422	-.278	.427	-.381	.382	-.427
AUTO_11	.199	.203	.298	.242	-.024	.466	.414	.522	.518	-.246	1.000	.443	.353	.410	-.289	.311	-.258	.348
AUTO_12	.159	.198	.410	.263	-.227	.218	.429	.616	.521	-.386	.443	1.000	.594	.389	-.293	.469	-.622	.405
AUTO_13	.165	.198	.368	.343	-.264	.405	.514	.506	.489	-.422	.353	.594	1.000	.524	-.150	.408	-.506	.392
AUTO_14	.230	.057	.364	.388	-.219	.407	.335	.381	.331	-.278	.410	.389	.524	1.000	-.143	.342	-.247	.403
AUTO_15	-.026	.191	.034	.014	.193	-.166	-.053	-.311	-.352	.427	-.289	-.293	-.150	-.143	1.000	-.280	.378	-.156
AUTO_16	-.010	.258	.280	.208	-.300	.264	.101	.486	.481	-.381	.311	.469	.408	.342	-.280	1.000	-.386	.423
AUTO_17	-.194	-.126	-.383	-.200	.341	-.200	-.365	-.500	-.485	.382	-.258	-.622	-.506	-.247	.378	-.386	1.000	-.409
AUTO_18	.184	.182	.300	.269	-.190	.265	.275	.368	.451	-.427	.348	.405	.392	.403	-.156	.423	-.409	1.000

Note: AUTO_1 – AUTO_18 represent the 18 items from the *Automisation* scale.

The inter-item correlation matrix indicated that AUTO_5, AUTO_10, AUTO_15 and AUTO_17 consistently correlated negatively but in terms of magnitude on par with the other items in the *automisation* sub-scale. The items appeared in the LPQ as follows:

- AUTO_5: I found that a lack of knowledge/experience hindered me from making sense of – and solving unfamiliar first semester engineering problems.
- AUTO_10: After I have written a test, I cannot recall much of the first semester engineering learning material that the test was written on.
- AUTO_15: I did understand the engineering work covered during the first semester at some point but I can no longer recall most of it.
- AUTO_17: I do not feel confident in the area of my first semester engineering modules.

All these items represent denotations of a lack of competency on the *automisation* competency whereas the remaining sixteen items denote competence at automisation. To address the negative correlations of these items, the items were reflected and the analysis was re-run. The Cronbach's alpha increased significantly from .667 to a satisfactory .879 (see Table 4.13). The means in the item statistics fell in a range from 2.68 to 4.05 (on a 7-point scale) and the standard deviations from .622 to 1.151. The refection of the scale of the negatively worded items affected the items means but did not affect the item standard deviations. AUTO_1 and AUTO_6, therefore, still showed themselves as outliers in the distribution of item standard deviations.

Table 4.13

Automisation reflected items, item analysis results

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.879	.884	18

Item Statistics

	Mean	Std. Deviation	N
AUTO_1	4.0175	.65151	114
AUTO_2	3.2281	1.03081	114
AUTO_3	3.8860	.84935	114
AUTO_4	4.0263	.73425	114
AUTO_5R	4.8070	1.15120	114
AUTO_6	4.0526	.62176	114
AUTO_7	3.9649	.70309	114
AUTO_8	3.3333	.87913	114
AUTO_9	3.2018	.99716	114
AUTO_10R	5.1579	1.11767	114
AUTO_11	3.6140	.80385	114
AUTO_12	3.2895	1.06200	114
AUTO_13	3.6842	.87559	114
AUTO_14	3.6404	.81063	114
AUTO_15R	5.0526	1.00302	114

AUTO_16	2.8860	1.06230	114
AUTO_17R	5.3158	1.14688	114
AUTO_18	3.2193	1.00229	114

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
AUTO_1	66.2609	88.019	.311	.400	.879
AUTO_2	67.0435	86.761	.230	.298	.884
AUTO_3	66.4000	83.119	.541	.554	.872
AUTO_4	66.2609	85.686	.439	.509	.875
AUTO_5R	65.4870	84.673	.291	.306	.883
AUTO_6	66.2261	86.334	.478	.505	.875
AUTO_7	66.3130	84.726	.544	.587	.873
AUTO_8	66.9565	80.533	.687	.598	.867
AUTO_9	67.0870	79.606	.652	.551	.867
AUTO_10R	65.1304	80.974	.497	.470	.874
AUTO_11	66.6696	83.486	.552	.503	.872
AUTO_12	67.0000	77.930	.700	.614	.865
AUTO_13	66.5913	80.946	.670	.611	.867
AUTO_14	66.6348	83.743	.529	.437	.873
AUTO_15R	65.2348	85.216	.324	.439	.880
AUTO_16	67.4000	80.207	.573	.515	.870
AUTO_17R	64.9739	78.026	.635	.571	.868
AUTO_18	67.0609	81.163	.559	.394	.871

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	4.759	3.851	5.298	1.447	1.376	.178	27
Item Variances	1.665	1.008	2.502	1.494	2.481	.191	27
Inter-Item Correlations	.349	-.355	.800	1.155	-2.250	.031	27

Table 4.13 (continued)

Automisation reflected items, item analysis results

Inter-Item Correlation Matrix

	AUTO_1	AUTO_2	AUTO_3	AUTO_4	AUTO_5R	AUTO_6	AUTO_7	AUTO_8	AUTO_9	AUTO_10R	AUTO_11	AUTO_12	AUTO_13	AUTO_14	AUTO_15R	AUTO_16	AUTO_17R	AUTO_18
AUTO_1	1.000	.205	.419	.332	-.031	.413	.446	.237	.117	.154	.199	.159	.165	.230	.026	-.010	.194	.184
AUTO_2	.205	1.000	.343	.121	-.022	.188	.231	.179	.205	.091	.203	.198	.198	.057	-.191	.258	.126	.182
AUTO_3	.419	.343	1.000	.572	.231	.347	.482	.383	.215	.150	.298	.410	.368	.364	-.034	.280	.383	.300
AUTO_4	.332	.121	.572	1.000	.111	.482	.516	.370	.210	.038	.242	.263	.343	.388	-.014	.208	.200	.269
AUTO_5R	-.031	-.022	.231	.111	1.000	.027	.166	.055	.127	.251	.024	.227	.264	.219	.193	.300	.341	.190
AUTO_6	.413	.188	.347	.482	.027	1.000	.470	.372	.311	.103	.466	.218	.405	.407	.166	.264	.200	.265
AUTO_7	.446	.231	.482	.516	.166	.470	1.000	.434	.376	.097	.414	.429	.514	.335	.053	.101	.365	.275
AUTO_8	.237	.179	.383	.370	.055	.372	.434	1.000	.589	.360	.522	.616	.506	.381	.311	.486	.500	.368
AUTO_9	.117	.205	.215	.210	.127	.311	.376	.589	1.000	.432	.518	.521	.489	.331	.352	.481	.485	.451
AUTO_10R	.154	.091	.150	.038	.251	.103	.097	.360	.432	1.000	.246	.386	.422	.278	.427	.381	.382	.427
AUTO_11	.199	.203	.298	.242	.024	.466	.414	.522	.518	.246	1.000	.443	.353	.410	.289	.311	.258	.348
AUTO_12	.159	.198	.410	.263	.227	.218	.429	.616	.521	.386	.443	1.000	.594	.389	.293	.469	.622	.405
AUTO_13	.165	.198	.368	.343	.264	.405	.514	.506	.489	.422	.353	.594	1.000	.524	.150	.408	.506	.392
AUTO_14	.230	.057	.364	.388	.219	.407	.335	.381	.331	.278	.410	.389	.524	1.000	.143	.342	.247	.403
AUTO_15R	.026	-.191	-.034	-.014	.193	.166	.053	.311	.352	.427	.289	.293	.150	.143	1.000	.280	.378	.156
AUTO_16	-.010	.258	.280	.208	.300	.264	.101	.486	.481	.381	.311	.469	.408	.342	.280	1.000	.386	.423
AUTO_17R	.194	.126	.383	.200	.341	.200	.365	.500	.485	.382	.258	.622	.506	.247	.378	.386	1.000	.409
AUTO_18	.184	.182	.300	.269	.190	.265	.275	.368	.451	.427	.348	.405	.392	.403	.156	.423	.409	1.000

Note: AUTO_1 – AUTO_4, AUTO_6 – AUTO_9, AUTO_11 – AUTO_14, AUTO_16, AUTO_18 represent the 14 items from the *Automisation* scale that were not reflected and AUTO_5R, AUTO_10R, AUTO_15R, AUTO_17R represent the 4 items from the *Automisation* scale that were reflected.

The inter item correlation-matrix indicated that items AUTO_1, AUTO_2, AUTO_R5, AUTO_R10, AUTO_16 and AUTO_18 in the *automisation* sub-scale consistently correlated low with the other items in the sub-scale. In the distribution of corrected item-total correlations items AUTO_2 and AUTO_5R showed themselves as outliers and to a somewhat lesser degree also items AUTO_1 and AUTO_15R. Although somewhat less pronounced the same trend revealed itself in the distribution of squared multiple correlations. As can be seen in Table 4.13 AUTO_2 squared multiple correlations were calculated as .298 with the rest of the items squared multiple correlations ranging from .306 to .614. The problematic nature of these items also expresses itself in the finding that there would be an increase in the Cronbach's alpha if AUTO_2, AUTO_5R and AUTO_15R were deleted whereas the deletion of item AUTO_1 would leave the internal consistency reliability unaffected. The response to these items where therefore underpinned by a different source of variance than that governing the response to the remaining items thereby causing these items to respond out of step and not in unison with the remaining items. It was consequently decided to delete these items and run the item analysis again. The Cronbach's alpha improved from .879 to .883.

4.5 DIMENSIONALITY ANALYSIS

The items that were proposed to reflect participants standing on each of the latent variable comprising the proposed learning potential structural model were meant to function as essentially one-dimensional sets of items, except for the items comprising the Academic Self-Leadership scale. The purpose of each of these individual items was to operate as stimuli to which test takers respond with behaviour that is primarily an expression of that specific one-dimensional underlying latent variable. The intention behind this was to establish a relatively uncontaminated measure of the specific latent variables.

Factor analysis is a family of multivariate statistical procedures that aims to condense a large number of observed variables (the various items in each sub-scale) into highly correlated groups that measure a single underlying construct (Allen & Yen, 1979). A factor analytic model is primarily focused on how, and the extent to which, values on the observed variables are generated by underlying latent variables or factors (Byrne, 2001). The factor loading pattern and the parameters characterising the regression paths from the factors to the observed variables, i.e. factor loadings, are of crucial importance in this instance. Allen and Yen (1979) describe factor loading as the slope of the regression of an observed variable on the underlying factor that it represents. According to Byrne (2001) inter-factor relations are of interest, however any regression structure amongst them is not considered in the factor-analytic model. The factor-analytic approach assumes that each variable is a linear

combination of some number of common factors and a unique factor. Stanek (1995, p. 9), states that this linear combination can be presented as follows:

$Z_j = [\Sigma]_k(a_{jk}S_k) + a_juS_ju$

Where:

z - standardised variable;

a - factor loading;

S - -common factor or factor score;

j - index for variables;

k - index for factors;

u - denotes the unique portion.

The uni-dimensionality assumption and the success with which each item, along with the remaining items in the particular scale, measures the specific latent variable it was designed to reflect was evaluated by performing unrestricted principal axis factor analyses with oblique rotation on the various scales.

Item that were deleted in the item analysis were excluded from the factor analyses of the various scales. The eigenvalue-greater-than-one rule and the scree test were used to decide how many factors to extract in-order to explain the observed correlation matrix (Tabachnick & Fidell, 2007). Factor loadings greater than .50 were considered satisfactory.

4.5.1 Time Cognitively Engaged

In the item analysis items TCE_9 and TCE_14 were identified as poor items and therefore they were deleted from the Time Cognitively Engaged scale. Based on the results of the item analysis the dimensionality analysis was therefore performed without items TCE_9 and TCE_14. The majority of the correlations in the observed inter-item correlation matrix were larger than .30 and all were statistically significant ($p < .05$) indicating the factor analysability of the inter-item correlation matrix. The factor analysability of the scale was in addition evaluated by means of the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. It is used to reflect the ratio 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, summed across all correlations. When the KMO achieves a value larger than .60, the correlation matrix is deemed factor analysable (Tabachnick & Fidell, 2007). The *Time Cognitively Engaged* scale obtained a KMO of .884 providing sufficient evidence that the scale

is factor analysable. The Bartlett's Test of Specificity was used to test the null hypothesis that the correlation matrix is an identity matrix in the population (i.e., the diagonal contains 1's and all the off-diagonal elements are zero's) (Tabachnick & Fidell, 2007). The Bartlett's test indicated that H_0 can be rejected ($p < .05$), corroborating the KMO's findings that the correlation matrix was factor analysable.

Three factors had to be extracted in-order to adequately explain the observed correlation matrix, which is contrary to the proposed hypothesis of one factor in the original design of the scale. Three factors obtained eigenvalues greater than 1 with the scree plot also depicting that three factors had to be extracted in-order to sufficiently explain the observed correlation matrix. The pattern matrix is depicted in Table 4.14.

Table 4.14

Pattern matrix for the Time Cognitively Engaged scale

	Factor		
	1	2	3
TCE_4	**.966**	-.055	-.098
TCE_12	**.855**	-.032	.130
TCE_5	**.846**	.095	-.043
TCE_13	**.740**	.069	.159
TCE_3	**.731**	.149	.034
TCE_17	**.695**	-.063	.020
TCE_11	**.462**	.246	.151
TCE_10	.072	**.883**	-.130
TCE_1	.040	**.863**	-.055
TCE_2	.171	**.681**	.082
TCE_7	-.168	**.620**	.271
TCE_6	.033	**.482**	.063
TCE_16	.036	-.079	**.867**
TCE_15	.106	.061	**.679**
TCE_8	.036	.116	**.657**

Note: TCE_1 – TCE_17 represent the 15 items from the *Time Cognitively Engaged* scale (items TCE_9 and TCE_14 were deleted).

The items that load onto the first factor all appear to refer to *cognitive engagement in the present moment in class*. The items that load onto the second factor appear to refer to *time spent by students outside of normal class time in-order to master the study material*. The items that load onto the third and last factor refer to the individuals' engagement or *focus when studying course material*. Although one factor was originally proposed the factor fission obtained on this scale nonetheless to some degree made substantive theoretical sense. The three factors that emerged from the factor analysis can therefore be interpreted as narrower facets of a second-order time cognitively engaged factor.

Only 13% of the inter-item correlations estimated from the extracted factor structure deviated more than .05 from the observed inter-item correlation matrix. The extracted 3-factor factor

structure therefore presents a valid (i.e., permissible) and credible explanation of the observed inter-item correlation matrix.

To determine how well the items of the *Time Cognitively Engaged* scale reflect a single underlying latent variable an analysis was subsequently ran where the extraction of a single factor was forced. The loadings of the items on the single extracted factor as can be seen in Table 4.15. All items loaded onto the one factor with factor loadings larger than .50, except TCE_6. TCE_6 obtained a factor loading of .461. Although falling below the critical value of .50 item TCE_6 was nonetheless retained. The reproduced correlation matrix indicated that 76 of the 105 inter-item residuals correlations (72%) had absolute values greater than .05 were obtained reflecting the fact that the single-factor factor solution did not provide a credible explanation for the observed inter-item correlation matrix. It was nonetheless concluded that all 15 items that survived the item analysis could be used as indicators to reflect the *time cognitively engaged* latent variable interpreted as a second-order factor.[26]

Table 4.15

Factor matrix when forcing the extraction of a single factor for the Time Cognitively Engaged scale

	Factor 1
TCE_13	.832
TCE_12	.823
TCE_3	.798
TCE_5	.793
TCE_2	.754
TCE_11	.728
TCE_4	.726
TCE_1	.670
TCE_10	.660
TCE_15	.619
TCE_8	.586
TCE_17	.580
TCE_16	.566
TCE_7	.530
TCE_6	.461

Note: TCE_1 – TCE_17 represent the 15 items from the *Time Cognitively Engaged* scale (items TCE_9 and TCE_14 were deleted).

The reliability of the second-order time cognitively engaged factor score as an unweighted linear composite of three first-order time cognitively engaged factor scores was subsequently

[26] It is acknowledged that the fitting of a second-order measurement model in which the three extracted factors are represented by the individual items that loaded on them and the three narrower facets load on a second-order time cognitively engaged factor would have provided a methodologically better evaluation of the individual items as indicators of the second-order factor. This would have allowed the testing of the statistical significance of the indirect effects of the second-order factor on the item indicators by calculating estimates of these indirect effects via the LISREL CO command.

calculated via a formula proposed by Nunnally (1978) along with the reliability of the three first-order *time cognitively engaged* factor scores[27],[28].When the multidimensional nature of the Time Cognitively Engaged scale was ignored in the calculation of the coefficient of internal consistency a value of .927 (S_t^2=206.972) was obtained. When the reliability of the weighted composite is more appropriately calculated a reliability coefficient of .948 is obtained. The Cronbach alphas calculated for the three subscales formed from the loading pattern shown in Table 4.15 were .930 for the items loading on factor 1 (S_1^2=72.447), .862 for the items loading on factor 2 (S_2^2=29.920) and .825 for the items loading on factor 3 (S_3^2=8.696).

4.5.2 Academic Self-Leadership

Academic self-leadership was measured using an adapted version of the Revised Self-Leadership Questionnaire (RSLQ) developed by Houghton and Neck (2002). The RSLQ conceptualised academic self-leadership in terms of nine factors, namely, self-goal setting, self-reward, self-punishment, self-observation, self-cueing, natural rewards, visualising successful performance, self-talk and evaluating beliefs and assumptions (Houghton & Neck, 2002). Given the multidimensional nature of the academic self-leadership scale confirmatory factor analysis was used to fit the hypothesised 9-factor model implied by the scoring key of the RSLQ (see Table 4.3) rather than perform a series of exploratory factor analyses on each of the 9 subscales. The latter option would also have been problematic because of the fact that in the Burger (2012) adaptation of the RSLQ at least 3 of the subscales only contain two items.

Before fitting the 9-factor measurement model with the individual items as indicators the multivariate normality null hypothesis was first tested. Table 4.16 indicates that the null hypothesis that the multivariate item distribution follows a multivariate normal distribution had to be rejected ($p<.05$). The multivariate item distribution was subsequently normalised. As indicated in Table 4.17 the attempt at normalising the data reduced the deviation from multivariate normality but not to a degree that the sample deviation could be explained in terms of sampling error under the multivariate null hypothesis ($p<.05$). The normalised data was

[27] $1-\left(\frac{\left[\sum_{i=1}^{3} S_i^2-\sum_{i=1}^{3} rtti S_i^2\right]}{S_t^2}\right)$

[28] The calculation of the reliability of the composite was considered important in the current study because problems with the fit of the structural model forced the use of multiple regression to examine the path-specific substantive hypotheses. In the multiple regression analyses total scores were used to represent the various latent variables in the model.

consequently analysed using robust maximum likelihood estimation by analysing the inter-item covariance matrix[29].

Table 4.16

Test of multivariate normality of the distribution of ASL items before normalisation

Skewness			Kurtosis			Skewness and Kurtosis	
Value	Z-Score	P-Value	Value	Z-Score	P-Value	Chi-Square	P-Value
190.979	16.708	0.000	660.030	8.542	0.000	352.137	0.000

Table4.17

Test of multivariate normality of the distribution of ASL items after normalisation

Skewness			Kurtosis			Skewness and Kurtosis	
Value	Z-Score	P-Value	Value	Z-Score	P-Value	Chi-Square	P-Value
186.844	15.847	0.000	656.438	8.349	0.000	320.847	0.000

The 9-factor academic self-leadership measurement model showed close fit (p>.05). The phi matrix, however was not positive definite with the correlation between *self-goal setting* and *self-cuing* substantially exceeding unity (ϕ_{51}=1.643). This clearly seriously challenged the claim that the revised version of the RSLQ displayed discriminant validity in the measurement of the 9 first-order academic self-leadership factors. The correlation in question was subsequently set to unity thereby effectively collapsing the two dimensions into one. The *self-cuing* refers to the creation of reminders via notes and lists on what needs to be accomplished. The connotative meaning of this dimension is very close to that of the *self-goal setting* dimension. Hence the collapse of the two first-order factors into one was not regarded as a significant outcome that totally invalidated the RSQL.

The standardised solution of the fitted 9-factor academic self-leadership measurement model with the correlation between *self-goal setting* and *self-cuing* constrained to unity is shown in Figure 4.1. The full array of fit statistics produced by LISREL 8.8 is shown in Table 4.18.

[29] The responses to the RSLQ items are recorded on a 7-point scale.

Table 4.18

Fit statistics for the 9-factor academic self-leadership measurement model with the correlation between SGS and SC constrained to 1

Goodness of Fit Statistics
Degrees of Freedom = 195
Minimum Fit Function Chi-Square = 343.299 (P = 0.00)
Normal Theory Weighted Least Squares Chi-Square = 327.291 (P = 0.00)
Satorra-Bentler Scaled Chi-Square = 273.767 (P = 0.000170)
Estimated Non-centrality Parameter (NCP) = 78.767
90 Percent Confidence Interval for NCP = (39.065 ; 126.503)
Minimum Fit Function Value = 3.038
Population Discrepancy Function Value (F0) = 0.697
90 Percent Confidence Interval for F0 = (0.346 ; 1.119)
Root Mean Square Error of Approximation (RMSEA) = 0.0598
90 Percent Confidence Interval for RMSEA = (0.0421 ; 0.0758)
P-Value for Test of Close Fit (RMSEA < 0.05) = 0.168
Expected Cross-Validation Index (ECVI) = 3.856
90 Percent Confidence Interval for ECVI = (3.505 ; 4.279)
ECVI for Saturated Model = 4.885
ECVI for Independence Model = 16.786
Chi-Square for Independence Model with 253 Degrees of Freedom = 1850.822
Independence AIC = 1896.822
Model AIC = 435.767
Saturated AIC = 552.000
Independence CAIC = 1982.754
Model CAIC = 738.399
Saturated CAIC = 1583.191
Normed Fit Index (NFI) = 0.852

The deviation from close fit in the sample for the fitted 8-factor measurement model was statistically insignificant (p>.05) and the close fit null hypothesis was not rejected (p>.05). Unfortunately the phi matrix was still not positive definite. None of the ϕ_{ij} estimates returned inadmissible values. Weighted linear composites of the first-order academic self-leadership factors, however, probably correlated unity with one or more of the first-order factors. It is acknowledged that this erodes confidence in the RSLQ CFA results. It was nonetheless decided to interpret the measurement model parameter estimates.

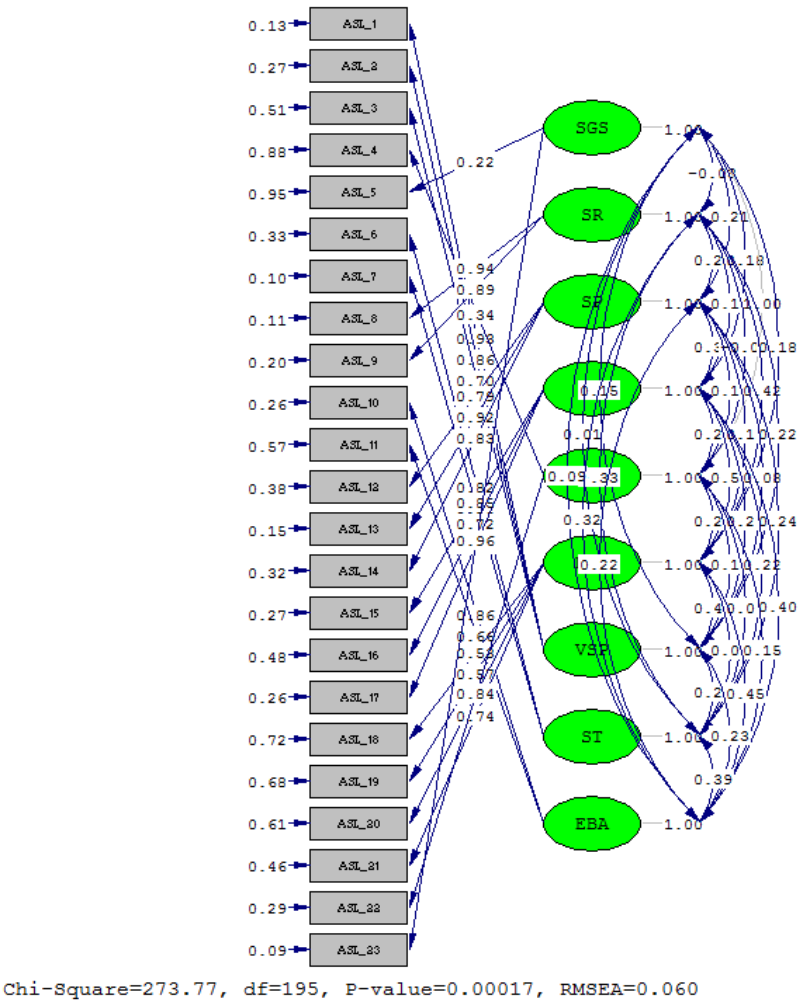


***Figure 4.1*: Standardised solution of the 9-factor academic self-leadership measurement model.**

The unstandardised factor loading matrix Λ^X is shown in Table 4.19. Table 4.19 indicates that all items statistically significantly load on the academic leadership factor they were earmarked to reflect (p<.05)

Table 4.19

Unstandardised Λ^X for the RSLQ

	SGS	SR	SP	SO	SC	NRS
ASL_1						
ASL_2						
ASL_3						
ASL_4					0.566 (-0.182) 3.115	
ASL_5	0.337 (-0.167) 2.01					
ASL_6						
ASL_7						

ASL_8		1.634 (-0.128) 12.813				
ASL_9		1.438 (-0.13) 11.085				
ASL_10						
ASL_11						
ASL_12			1.129 (-0.119) 9.517			
ASL_13			1.298 (-0.111) 11.695			
ASL_14			1.273 (-0.117) 10.913			
ASL_15				1.288 (-0.123) 10.426		
ASL_16				0.92 (-0.108) 8.559		
ASL_17				1.142 (-0.104) 10.954		
ASL_18						0.716 (-0.136) 5.272
ASL_19						0.812 (-0.165) 4.913
ASL_20						0.796 (-0.136) 5.843
ASL_21						0.972 (-0.11) 8.869
ASL_22					1.485 (-0.172) 8.62	
ASL_23	1.662 (-0.181) 9.182					

Table 4.19 *(continued)*

Unstandardised Λ^x for the RSLQ

	VSP	ST	EBA
ASL_1	1.387		
	(-0.111)		
	12.457		
ASL_2	1.122		
	(-0.122)		
	9.225		
ASL_3	0.989		
	(-0.125)		
	7.929		
ASL_4			
ASL_5			
ASL_6		1.328	
		(-0.143)	
		9.266	
ASL_7		1.52	
		(-0.132)	
		11.53	
ASL_8			
ASL_9			
ASL_10			1.192
			(-0.169)
			7.059
ASL_11			0.847
			(-0.13)
			6.513
ASL_12			
ASL_13			
ASL_14			
ASL_15			
ASL_16			
ASL_17			
ASL_18			
ASL_19			
ASL_20			
ASL_21			
ASL_22			
ASL_23			

Note: ASL_1 – TCE_23 represent the 23 items from the *Academic Self-leadership* scale.

The completely standardised Λ^x is shown in Table 4.20.

Table 4.20

Completely standardised Λ^x for the RSLQ

	SGS	SR	SP	SO	SC	NRS
ASL_1						
ASL_2						
ASL_3						
ASL_4					0.343	
ASL_5	0.218					
ASL_6						
ASL_7						
ASL_8		0.942				
ASL_9		0.893				

ASL_10					
ASL_11					
ASL_12		0.786			
ASL_13		0.92			
ASL_14		0.826			
ASL_15			0.852		
ASL_16			0.721		
ASL_17			0.859		
ASL_18					0.526
ASL_19					0.566
ASL_20					0.628
ASL_21					0.738
ASL_22				0.842	
ASL_23	0.956				

Table 4.20 (continued)

Completely standardised Λ^x for the RSLQ

	VSP	ST	EBA
ASL_1	0.932		
ASL_2	0.857		
ASL_3	0.697		
ASL_4			
ASL_5			
ASL_6		0818	
ASL_7		0949	
ASL_8			
ASL_9			
ASL_10			
ASL_11			0862
ASL_12			0658
ASL_13			
ASL_14			
ASL_15			
ASL_16			
ASL_17			
ASL_18			
ASL_19			
ASL_20			
ASL_21			
ASL_22			
ASL_23			

Note: ASL_1 – TCE_23 represent the 23 items from the *Academic Self-leadership* scale.

Table 4.20 indicates that the items ASL_4 and ASL_5 were insensitive items that failed to discriminate between relatively small differences on the latent academic self-leadership dimensions that they were designated to reflect[30] (*self-goal setting* and *self-cuing*). All the

[30] It is acknowledged that because ϕ_{51} had been constrained to unity *self-goal setting* and self-cuing actually refer to the same latent academic self-leadership dimension.

remaining items met the $\lambda_{ij} \geq .50$ criterion. The latent academic self-leadership dimension these two items were meant to reflect only explained 11.7% and 4.8% of the variance in these two items (R^2 can be derived by squaring the completely standardised factor loadings in Table 4.20). These two items were consequently deleted from the further analysis.

The unstandardised measurement error variance matrix Θ_δ is shown in Table 4.21.

Table 4.21

Unstandardised Θ_δ for the RSLQ

ASL_1	ASL_2	ASL_3	ASL_4	ASL_5	ASL_6
0.293	0.454	1.036	2.404	2.261	0.874
-0.138	-0.168	-0.142	-0.305	-0.263	-0.305
2.114	2.699	7.309	7.876	8.589	2.87
ASL_7	ASL_8	ASL_9	ASL_10	ASL_11	ASL_12
0.257	0.337	0.523	0.49	0.938	0.788
-0.309	-0.249	-0.234	-0.359	-0.189	-0.155
0.833	1.355	2.238	1.364	4.967	5.068
ASL_13	ASL_14	ASL_15	ASL_16	ASL_17	ASL_18
0.304	0.752	0.627	0.784	0.463	1.339
-0.133	-0.146	-0.175	-0.15	-0.141	-0.18
2.292	5.153	3.577	5.239	3.29	7.436
ASL_19	ASL_20	ASL_21	ASL_22	ASL_23	
1.399	0.974	0.79	0.906	0.262	
-0.292	-0.182	-0.148	-0.397	-0.55	
4.788	5.345	5.331	2.282	0.476	

Note: ASL_1 – TCE_23 represent the 23 items from the *Academic Self-leadership* scale.

Even when evaluating the statistical significance of the measurement error variance estimates via a one-tailed test the error variance estimates obtained for items ASL_7, ASL_8, ASL_10 and ASL_23 were found to be statistically insignificant ($p>.05$). As attractive as error free measurement would be these findings further eroded confidence in the success with which the academic self-leadership construct had been operationalised in the current study. These items were retained in further analyses.

The reliability of the academic self-leadership total score[31] as an unweighted linear composite of eight first-order academic self-leadership factor scores was subsequently calculated via a formula proposed by Nunnally (1978) along with the reliability of the eight first-order *academic self-leadership* factor scores. When the multidimensional nature of the Academic Self-leadership scale was ignored in the calculation of the coefficient of internal consistency a value

[31]Items ASL_5 and ASL_23 were excluded. They comprised the self-goal setting scale. A Cronbach alpha of .30 and S_1^2= 6.351 was obtained for the self-goal setting scale

of .828 (S_t^2= 214.868) was obtained. When the reliability of the weighted composite is more appropriately calculated a reliability coefficient of .914 is obtained. The Cronbach alphas calculated for the eight subscales formed from the loading pattern shown in Table 4.20 were .914 for the items loading on factor 2 (S_2^2= 10.310), .869 for the items loading on factor 3 (S_3^2= 15.275), .844 for the items loading on factor 4 (S_4^2= 12.984), .434 for the items loading on factor 5 (S_5^2= 7.456), .697 for the items loading on factor 6 (S_6^2= 15.191), .867 for the items loading on factor 7 (S_7^2= 14.085), .862 for the items loading on factor 8 (S_8^2= 9.147) and .703 for the items loading on factor 9 (S_9^2= 5.497).

4.5.3 Academic Self-Efficacy

In the item analysis items ASE_3 was identified as a poor item and therefore it was deleted from the *Academic Self-Efficacy* scale. Based on the results of the item analysis the dimensionality analysis was therefore performed without ASE_3. The majority of the correlations in the observed inter-item correlation matrix were larger than .30 and all were statistically significant ($p < .05$) indicating the factor analysability of the correlation matrix. The *Academic Self-Efficacy* scale obtained a KMO of .877 providing sufficient evidence that the scale was factor analysable. The Bartlett's test indicated that the null hypothesis that the correlation matrix is an identity matrix in the population can be rejected ($p < .05$), substantiating the KMO's findings that the correlation matrix was factor analysable.

Two factors had to be extracted in-order to adequately explain the observed correlation matrix, which is contrary to the proposed hypothesis of one factor in the original design of the scale. Two factors obtained eigenvalues greater than 1 with the scree plot also suggested (albeit somewhat ambiguously) that two factors had to be extracted in-order to sufficiently explain the observed correlation matrix. The pattern matrix is depicted in Table 4.22.

Table 4.22
Pattern matrix for the Academic Self-Efficacy scale

	1	2
ASE_2	**.880**	.210
ASE_6	**.789**	-.031
ASE_4	**.702**	-.065
ASE_1	**.559**	-.172
ASE_5	**.503**	-.323
ASE_7	**.451**	-.330
ASE_12	**.427**	-.266
ASE_9	-.054	**-.887**
ASE_10	.002	**-.856**
ASE_8	.060	**-.753**
ASE_11	.317	**-.517**

Note: ASL_1, ASL_2, ASL_4 – TCE_12 represent the 11 items from the *Academic Self-leadership* scale (item ASL_3 was deleted).

The items that loaded onto the first factor appear to reflect the individual's *belief in his/her ability to do the work covered in his/her engineering course*. The items that loaded onto the second factor appear to reflect more the individual's *belief in their own ability to achieve the goals that they set for themselves specifically pertaining to engineering*. Although one factor was originally proposed the factor fission obtained on this scale nonetheless to some degree made substantive theoretical sense. The two factors that emerged from the factor analysis can therefore be interpreted as narrower facets of a second-order *academic self-efficacy* factor.

Only 34% of the inter-item correlations estimated from the extracted factor structure deviated more than .05 from the observed inter-item correlation matrix. The extracted 2-factor factor structure therefore presents a valid (i.e., permissible) and credible explanation of the observed inter-item correlation matrix.

To determine how well the items of the *Academic Self-Efficacy* scale reflect a single underlying latent variable an analysis was run where the extraction of a single factor was forced. The loading of the items on the single extracted factor can be seen in Table 4.. All items loaded onto the one factor with factor loadings larger than .50. The reproduced correlation matrix indicated that 32 (58%) nonredundant residuals with absolute values greater than .05 were obtained, which reflects the known fact that the single-factor factor solution does not provide a valid and credible explanation for the observed inter-item correlation matrix. It was nonetheless concluded that all 11 items that survived the item analysis could be used as indicators to reflect the *academic self-efficacy* latent variable interpreted as a second-order factor.

Table 4.23

Factor matrix when forcing the extraction of a single factor for the Academic Self-Efficacy scale

	Factor 1
ASE_11	.749
ASE_5	.749
ASE_10	.739
ASE_6	.730
ASE_9	.711
ASE_8	.710
ASE_7	.707
ASE_4	.690
ASE_1	.659
ASE_12	.627
ASE_2	.587

Note: ASL_1, ASL_2, ASL_4 – TCE_12 represent the 11 items from the *Academic Self-leadership* scale (item ASL_3 was deleted).

The reliability of the second-order *academic self-efficacy* score as an unweighted linear composite of two first-order *academic self-efficacy* factor scores was subsequently calculated via a formula proposed by Nunnally (1978) along with the reliability of the two first-order *academic self-efficacy* factor scores. When the multidimensional nature of the Academic Self-efficacy scale was ignored in the calculation of the coefficient of internal consistency a value of .912 (S_t^2=102.295) was obtained. When the reliability of the weighted composite is more appropriately calculated a reliability coefficient of 0.924 is obtained. The Cronbach alphas calculated for the two subscales formed from the loading pattern shown in Table 4.22 were .874 for the items loading on factor 1 (S_1^2= 42.273) and .879 for the items loading on factor 2 (S_2^2= 20.104).

4.5.4 Conscientiousness

In the item analysis item CON_3 was identified as a poor item and therefore it was deleted from the *Conscientiousness* scale. Based on the results of the item analysis the dimensionality analysis was therefore performed without CON_3. The observed correlation matrix indicated that majority of the correlations were larger than .30 and were statistically significant ($p < .05$). The *Conscientiousness* scale obtained a KMO of .807. These findings provided sufficient evidence that the scale is factor analysable. The Bartlett's test indicated that the null hypothesis that the inter-item correlation matrix is an identity matrix in the parameter can be rejected ($p < .05$), substantiating the KMO's findings that the correlation matrix was factor analysable.

Two factors had to be extracted in-order to adequately explain the observed correlation matrix, which is contrary to the proposed hypothesis of one factor in the original design of the scale. Two factors obtained eigenvalues greater than 1 with the scree plot also suggesting that two factors had to be extracted in-order to sufficiently explain the observed correlation matrix. The pattern matrix is depicted in Table 4.24.

The items that load onto the first factor appears to reflect the individual's *commitment to and diligence in his/her engineering course and the requirements of the course*. The second item reflects the individuals *planning with regards to study time and the execution of the set-out study timetable*. Although one factor was originally proposed the factor fission obtained on this scale nonetheless to some degree made substantive theoretical sense.

Table 4.24

Pattern matrix for the Conscientiousness scale

	Factor	
	1	2
CON_5	**.861**	-.040
CON_4	**.824**	-.078
CON_8	**.793**	.028
CON_6	**.736**	.060
CON_1	**.699**	.029
CON_2	**.631**	-.039
CON_9	**.492**	.077
CON_12	-.039	**.927**
CON_10	-.118	**.902**
CON_11	.079	**.805**
CON_7	.178	**.631**

Note: CON_1, CON_2, ASL_4 – CON_12 represent the 11 items from the *Conscientiousness* scale (item CON_3 was deleted).

The two factors that emerged from the factor analysis can therefore be interpreted as narrower facets of a second-order *conscientiousness* factor. Forty-seven (47%) of the inter-item correlations estimated from the extracted factor structure deviated more than .05 from the observed inter-item correlation matrix. The extracted 2-factor factor structure therefore presents a somewhat tenuous explanation for the observed inter-item correlation matrix. The analysis was subsequently re-ran forcing the extraction of three factors. Items CON_1 and CON_2 now loaded on factor 3 rather than on factor1. The percentage large residual correlations reduced to 18%. The identity of factor 3 could, however, not be clearly distinguished from the identity of factor 1. It was therefore decided to retain the 2-factor solution.

To determine how well the items of the *Conscientiousness* scale reflect a single underlying latent variable an analysis was run where the extraction of a single factor was forced. The loading of the items onto the single extracted factor as can be seen in
Table 4.25. All items loaded onto the one factor with factor loadings larger than .50, except for CON_10 that obtained a factor loading just marginally lower that the critical value of .50 (.487). This item was nonetheless still deemed as a satisfactory indicator of conscientiousness interpreted as a second-order factor. The reproduced correlation matrix indicated that 42 (76%) nonredundant residuals with absolute values greater than .05 were obtained, which reflects the known fact that the rotated factor solution does not provide a credible explanation for the observed inter-item correlation matrix. It was nonetheless concluded that all 11 items that survived the item analysis could be used as indicators to reflect the *academic self-efficacy* latent variable interpreted as a second-order factor.

Table 4.25

Factor matrix when forcing the extraction of a single factor for the Conscientiousness scale

	Factor 1
CON_8	.762
CON_5	.761
CON_6	.731
CON_4	.699
CON_1	.673
CON_11	.617
CON_7	.607
CON_12	.571
CON_2	.561
CON_9	.521
CON_10	.491

Note: CON_1, CON_2, ASL_4 – CON_12 represent the 11 items from the *Conscientiousness* scale (item CON_3 was deleted).

The reliability of the second-order *conscientiousness* score as an unweighted linear composite of two first-order *conscientiousness* factor scores was subsequently calculated via a formula proposed by Nunnally (1978) along with the reliability of the two first-order *conscientiousness* factor scores. When the multidimensional nature of the *Conscientiousness* scale was ignored in the calculation of the coefficient of internal consistency a value of .876 (S_t^2=117.863) was obtained. When the reliability of the weighted composite is more appropriately calculated a reliability coefficient of .919 is obtained. The Cronbach alphas calculated for the two subscales formed from the loading pattern shown in Table 4.24 24 were .881 for the items loading on factor 1 (S_1^2=47.009) and .894 for the items loading on factor 2 (S_2^2=37.637).

4.5.5 Learning Motivation

No items were flagged in the item analysis as problematic. The exploratory factor analysis was therefore performed on all the items originally included in the *Learning Motivation* scale. The observed correlation matrix indicated that majority of the correlations were larger than .30 and all were statistically significant ($p < .05$). The *Learning Motivation* scale obtained a KMO of .856. These findings provided sufficient evidence that the scale was factor analysable. The Bartlett's test indicated that the null hypothesis that the inter-item correlation matrix is an identity matrix in the parameter can be rejected ($p < .05$), substantiating the KMO's findings that the correlation matrix was factor analysable.

One factor was extracted in-order to adequately explain the observed correlation matrix, which is in-line with the proposed hypothesis of one factor in the original design of the scale. One

factor obtained an eigenvalue greater than 1 with the scree plot also suggesting that one factor should be extracted in-order to sufficiently explain the observed correlation matrix. All the factor loadings were bigger than .60 and 4 (26%) nonredundant residuals with absolute values greater than .05 were obtained, which suggests that the single-factor factor solution provides a valid and credible explanation for the observed inter-item correlation matrix. The resultant factor structure is depicted in Table 4.26. The uni-dimensionality assumption for this scale was therefore corroborated.

Table 4.26

Factor matrix Learning Motivation

	Factor 1
LMOT_3	.892
LMOT_4	.844
LMOT_2	.706
LMOT_5	.706
LMOT_6	.635
LMOT_1	.627

Note: LMOT_1 – LMOT_6 represent the 11 items from the *Learning Motivation* scale.

4.5.6 Transfer of Knowledge

In the item analysis items TK_11 and TK_24R were identified as possible poor items, however it was decided due to the small increase in the Cronbach's alpha that the deletion of the items would bring not to delete these two items. Based on the results of the item analysis the dimensionality analysis was therefore performed with these two items included. The observed correlation matrix indicated that majority of the correlations were larger than .30 and were statistically significant ($p < .05$). The *Transfer of Knowledge* scale obtained a KMO of .896. These findings provided sufficient evidence that the scale is factor analysable. The Bartlett's test indicated that the null hypothesis that the inter-item correlation matrix is an identity matrix can be rejected ($p < .05$), substantiating the KMO's findings that the correlation matrix was factor analysable. Five factors had to be extracted based on the eigenvalues-greater-than-1 rule. The scree plot was rather ambivalent but could be interpreted to suggest the extraction of 4 factors. The extracted 5-factor solution adequately explained the observed correlation matrix with only 19% of the residual correlations larger than .05. The pattern matrix is shown in Table 4.27. Through closer observation, it was detected that items TK_1R, TK_5, TK_6, TK_7, TK_10R, TK_13, and TK_27 had a similar loading pattern across more than one of the extracted factors; therefore, it was decided to delete these items that cross-loaded and run the analysis again.

Table 4.27

Pattern matrix for the Transfer of Knowledge scale

	1	2	3	4	5
TK_21	**.814**	.069	.112	-.080	.077
TK_16	**.660**	-.051	-.113	.045	-.104
TK_15	**.618**	.174	.132	.090	-.222
TK_14	**.546**	.027	-.155	.082	-.277
TK_17	**.536**	.108	.006	.247	-.225
TK_22	**.482**	-.078	-.170	.209	-.054
TK_13	.383	-.032	-.278	.084	-.363
TK_6	.344	-.103	-.286	.251	-.182
TK_20R	-.046	**.891**	.055	.029	-.052
TK_19R	.081	**.748**	-.134	.112	-.098
TK_23R	.029	**.711**	-.061	-.130	-.189
TK_25R	-.137	**.646**	-.190	.148	-.163
TK_24R	.227	**.643**	-.036	-.038	.283
TK_9R	-.016	.084	**-.845**	-.111	.009
TK_8R	-.040	.240	**-.682**	-.085	-.079
TK_18R	-.006	.329	**-.507**	.301	.127
TK_7	.301	-.243	-.429	.105	-.378
TK_10R	.157	.351	-.380	-.287	.039
TK_11	-.089	-.087	.291	**.702**	-.146
TK_2	.222	.091	.001	**.647**	.174
TK_26	.095	-.052	-.352	**.526**	-.107
TK_4	.066	.249	-.045	**.518**	-.253
TK_5	.403	.001	-.155	.404	.029
TK_12	.200	.199	.092	.077	**-.629**
TK_3	.303	.150	.019	.060	**-.572**
TK_1R	.036	.271	-.269	-.059	-.368
TK_27	.233	.056	-.142	.116	-.274

Note: TK_2 – TK_7, TK_11 – TK_17, TK_21- TK_22, TK_26, TK_27 represent the 17 items from the *Knowledge Transfer* scale that were not reflected and TK_1R, TK_8R - TK_10R, TK_18R -TK_20R, TK_23R – TK_25R represent the 10 items from the *Knowledge Transfer* scale that were reflected.

The analysis was subsequently run again without the deleted items. The eigenvalue-greater-than-one rule again indicated the extraction of 5 factors. Item TK_12 now showed itself to cross load on factors 1 and 5. It was decided to also delete TK_12 and again run the EFA.

After the items were deleted only four factors had to be extracted in-order to adequately explain the observed correlation matrix. The extracted 4-factor factor structure was found to present a valid and credible explanation for the observed inter-item correlation matrix in that only 14% of the residual correlations were greater than .05. Although one less factor was extracted, it is still contrary to the proposed hypothesis of one factor in the original design of the scale. Four factors obtained eigenvalues greater than 1 with scree plot also suggesting that four factors had to be extracted in-order to sufficiently explain the observed correlation matrix. The pattern matrix is depicted in Table 4.28.

Table 4.28

Pattern matrix for the reduced Transfer of Knowledge scale

	1	2	3	4
TK_16	**.822**	.130	-.149	-.047
TK_21	**.740**	-.027	.098	-.112
TK_15	**.733**	-.160	.112	.069
TK_14	**.707**	-.020	-.172	.077
TK_17	**.669**	-.075	-.021	.228
TK_3	**.525**	-.157	-.010	.198
TK_22	**.511**	.065	-.109	.211
TK_20R	-.062	**-.918**	.076	.017
TK_19R	.106	**-.768**	-.087	.132
TK_23R	.110	**-.731**	-.067	-.119
TK_25R	-.085	**-.671**	-.199	.134
TK_24R	.079	**-.639**	.001	-.150
TK_9R	.038	.000	**-.916**	-.119
TK_8R	.054	-.161	**-.751**	-.072
TK_18R	-.009	-.332	**-.417**	.227
TK_11	-.017	.166	.190	**.717**
TK_4	.159	-.236	-.062	**.622**
TK_26	.168	.043	-.315	**.552**
TK_2	.160	-.074	.047	**.550**

Note: TK_2 – TK_4, TK_11, TK_13 – TK_17, TK_22, TK_26, represent the 11 items from the *Knowledge Transfer* scale that were not reflected and TK_8R, TK_9R, TK_18R -TK_20R, TK_23R – TK_25R represent the 8 items from the *Knowledge Transfer* scale that were reflected (items TK_1R, TK_5, TK_6, TK_7, TK_10R, TK_12, TK_13, and TK_27 were deleted).

The first factor refers to the individual's *ability to effectively identify and combine different elements of a problem that he/she is faced with in-order to solve the problem*. The second factor refers to the individual's *inability to make sense of the work or problem that he/she was faced with*. The third factor refers to the individuals *need for assistance in-order to make sense of work that they didn't understand or in-order to solve a new problem*. The fourth factor refers to the individual's *ability to transfer previously obtained knowledge in-order to make sense of and solve a novel problem*. Although one factor was originally proposed the factor fission obtained on this scale nonetheless to some degree made substantive theoretical sense. The four factors that emerged from the factor analysis can therefore be interpreted as narrower facets of a second-order *transfer of knowledge* factor.

To determine how well the items of the *Transfer of Knowledge* scale reflect a single underlying latent variable an analysis was run where the extraction of a single factor was forced. The manner in which the retained transfer of knowledge items loaded onto the single extracted factor as can be seen in Table 4.29. All items loaded onto the one factor with factor loadings larger than .50 being obtained for all of the items, except for TK_2, TK_24R and TK_11 that obtained a factor loading lower than .50. Items TK_24R and TK_2 were still deemed as satisfactory. Items TK_11 obtained a factor loading lower than .20 and was therefore deemed as unsatisfactory and therefore deleted. The analysis was ran again (see Table 4.30) without

the deleted item. The reproduced correlation matrix indicated that 128 (83%) nonredundant residuals with absolute values greater than .05 were obtained, which reflects the fact that the single-factor factor solution does not provide a credible explanation for the observed inter-item correlation matrix. It was nonetheless concluded that the 18 retained items that survived the dimensionality analysis could be used as indicators to reflect the *transfer of knowledge* latent variable interpreted as a second-order factor.

Table 4.29

Factor matrix when forcing the extraction of a single factor for the reduced Transfer of Knowledge scale

	Factor 1
TK_19R	.768
TK_14	.760
TK_17	.750
TK_15	.696
TK_3	.675
TK_4	.671
TK_16	.654
TK_18R	.620
TK_25R	.607
TK_26	.597
TK_23R	.592
TK_8R	.574
TK_22	.565
TK_20R	.556
TK_21	.515
TK_9R	.511
TK_2	.448
TK_24R	.445
TK_11	.121

Note: TK_2 – TK_4, TK_11, TK_13 – TK_17, TK_22, TK_26, represent the 11 items from the *Knowledge Transfer* scale that were not reflected and TK_8R, TK_9R, TK_18R -TK_20R, TK_23R – TK_25R represent the 8 items from the *Knowledge Transfer* scale that were reflected (items TK_1R, TK_5, TK_6, TK_7, TK_10R, TK_12, TK_13, and TK_27 were deleted).

Table 4.30

Factor matrix when forcing the extraction of a single factor for the reduced Transfer of Knowledge scale with TK_11 deleted

	Factor 1
TK_19R	.774
TK_14	.758
TK_17	.745
TK_15	.692
TK_3	.672
TK_4	.663
TK_16	.651
TK_18R	.623
TK_25R	.612

TK_23R	.600
TK_26	.591
TK_8R	.582
TK_20R	.562
TK_22	.561
TK_9R	.519
TK_21	.513
TK_24R	.453
TK_2	.439

Note: TK_2 – TK_4, TK_11, TK_13 – TK_17, TK_22, TK_26, represent the 11 items from the *Knowledge Transfer* scale that were not reflected and TK_8R, TK_9R, TK_18R -TK_20R, TK_23R – TK_25R represent the 8 items from the *Knowledge Transfer* scale that were reflected (items TK_1R, TK_5, TK_6, TK_7, TK_10R, TK_12, TK_13, and TK_27 were deleted).

The reliability of the second-order *transfer of knowledge* score as an unweighted linear composite of four first-order *transfer of knowledge* factor scores was subsequently calculated via a formula proposed by Nunnally (1978) along with the reliability of the two first-order *transfer of knowledge* factor scores. When the multidimensional nature of the *Transfer of Knowledge* scale was ignored in the calculation of the coefficient of internal consistency a value of .932 (S_t^2= 232.945) was obtained. When the reliability of the weighted composite is more appropriately calculated a reliability coefficient of .941 is obtained. The Cronbach alphas calculated for the two subscales formed from the loading pattern shown in Table 4.28 were .887 for the items loading on factor 1 (S_1^2= 30.913), .885 for the items loading on factor 2 (S_2^2= 36.541), .820 for the items loading on factor 3 (S_3^2= 14.612) and .762 for the items loading on factor 4 (S_4^2= 14.742).

4.5.7 Automisation

In the item analysis items AUTO_2, AUTO_5R and AUTO_15R, were identified as poor items and therefore were deleted from the scale. Based on the results of the item analysis the dimensionality analysis was performed without these items. The observed correlation matrix indicated that majority of the correlations were larger than .30 and were statistically significant ($p < .05$). The *Automisation* scale obtained a KMO of .867 providing sufficient evidence that the scale is factor analysable. The Bartlett's test indicated that H_0 can be rejected ($p < .05$), substantiating the KMO's findings that the correlation matrix was factor analysable. Two factors had to be extracted in terms of the eigenvalue-greater-than-one rule. The scree plot also suggested the extraction of two factors. The 2-factor factor structure reasonably adequately explained the observed correlation matrix with 39% of the residual correlations greater than .05. Through closer observation, it was found that AUTO_14 had a similar loading

pattern across the two extracted factors it was therefore decided to delete this cross-loading item and run the analysis again.

The analysis was run again without the four deleted items. Two factors had to be extracted in-order to adequately explain the observed correlation matrix, which is contrary to the proposed hypothesis of one factor in the original design of the scale. Two factors obtained eigenvalues greater than 1 with the pattern matrix also depicting that two factors had to be extracted in-order to sufficiently explain the observed correlation matrix. The pattern matrix is depicted in Table 4.31.

Table 4.31

Pattern matrix for the reduced Automisation scale

	1	2
AUTO_9	**.751**	.000
AUTO_12	**.733**	.085
AUTO_16	**.685**	-.099
AUTO_10R	**.656**	-.176
AUTO_17R	**.644**	.065
AUTO_8	**.639**	.217
AUTO_13	**.587**	.226
AUTO_18	**.553**	.082
AUTO_11	**.423**	.266
AUTO_4	-.027	**.723**
AUTO_7	.110	**.715**
AUTO_3	.133	**.607**
AUTO_6	.091	**.605**
AUTO_1	-.088	**.600**

Note: AUTO_1, AUTO_3 – AUTO_4, AUTO_6 – AUTO_9, AUTO_11 – AUTO_13, AUTO_16, AUTO_18 represent the 12 items from the *Automisation* scale that were not reflected and AUTO_10R, AUTO_17R represent the 2 items from the *Automisation* scale that were reflected (items AUTO_2, AUTO_5R, AUTO_14, and AUTO_15R)

The first factor refers to the extent to which the individual has *internalised the material that was covered during the semester and the level to which they have mastered the material*. The second factor referred to *knowledge that the individual had already internalised and the extent to which it could be used to make sense of novel problems they encountered in his/her engineering course*. Although one factor was originally proposed the factor fission obtained on this scale nonetheless to some degree made substantive theoretical sense. The two factors that emerged from the factor analysis can therefore be interpreted as narrower facets of a second-order *automisation* factor.

To determine how well the items of the *Automisation* scale reflect a single underlying latent variable an analysis was run where the extraction of a single factor was forced. The manner in which the retained items of the Automisation scale load onto the single extracted factor as

can be seen in Table 4.32. All items loaded onto the one factor with factor loadings larger than .50, except for AUTO_10R and AUTO_1 that obtained a factor loading lower than .50. Item AUTO_10R was still deemed as satisfactory obtaining a factor loading of .470. Item AUTO_1 obtained a factor loading of .364, which was deemed as unsatisfactory and therefore it was deleted. The analysis was ran again without AUTO_1 (see Table 4.33). The reproduced correlation matrix indicated that 38 (48%) nonredundant residuals with absolute values greater than .05 were obtained, which reflects the fact that the single-factor factor solution does not provide a credible explanation for the observed inter-item correlation. It was nonetheless concluded that the13 retained items that survived the dimensionality analysis could be used as indicators to reflect the *automisation* latent variable interpreted as a second-order factor.

Table 4.32

Factor matrix when forcing the extraction of a single factor for the reduced Automisation scale

	Factor 1
AUTO_8	.762
AUTO_12	.742
AUTO_13	.720
AUTO_9	.688
AUTO_17R	.645
AUTO_7	.626
AUTO_11	.599
AUTO_18	.575
AUTO_3	.573
AUTO_16	.551
AUTO_6	.534
AUTO_4	.503
AUTO_10R	.465
AUTO_1	.364

Note: AUTO_1, AUTO_3 – AUTO_4, AUTO_6 – AUTO_9, AUTO_11 – AUTO_13, AUTO_16, AUTO_18 represent the 12 items from the *Automisation* scale that were not reflected and AUTO_10R, AUTO_17R represent the 2 items from the *Automisation* scale that were reflected (items AUTO_2, AUTO_5R, AUTO_14, and AUTO_15R)

The reliability of the second-order *automisation* score as an unweighted linear composite of two first-order *automisation* factor scores was subsequently calculated via a formula proposed by Nunnally (1978) along with the reliability of the two first-order *automisation* factor scores. When the multidimensional nature of the *Transfer of Knowledge* scale was ignored in the calculation of the coefficient of internal consistency a value of .883 (S_t^2= 64.194) was obtained. When the reliability of the weighted composite is more appropriately calculated a reliability coefficient of .90 is obtained. The Cronbach alphas calculated for the two subscales formed from the loading pattern shown in Table 4.31 were .874 for the items loading on factor 1 (S_1^2= 40.388) and .800 for the items loading on factor 2 (S_2^2= 7.130).

Table 4.33

Factor matrix Automisation AUTO_1 deleted

	Factor 1
AUTO_8	.770
AUTO_12	.757
AUTO_13	.717
AUTO_9	.706
AUTO_17R	.655
AUTO_11	.602
AUTO_7	.597
AUTO_18	.577
AUTO_16	.575
AUTO_3	.557
AUTO_6	.510
AUTO_4	.493
AUTO_10R	.476

Note: AUTO_2, AUTO_3 – AUTO_4, AUTO_6 – AUTO_9, AUTO_11 – AUTO_13, AUTO_16, AUTO_18 represent the 11 items from the Automisation scale that were not reflected and AUTO_10R, AUTO_17R represent the 2 items from the Automisation scale that were reflected (items Auto_1, AUTO_2, AUTO_5R, AUTO_14, and AUTO_15R)

4.6 ITEM AND DIMENSIONALITY ANALYSIS: CONCLUDING REMARKS

The purpose of the item and dimensionality analysis was to gain an understanding into the psychometric integrity of the indicator variables that were proposed to be representative of each of the latent variables. The initial item analysis indicated that five of the seven behavioural scales that were analysed achieved an alpha value exceeding .80. The *Transfer of Knowledge* and *Automisation* scales indicated Cronbach's alphas of .761 and .667. After some of the items in these two scales were reflected both of these scales achieved a Cronbach's alpha value exceeding .80. The item statistics revealed some poor items in the various scales, which were flagged, and after gaining a basket of evidence incriminating these items, seven items were deleted across the seven scales[32]. The dimensionality analyses indicated that only one (*Learning Motivation*) of the seven scales met the uni-dimensionality assumption. In two of the scales where more than one factor was extracted items loaded similarly across more than one of the extracted factors. These eight items were deleted from the two scales. In the six scales that did not meet the hypothesised uni-dimensionality assumption the items were successfully forced onto a single factor solution. Four items were deleted due to unsatisfactory loadings on two of the extracted single factors[33]. When the reliability analysis was repeated on the narrower facets identified via the dimensionality analysis satisfactory reliability coefficients were obtained.

[32] The items that were deleted are:TCE_9, TCE_14, ASE_3, CON_3, AUTO_2, AUTO_5R and AUTO_15R
[33] The items that were deleted are: ASL_4, ASL_5, TK_12 and AUTO_1

4.7 TEST OF UNIVARIATE AND MULTIVARIATE NORMALITY

The overarching and path-specific substantive hypotheses were evaluated by fitting the comprehensive LISREL model[34]. To fit the comprehensive LISREL model the structural model had to be operationalised via the measurement model. The small sample size precluded any possibility of even considering the use of individual items as indicators to operationalise the latent variables comprising the structural model. Two item parcels were consequently created for the *time cognitively engaged*, *academic self-leadership*, *academic self-efficacy, conscientiousness*, *learning motivation*, *transfer*, *automisation*, *fluid intelligence* and *information processing capacity* latent variables by calculating the mean of the even and uneven numbered items. A single total score was used to represent the *prior learning* and the *learning performance* latent variables. The mathematics mark obtained in matric was used to operationalise *prior learning for first-year respondents.* The engineering mathematics mark obtained in the current year of study[35] was used to operationalise *learning performance*. The orthoganalising procedure (Little et al., 2006) used to operationalise the latent interaction effects in the structural model was described in Chapter 3.

Post learning was a new latent variable that the current study introduced into the learning potential structural model. It was considered a rather pivotal latent variable in the sense that it allowed the proposed structural model to formally acknowledge the spiralling dynamics of learning. At the heart of learning lies the two behavioural learning competencies of *transfer of knowledge* and *automisation*. The extent to which transfer of knowledge occurs is (*inter alias*) determined by the level of fluid intelligence, the level of crystallised intelligence relevant to the learning material (or level of prior learning) and the interaction between the two. The current study would want to hypothesise that this is true for transfer in the classroom but also transfer in subsequent learning. Learning (i.e. *transfer of knowledge*) also takes place during examinations or tests when learners are confronted with novel learning material/problems in which they need to create meaningful structure. Here again the extent to which transfer (or

[34] The comprehensive LISREL model consists of the measurement model that specifies the structural relationships that were hypothesised to exist between the latent variables and the indicator variables and the structural model that specifies the structural relationships that were hypothesised to exist between the latent variables.

[35] Initially the intention was to only sample from the sampling population of first year engineering students at Stellenbosch University and to use their engineering mathematics mark obtained at the end of the first semester as a measure of learning performance. A too small number of respondents that agreed to complete the research questionnaire forced the redefinition of the sampling population to also include non-final year and final year engineering students. This in turn necessitated finding an alternative measures that reflected the respondents level of learning performance and their level of crystallised mathematical knowledge at the outset of the development opportunity. In the case of non-final year and final year engineering students learning performance was measured by their average mark for all their subjects obtained at the end of the first semester. Prior learning for non-final year and final year engineering students was measured by the average mathematics mark obtained in the year preceding their current year of study. It is acknowledged that this introduced unwanted non-relevant systematic variance in these indicator variables. This is acknowledged as a methodological limitation.

then *learning performance during evaluation*) occurs is (*inter alias*) determined by the level of fluid intelligence, the level of crystallised intelligence relevant to the learning material (or level of *post learning* at the end of the development module on which the examination or test is written) and the interaction between the two. Initially the intention was to measure *post knowledge* by constructing a test that purely measures the extent to which newly derived mathematical insight during the development model had been successfully automated and lies ready to be used as the basis for subsequent transfer onto the novel problems presented in the examination or test. What distinguishes a measure of *post knowledge* (or *prior knowledge* for that matter) from a measure of *learning performance* is therefore that the test stimuli had been encountered in the development module in the case of the former but not in the case of the latter. This clearly required input from subject matter experts familiar with the content of module in question. Despite the pivotal role that *post learning* was hypothesised to play in the psychological mechanism regulating differences in *learning performance,* and despite that fact that it was in principle practically feasible to measure the construct (although practically challenging[36]), the current study nonetheless failed to include a scale to measure this construct in the composite research questionnaire purely due to a highly unfortunate oversight. This omission necessitated the revision of the originally hypothesised structural model that was derived via theorising in Chapter 2[37].

In-order to continue with structural equation modelling a number of critical assumptions had to be met. To be able to continue with the main analyses it was required to assess the extent to which the data complies with these assumptions. According to Mels (2003) failure of the data to satisfy these assumptions can seriously erode the quality of obtained solutions. One factor in particular that was considered was the effect of non-normality. According to Mels (2003), the default method of estimation when fitting measurement and structural models to continuous data (maximum likelihood estimation) assumes that the distribution of indicator variables follows a multivariate normal distribution (Mels, 2003). Mels (2003) as well as Du Toit and Du Toit (2001), state that the inability to satisfy this assumption results in incorrect standard errors and chi-square estimates.

When evaluating structural models through LISREL, the individual items comprising the scales can be used to operationalise the latent variables comprising the model. This, however, can be problematic due to the fact that it can lead to cumbersome comprehensive models in which a large number of model parameters have to be estimated. A possible solution is the formation of item parcels of indicator variables from the items of each scale used to operationalise the

[36] The fact that the study had to extend the sampling population from first year engineering students to all undergraduate Engineering students registered at Stellenbosch University in 2017 substantially exacerbated the practical challenge.
[37] The reduced learning potential structural model is described in paragraph 4.8.

latent variables in the structural model. The results that were obtained in the item and exploratory factor analysis warranted the formation of item parcels for each of the latent variables. In-order to create these item parcels (composite variables) even and uneven numbered items were grouped together[38] in SPSS by calculating the mean and imported into PRELIS. The items that were deleted during the item and dimensionality analysis were not included in the item parcels. The univariate and multivariate normality of the composite item parcels in this study was evaluated via PRELIS. These results are depicted in Table 4.34 and Table 4.35 below.

Table 4.34

Test of univariate normality before normalisation

Variable	Z-Score	P-Value	Z-Score	P-Value	Chi-Square	P-Value
ZTCE_P1	-1.728	0.084	0.149	0.882	3.008	0.222
ZTCE_P2	-1.936	0.053	0.899	0.369	4.555	0.103
ZASE_P1	-0.912	0.362	-0.640	0.522	1.240	0.538
ZASE_P2	-2.228	0.026	-0.163	0.871	4.992	0.082
ZCON_P1	-0.688	0.491	-0.176	0.860	0.505	0.777
ZCON_P2	-0.856	0.392	0.268	0.789	0.804	0.669
ZLMOT_P1	-1.862	0.063	0.019	0.985	3.468	0.177
ZLMOT_P2	-1.421	0.155	-1.298	0.194	3.705	0.157
ZTK_P1	1.245	0.213	0.655	0.512	1.979	0.372
ZTK_P2	-1.467	0.142	2.213	0.027	7.050	0.029
ZAUTO_P1	-2.775	0.006	2.709	0.007	15.039	0.001
ZAUTO_P2	-1.079	0.280	0.476	0.634	1.391	0.499
ZASL_P1	1.044	0.297	1.074	0.283	2.242	0.326
ZASL_P2	0.603	0.546	1.422	0.155	2.387	0.303
ZLP	-4.722	0.000	4.254	0.000	40.396	0.000
RES_1	-5.950	0.000	5.183	0.000	62.266	0.000
RES_2	-5.189	0.000	5.477	0.000	56.926	0.000
RES_3	-4.838	0.000	4.782	0.000	46.270	0.000
RES_4	-3.957	0.000	5.407	0.000	44.894	0.000
RES_5	0.706	0.480	3.423	0.001	12.216	0.002
RES_6	-2.005	0.045	4.957	0.000	28.593	0.000
RES_7	-4.357	0.000	5.008	0.000	44.063	0.000
RES_8	-2.411	0.016	5.666	0.000	37.924	0.000
RES_9	-5.024	0.000	6.368	0.000	65.796	0.000
RES_10	-1.948	0.051	6.865	0.000	50.923	0.000

Note: ZTCE_PI, ZTCE_P2, ZASE_P1, ZASE_P2, ZCON_P1, ZCON_P2, ZLMOT_P1, ZLMOT_P2, ZTK_P1, ZTK_P2, ZAUTO_P1, ZAUTO_P2, ZASL_P1, ZASL_P2 and ZLP represent the standardised item parcels for the *Time Cognitively Engaged, Academic Self-efficacy, Conscientiousness, Learning Motivation, Transfer of Knowledge, Automisation, Academic Self-Leadership* and *Learning Performance* latent variables. RES_1 – RES_10 are the standardised indicators for the latent interaction effects in the reduced learning potential structural model

Table 4.35

Test of multivariate normality before normalisation

Skewness			Kurtosis			Skewness and Kurtosis	
Value	**Z-Score**	**P-Value**	**Value**	**Z-Score**	**P-Value**	**Chi-Square**	**P-Value**
256.629	20.916	0.000	787.334	9.536	0.000	528.404	0.000

[38] It is acknowledged that literature generally recommends the formation of unidimensional parcels. In the current study this would have required that the formation of parcels be guided by the pattern matrices.

The observed chi-square value for skewness and kurtosis indicates that eight of the thirty indicator variables failed the test of univariate normality (p<.05). The null hypothesis that the data follows a multivariate normal distribution also had to be rejected (X^2 = 671.648; p<.05). Since the assumption of multivariate normality is of critical importance in structural equation modelling it was decided to normalise the variables through PRELIS. The results for the normalised data are presented in Table 4.36 and Table 4.37.

Table 4.36

Test of univariate normality after normalisation

Variable	Z-Score	P-Value	Z-Score	P-Value	Chi-Square	P-Value
ZTCE_P1	-0.017	0.987	0.097	0.922	0.010	0.995
ZTCE_P2	-0.020	0.984	0.106	0.915	0.012	0.994
ZASE_P1	0.026	0.979	0.020	0.984	0.001	0.999
ZASE_P2	-0.005	0.996	0.000	1.000	0.000	1.000
ZCON_P1	-0.076	0.939	-0.034	0.973	0.007	0.997
ZCON_P2	0.006	0.996	0.120	0.905	0.014	0.993
ZLMOT_P1	-0.274	0.784	-0.346	0.729	0.195	0.907
ZLMOT_P2	-0.228	0.820	-0.338	0.735	0.167	0.920
ZTK_P1	0.014	0.988	0.092	0.927	0.009	0.996
ZTK_P2	-0.008	0.994	0.096	0.923	0.009	0.995
ZAUTO_P1	-0.028	0.978	0.135	0.892	0.019	0.990
ZAUTO_P2	0.010	0.992	0.115	0.908	0.013	0.993
ZASL_P1	-0.007	0.995	0.112	0.911	0.013	0.994
ZASL_P2	-0.002	0.999	0.089	0.929	0.008	0.996
ZLP	0.096	0.923	-0.064	0.949	0.013	0.993
RES_1	0.000	1.000	0.118	0.906	0.014	0.993
RES_2	0.000	1.000	0.118	0.906	0.014	0.993
RES_3	0.000	1.000	0.118	0.906	0.014	0.993
RES_4	0.000	1.000	0.118	0.906	0.014	0.993
RES_5	0.000	1.000	0.118	0.906	0.014	0.993
RES_6	-0.001	0.999	0.117	0.907	0.014	0.993
RES_7	0.000	1.000	0.118	0.906	0.014	0.993
RES_8	0.001	0.999	0.117	0.907	0.014	0.993
RES_9	0.000	1.000	0.118	0.906	0.014	0.993
RES_10	0.001	0.999	0.117	0.907	0.014	0.993

Note: ZTCE_PI, ZTCE_P2, ZASE_P1, ZASE_P2, ZCON_P1, ZCON_P2, ZLMOT_P1, ZLMOT_P2, ZTK_P1, ZTK_P2, ZAUTO_P1, ZAUTO_P2, ZASL_P1, ZASL_P2 and ZLP represent the standardised item parcels for the *Time Cognitively Engaged, Academic Self-efficacy, Conscientiousness, Learning Motivation, Transfer of Knowledge, Automisation, Academic Self-Leadership* and *Learning Performance* latent variables. RES_1 – RES_10 are the standardised indicators for the latent interaction effects in the reduced learning potential structural model.

Table 4.37

Test of multivariate normality after normalisation

Skewness			Kurtosis			Skewness and Kurtosis	
Value	Z-Score	P-Value	Value	Z-Score	P-Value	Chi-Square	P-Value
207.998	11.742	0.000	738.069	7.022	0.000	187.173	0.000

The normalisation procedure was successful in rectifying the univariate normality problem on all indicator variables as can be seen in Table 4.36. As can be seen in Table 4.37 the chi-square improved by decreasing from 528.404 to 187.173, however the null hypothesis that the data follows a multivariate normal distribution still had to be rejected ($p<.05$).

Seeing that the multivariate normality assumption was not satisfied maximum likelihood estimation, which is the default method when fitting the measurement and structural models to continuous data according to Mels (2003), could not be used. Du Toit and Du Toit (2001) state that the inappropriate analysis of continuous non-normal variables in structural equation models can result in incorrect standard errors and chi-square estimates. In-order to continue with the analysis an alternative method of estimation more suited to data not following a multivariate normal distribution had to be considered. The possible alternatives estimation methods proposed by Du Toit and Du Toit (2001) and Mels (2003) to use when fitting structural equation models to non-normal data are; weighted least squares (WLS), diagonally weighted least squares (DWLS) and robust maximum likelihood (RML). It was decided to make use of RML estimation in this study, which required the computation of an asymptotic covariance matrix via PRELIS. This was done in-order to enable the calculation of more appropriate fit indices in LISREL. Due to the improvement in the chi-square value after the normalisation of the data it was decided to make use of the normalised data to calculate the asymptotic covariance matrix.

4.8 EVALUATING THE FIT OF THE MEASUREMENT MODEL VIA CONFIRMATORY FACTOR ANALYSIS IN LISREL

The relationship between the learning potential latent variable and its manifest indicators are represented through the measurement model and is expressed through the following equation:

$$\mathbf{X} = \mathbf{\Lambda}^{x}\boldsymbol{\xi} + \boldsymbol{\delta} \quad \text{----------} [3]$$

The symbol $\mathbf{\Lambda}^{x}$ represents the 25 x 11 matrix of lambda coefficients[39] (λ), which indicate the loading of the indicators on their designated latent variables. The symbol $\boldsymbol{\xi}$ (ksi) is used to signify the 11 x 1 vector of latent variables and the symbol $\boldsymbol{\delta}$ (delta) is used to indicate a 25 x 1 vector of measurement error terms (Diamantopoulos & Siguaw, 2000). $\mathbf{X}$ is representative of a 25 x 1 vector of composite indicator variables. Equation 3 does not fully define the fitted

[39] In total there were 30 indicator variables and 14 latent variables. *Abstract thinking capacity*, *prior knowledge* and *information processing capacity* were, however, not included as main effects in the hypothesises structural model. These latent variables and their indicators were therefore not included in the measurement model.

measurement model. The 30 x 30 measurement error variance-covariance matrix Θ_δ and the 14 x 14 latent variable variance-covariance matrix Φ also need to be defined to fully specify the fitted measurement model. Since the measurement error terms were assumed to be uncorrelated Θ_δ was defined as a diagonal matrix. The latent variables comprising the structural model were assumed to be correlated hence the off-diagonal of Φ was freed to be estimated.

Confirmatory factor analysis was used to determine the extent to which the operationalisation of the latent variables comprising the structural model in terms of item parcels was successful. The operationalisation can be considered successful if the measurement model specified in the equation above can successfully reproduce the observed covariance matrix, meaning if the model fits well, and if the measurement model parameter estimates indicate that the majority of the variance in the indicator variables can be explained in terms of the latent variables they were asked to reflect.

The analysis was run to determine the fit of the estimated learning potential measurement model by testing the following hypotheses:

The exact fit null hypothesis:

$$H_{01a}: \text{RMSEA} = 0$$

$$H_{a1a}: \text{RMSEA} > 0$$

The close fit null hypothesis:

$$H_{01b}: \text{RMSEA} \leq .05$$

$$H_{a1b}: \text{RMSEA} > .05$$

In the first attempt to run the analysis the model failed to converge. The researchers recognised this as a potential problem before the data analysis was undertaken. Due to the length of the survey and the reluctance of people to fill in surveys, only 114 complete responses were obtained. The total number of freed parameters in the measurement model was 114[40]. As mentioned in section 3.8 under sampling elaborate measurement and structural models which contain more variables and have more freed parameters that have to be estimated, require larger sample sizes. In an attempt to reduce the number of freed parameters in the measurement model equality constraints were introduced in the specification of the measurement model.

[40] The number of freed parameters were made up of 25 λ_{ij},, 25 $\theta_{\delta ii}$, 9 $\theta_{\delta ik}$ and 55 ϕ_{jp}.

Measurement models describe the nature of the relationships that exist between indicator variables and the underlying (unidimensional) latent variables they reflect. The measurement model specification in Equation 3 can be extended by explicitly modelling the intercept of the regression of X_i on ξ_j[41]. Equation 4 specifies a measurement model in which the regression slopes as well as the regression intercepts are explicitly modelled.

$$\mathbf{X} = \tau + \Lambda^{X}\xi + \delta \text{----------} [4]$$

Where:

- X is a 25 x 1 column vector of observed indicator variable scores;
- τ is a 25 x 1 column vector of intercept terms describing the regression of X_i on ξ_j;
- Λ is a 25 x 11 matrix of slope terms describing the regression of X_i on ξ_j;
- ξ is a 11 x 1 column vector of (unidimensional) latent variables measured by X_i; and
- δ is a 25 x 1 column vector of measurement error terms representing random as well as systematic non-relevant sources of variance in X_i.

In addition, in specifying the relationships that exist between indicator variables and the underlying (unidimensional) latent variables they reflect:

- the measurement error terms were defined as independent of each other (i.e. the 25 x 25 measurement error variance-covariance matrix Θ_δ was specified to be a diagonal matrix); and
- the latent variables were allowed to correlate (i.e. 11 x 11 latent variable variance-covariance matrix Φ was specified as a full matrix).

Although this is too seldom explicitly acknowledged, Equation 4 and the description of Φ and Θ_δ still does not fully specify the measurement model. Measurement models can differ in terms of the assumptions made about the elements of τ, Λ^X, and Θ_δ. More specifically measurement models can differ in terms of the equality constraints they impose on the elements of τ, Λ^X, and Θ_δ. Graham (2006) distinguishes between the following four measurement models:

- The classically parallel model;
- The tau-equivalent model;
- The essentially tau-equivalent model; and
- The congeneric model

The classically parallel model constrains the elements of τ, Λ^X, and Θ_δ to be equal across the indicators of each latent variable. “All items must measure the same latent variable, on the same scale, with the same degree of precision, and with the same amount of error” (Raykov,

[41] In Equation 3 the intercept of the regression of X_i on ξ_j has been fixed to zero.

1997a, 1997b). All item true scores are assumed to be equal to one another, and all error scores are likewise equal across items" (Graham, 2006, p. 934). The classically parallel measurement model assumes that the regression of X_i on ξ_j coincides in terms of intercept, slope and error variance across the indicators of the same (unidimensional) latent variable.

The tau-equivalent model constrains the elements of $\boldsymbol{\tau}$, $\boldsymbol{\Lambda}^{\mathbf{X}}$ but not $\boldsymbol{\Theta}_{\boldsymbol{\delta}}$ to be equal across the indicators of each latent variable. This is done so "that individual items measure the same latent variable on the same scale with the same degree of precision, but with possibly different amounts of error (Raykov, 1997a, 1997b). The tau-equivalent model implies that although all item true scores are equal, each item has unique error terms" (Graham, 2006, p. 934). The tau-equivalent measurement model assumes that the regression of X_i on ξ_j coincides in terms of intercept and slope but not in terms of error variance across the indicators of the same (unidimensional) latent variable.

The essentially tau-equivalent model constrains the elements of $\boldsymbol{\Lambda}^{\mathbf{X}}$ to be equal across the indicators of each latent variable but not the elements of $\boldsymbol{\tau}$ and $\boldsymbol{\Theta}_{\boldsymbol{\delta}}$. "Essential tau-equivalence assumes that each item measures the same latent variable, on the same scale, but with possibly different degrees of precision (Raykov, 1997a). Again, as with the tau-equivalent model, the essentially tau-equivalent model allows for possibly different error variances" (Graham, 2006, p. 934). The essentially tau-equivalent measurement model assumes that the regression of X_i on ξ_j coincides in terms of slope but not in terms of intercept or error variance across the indicators of the same (unidimensional) latent variable.

The congeneric model allows the elements of $\boldsymbol{\tau}$, $\boldsymbol{\Lambda}^{\mathbf{X}}$ and $\boldsymbol{\Theta}_{\boldsymbol{\delta}}$ to be freely estimated across the indicators of each latent variable. "The congeneric model assumes that each individual item measures the same latent variable, with possibly different scales, with possibly different degrees of precision, and with possibly different amounts of error (Raykov, 1997a). Whereas the essentially tau-equivalent model allows item true scores to differ by only an additive constant, the congeneric model assumes a linear relationship between item true scores, allowing for both an additive and a multiplicative constant between each pair of item true scores" (Graham, 2006, p. 935). The congeneric measurement model assumes that the regression of X_i on ξ_j differs in terms of intercept, slope and error variance across the indicators of the same (unidimensional) latent variable.

These various measurement models define the options in terms of which the number of freed measurement model parameters could be reduced. The model requiring the largest number of freed model parameters is the least restricted congeneric model. Fitting the congeneric model as defined here would require a greater number of freed parameters to be estimated

than the measurement model defined in Equation 3 since it would also require the estimation of $\boldsymbol{\tau}$[42]. The classically parallel and tau-equivalent models presented the only (conventional) options[43] to reduce the number of freed parameters since they allowed the elements of to be fixed to zero and constrained to be equal across items. Since the tau-equivalent measurement model presented the less restrictive option of the two this option was considered first. If the measurement model defined in Equation 3 would be fitted with the elements of $\boldsymbol{\Lambda}^{\mathbf{x}}$ constrained to be equal across the indicators of each latent variable, the elements of $\boldsymbol{\tau}$ fixed to be equal and equal to zero but the freed diagonal elements of $\boldsymbol{\Theta}_{\boldsymbol{\delta}}$ freely estimated[44] for all indicators the number of freed parameters would only be marginally fewer than the number of observations in the data set.

The classically parallel model that constrains the elements of $\boldsymbol{\tau}$, $\boldsymbol{\Lambda}^{\mathbf{x}}$, and $\boldsymbol{\Theta}_{\boldsymbol{\delta}}$ to be equal across the indicators of each latent variable was therefore subsequently considered. Constraining the error variances of each latent variable to be equal further reduced the number of freed parameters down to 86[45] which solved the problem that the number of freed parameters exceed the number of observations in the sample.[46] The possibility of also constraining the elements of $\boldsymbol{\Phi}$ to be equal was considered. Doing so would reduce the number of freed measurement model parameters by a further 54 to only 32[47]. Very little any theoretical justification could, however, be offered when viewed from the perspective of measurement theory to defend such a step. It was decided to not also constrain the inter-latent variable correlation to be equal across all elements of $\boldsymbol{\Phi}$. The LISREL syntax file is shown in Appendix C.

The attempt to converge the model was not successful. LISREL issued a warning stating "Serious problems were encountered during minimization. Unable to continue iterations. Check your model and data." Moreover, the estimate for $\theta_{\delta 15,15}$ (the error variance for the learning performance indicator) was negative and inadmissible. Setting a starting value of .50 for $\lambda_{15,8}$ did not solve the problem. Changing the method of estimation from robust maximum likelihood estimation to robust diagonally least squares estimation allowed the model to converge with close fit but $\theta_{\delta 15,15}$ had an inadmissible negative value (albeit now only marginal

[42] Additionally requesting the estimation of the intercept terms would, however not affect the degrees of freedom as the increase in freed parameters would be offset by the increase in known pieces of information in the form of the indicator variable means.
[43] It was practically possible to also constrain other parameters (like ϕ_{ij}) to be equal
[44] The number of freed parameters for the tau-equivalent measurement model were 100 (11 λ_{ij},, 25 $\theta_{\delta ii}$, 9 $\theta_{\delta ik}$ and 55 ϕ_{jp}).
[45] The number of freed parameters were made up of 11 λ_{ij},, 11 $\theta_{\delta ii}$, 9 $\theta_{\delta ik}$ and 55 ϕ_{jp}.
[46] It is acknowledged that still would have left the serious problem that the ratio of freed parameters to observations would have been far from meeting the guidelines set by Bentler and Chou (1987).
[47] The number of freed parameters were made up of 11 λ_{ij},, 11 $\theta_{\delta ii}$, 9 $\theta_{\delta ik}$ and 1 ϕ_{jp}.

negative). Setting a starting value of .50 for $\lambda_{15,8}$ under robust diagonally least squares estimation resulted in a model that converged without any inadmissible values. The measurement model did obtain close fit. The root mean square error of approximation (RMSEA) indicates the discrepancy between the observed population co-variance matrix (Σ) and the estimated population co-variance matrix ($\Sigma^{\wedge}$) implied by the model per degree of freedom (Burger, 2012). A RMSEA value below .05 is generally regarded as indicative of good model fit, values above .05 but less than .08 are indicative of reasonable fit, values greater than .08 but less than .10 are indicative of mediocre fit and values exceeding .10 are regarded as indicative of poor fit. As can be seen in the goodness of fit statistics in Table 4.38 the model obtained a RMSEA value of .00 thus indicating exact fit in the sample. Although the close fit hypothesis was not rejected ($p>.05$) the exact fit null hypothesis was nonetheless still rejected ($p<.05$). The rest of the basket of fit indices did not support the verdict of the RMSEA statistic. Moreover, the majority of the measurement error variance estimates were statistically insignificant ($p>.05$). Attractive as perfectly reliable measures may be, it seriously raises suspicion if only two of eleven latent variables (*learning motivation* and the interaction between *abstract thinking capacity* and *time cognitively engaged*) were statistically significantly ($p<.05$) plagued by measurement error. These considerations, taken in conjunction with the fact that under robust maximum likelihood estimation the model only fitted reasonably (RMSEA=.074, $p<.05$) and returned an inadmissible solution, forced the researchers to conclude that the operationalisation of the latent variables comprising the structural model via the item parcels was not successful. The fitted measurement model therefore did not provide a sufficiently credible description of the process that generated the observed inter-item parcel covariance matrix to have faith in the measurement model parameter estimates or the item parcels. There was therefore no justification in interpreting the measurement model parameters. Moreover, there was no justification in proceeding with the fit of the structural model via structural equation modelling.

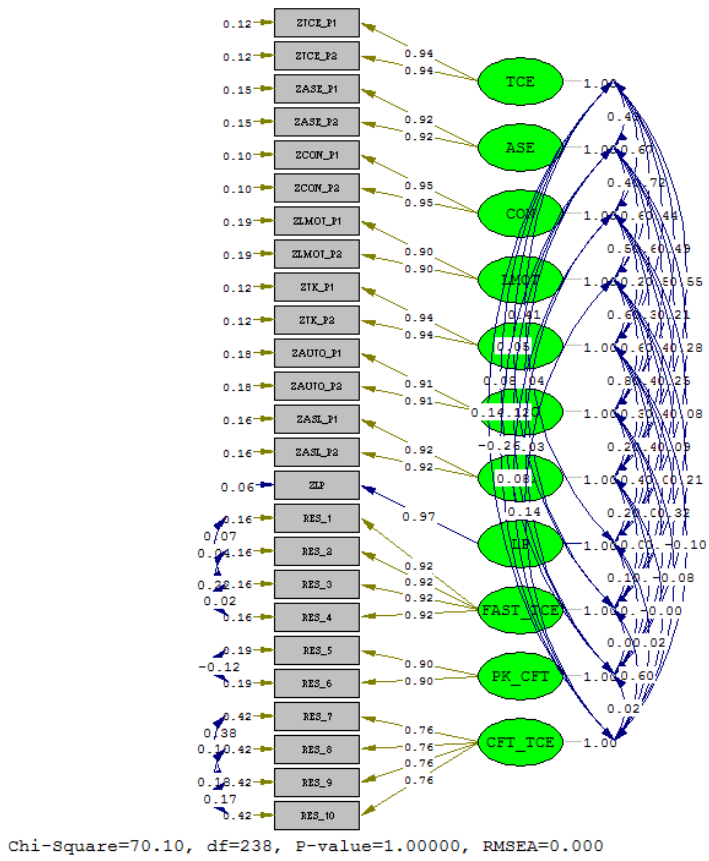


Figure 4.2: ***Representation of the fitted Learning Potential Measurement Model***

Table 4.38

Goodness of Fit Statistics for the Learning Potential Measurement Model

Degrees of Freedom = 238[48]
Normal Theory Weighted Least Squares Chi-Square = 70.103 (P = 1.000)
Satorra-Bentler Scaled Chi-Square = 824.782 (P = 0.0)
Estimated Non-centrality Parameter (NCP) = 0.0
90 Percent Confidence Interval for NCP = (0.0 ; 0.0)
Minimum Fit Function Value = 0.626
Population Discrepancy Function Value (F0) = 0.0
90 Percent Confidence Interval for F0 = (0.0 ; 0.0)
Root Mean Square Error of Approximation (RMSEA) = 0.0
90 Percent Confidence Interval for RMSEA = (0.0 ; 0.0)
P-Value for Test of Close Fit (RMSEA < 0.05) = 1.000
Expected Cross-Validation Index (ECVI) = 3.679
90 Percent Confidence Interval for ECVI = (3.679 ; 3.679)
ECVI for Saturated Model = 5.804
ECVI for Independence Model = 37.302
Chi-Square for Independence Model with 300 Degrees of Freedom = 4127.820
Independence AIC = 4177.820
Model AIC = 244.103

[48] The degrees of freedom were calculated as (25826)/2 -87 =239. The number of freed parameters increased by one from 86 to 87 due to the setting of a starting value for $\lambda_{15,8}$.

Saturated AIC = 650.000
Independence CAIC = 4271.005
Model CAIC = 568.386
Saturated CAIC = 1861.401

Normed Fit Index (NFI) = 0.800
Non-Normed Fit Index (NNFI) = 0.807
Parsimony Normed Fit Index (PNFI) = 0.635
Comparative Fit Index (CFI) = 0.847
Incremental Fit Index (IFI) = 0.849
Relative Fit Index (RFI) = 0.748

Critical N (CN) = 40.608

Root Mean Square Residual (RMR) = 0.0513
Standardised RMR = 0.0518
Goodness of Fit Index (GFI) = 0.981
Adjusted Goodness of Fit Index (AGFI) = 0.973
Parsimony Goodness of Fit Index (PGFI) = 0.718

4.9 EVALUATING THE PATH SPECIFIC SUBSTANTIVE HYPOTHESES VIA MULTIPLE REGRESSION ANALYSIS

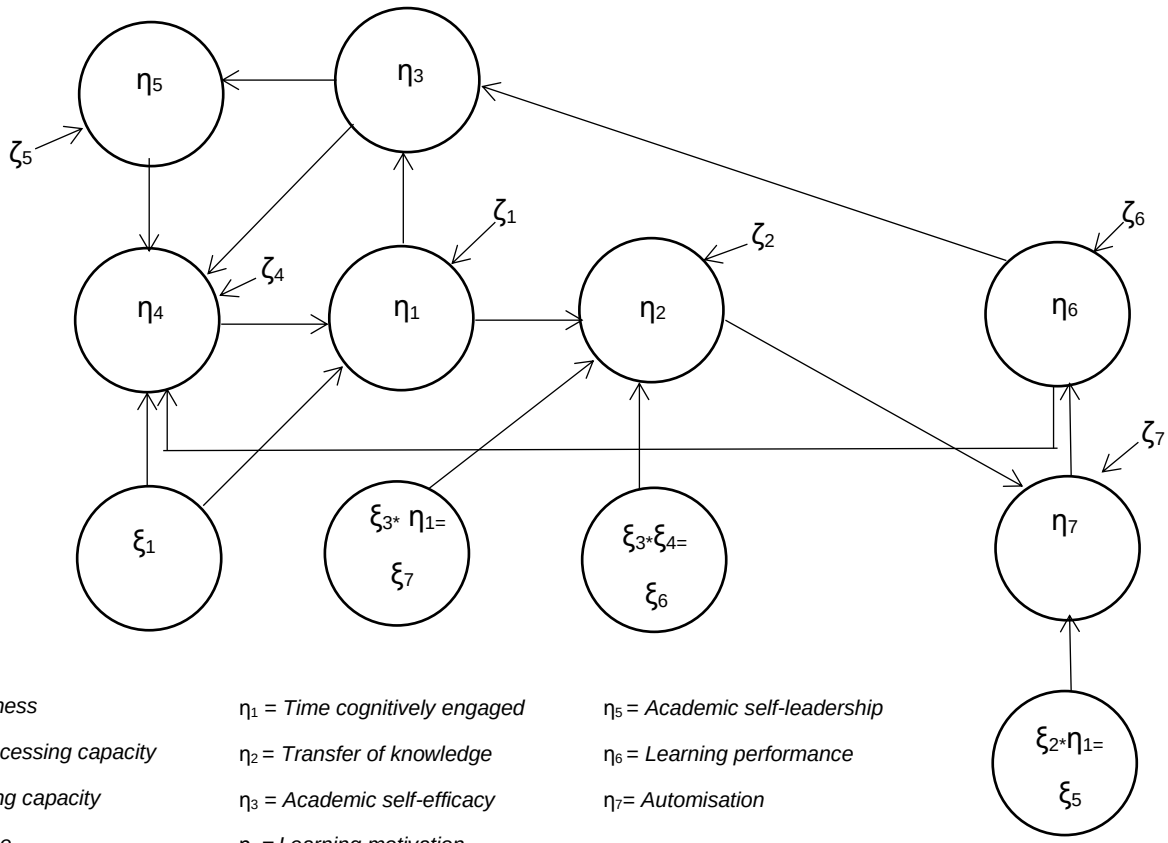
The failure to obtain gain sufficient faith in the success with which the item parcels operationalised the latent variables comprising the structural model precluded the possibility of fitting the structural model via the item parcel indicators. A number of possible alternative options could have been considered. The one alternative was to reduce the already reduced hypothesised learning potential model even further. This was not an attractive option as it would have required really aggressive pruning of the revised learning potential structural model to ensure an acceptable ratio of observations to freed model parameters (Bentler & Chao, 1987). A second option that could have been considered was to fit the revised learning potential structural model via partial least squares (PLS) (Hair, Ringle, and Sarstedt, 2011). This was not an attractive alternative because PLS is not a true structural equation modelling approach (Rönkkö, McIntosh, Antonakis & Edwards, 2016). Moreover it still would have had used the item parcel indicators for which the current study failed to find empirical CFA evidence that they provided valid and reliable reflections of the latent variables in the structural model.[49] The third alternative, and the alternative that was chosen[50], was to dissect the structural model into 7 separate regression models, fit each of these via multiple linear regression analysis and test the path-specific substantive hypotheses by testing the

[49] It is acknowledged that further model reduction and PLS were not at the time considered as possible routes to circumvent the dilemma caused by the failure of the learning potential measurement model. These considerations were introduced *post hoc* in response to legitimate questions raised by an examiner.
[50] Although the first two option were not originally considered, even if they were, the use of multiple regression analysis would still have been chosen as the best option in the current study under the circumstances.

significance of the partial regression slope coefficient estimates. The 7 regression models each took one of the endogenous latent variables in the reduced structural model as dependent variable. This is acknowledged as a methodological limitation. The explanation lies spread over the whole of the psychological mechanism regulating the level of learning performance achieved by learners. Taking the mechanism apart invariably results in a loss of meaning. Moreover, the use of multiple regression unavoidably requires the testing of the path-specific substantive hypotheses indirectly by testing path-specific operational hypotheses. Theoretical interest resides in the overall substantive research hypothesis and the path-specific substantive hypotheses. The use of linear multiple regression did not allow these to be tested directly. In addition, it needs to be confessed that, although the use of multiple regression requires the combination of the item parcels into single composite indicators for each latent variable, the faith in the success with which the single composite indicators operationalised the latent variables comprising the structural model was also to some degree compromised by the results obtained on the measurement model where each latent variable was operationalised via two item parcels.

The oversight of the researchers, confessed in paragraph 3.6.7, to operationalise *post-knowledge* and to collect data on this latent variable via the Qualtrics survey necessitated the elimination of the *post-knowledge* latent variable from the overarching substantive hypothesis originally developed through theorising in response to the research initiating question. The revised explanatory learning potential structural model is shown in Figure 4.3.

It was proposed in the original structural model that *automisation* has a statistically significant influence on *post knowledge,* which in-turn has a statistically significant effect on *learning performance.* The argument was made that once *automisation* took place on newly obtained knowledge it would be available to an individual to recall as *post knowledge,* which in itself and in interaction with *abstract thinking capacity* would affect an individual's *learning performance*. With the removal of *post knowledge* from the model the path from *automisation* to *post knowledge* was redirected to indicate that *automisation* has a statistically significant effect on *learning performance*. The researchers argued that the ability of an individual to *automate* newly obtained knowledge still plays an important part in an individual's ability to perform on a learning task and that it would be of value to have a path that indicates that a*utomisation* statistically significantly influences *learning performance*.



ξ_1 = *Conscientiousness*

ξ_2 = *Information processing capacity*

ξ_3 = *Abstract thinking capacity*

ξ_4 = *Prior knowledge*

$\xi_5 = \xi_2 * \eta_1$

$\xi_6 = \xi_3 * \xi_4$

$\xi_7 = \xi_3 * \eta_1$

η_1 = *Time cognitively engaged*

η_2 = *Transfer of knowledge*

η_3 = *Academic self-efficacy*

η_4 = *Learning motivation*

η_5 = *Academic self-leadership*

η_6 = *Learning performance*

η_7 = *Automisation*

***Figure 4.3*: Reduced Learning Potential Structural Model**

4.9.1 Operationalisation and research design

In-order to run the 7 regression analyses the mean of the item parcels, which were formed to operationalise the latent variables, were calculated. Two item parcels were originally calculated for each latent variable[51] by taking the mean of the even numbered and uneven numbered items. Once the item parcels means were calculated for example for TCE_1 and TCE_2, the mean of these two means were calculated to form one observed variable again M_TCE_1_2. This was done so that a single dependent observed variable could be regressed onto a one or more independent observed variables.

Ex post facto correlational research designs were used in which a single indicator represented each latent variable in the multiple regression model. The e*x post facto* correlational research design that guided the testing of hypotheses 2 (j=2), 3 (j=3), 4 (j=2), 5 (j=4) and 8 (j=2) is depicted in Figure 4.4.

$[X_{11}]$	..	$[X_{1j}]$	Y_{11}
$[X_{21}]$	..	$[X_{2j}]$	Y_{21}
:	..	:	:
$[X_{i1}]$	..	$[X_{ij}]$	Y_{i1}
:	..	:	:
$[X_{n1}]$	..	$[X_{nj}]$	Y_{n1}

Figure 4.4: Ex post facto correlational design

In the case of hypotheses 6 and 7 the effect of a single independent variable on the dependent variable was investigated. Hence the design was reduced to the observation of a single independent variable.

4.9.2 Path-specific and statistical hypotheses tested via multiple regression analysis

The path-specific hypotheses as originally formulated in paragraph 3.3 and paragraph 3.5 were subsequently rephrased for each of the 7 fitted regression models.

[51] There were two exceptions. *Learning performance during evaluation* and *prior knowledge* were from the outset represented by a single indicator variable.

Hypothesis 2[52]:

Conscientiousness (ξ_1) and l*earning motivation* (η_4) each statistically significantly explain unique variance in t*ime cognitively engaged* (η_1).

Hypothesis 2 was tested by operationalising each of the latent variables involved via a single indicator variable and fitting the regression model defined by equation 3a on the sample data as an estimate of the parametric regression model defined by equation 3b.

$Y_1=a+b_1X_1+b_2X_2+e$---------- [3a]

$Y_1=\alpha+\beta_1X_1+\beta_2X_2+\varepsilon$---------- [3b]

Where:

- Y_1 represents the observed *time cognitively engaged* score
- X_1 refers to the observed *conscientiousness* score
- X_2 represents the l*earning motivation* score

Operational hypothesis 2a:

The *conscientiousness* score (X_1) statistically significantly explains unique variance in the *time cognitively engaged* observed score (Y_1) that is not explained by l*earning motivation*

$$H_{02a}: \beta[X_1]=0 | \beta[X_2]\neq 0$$

$$H_{a2a}: \beta[X_1]>0 | \beta[X_2]\neq 0$$

Operational hypothesis 2b:

The l*earning motivation* score (X_2) statistically significantly explains unique variance in the *time cognitively engaged* observed score (Y_1) that is not explained by *conscientiousness*.

$$H_{02b}: \beta[X_2]=0 | \beta[X_1]\neq 0$$

$$H_{a2b}: \beta[X_2]>0 | \beta[X_1]\neq 0$$

[52] Hypothesis 1 still remains the overarching substantive hypothesis that posits that the reduced learning potential structural model provides a valid description of the psychological mechanism that regulates differences in learning performance during evaluation, despite the fact that it is not possible to test this hypothesis via multiple regression.

Hypothesis 3:

Time cognitively engaged (η_1), the ordinal interaction between *prior knowledge* (ξ_4) and *abstract reasoning capacity* (ξ_3) ($\xi_4 * \xi_3 = \xi_6$) and the ordinal interaction effect between *Gf* (*fluid intelligence* (ξ_3)) and *TCE* (*time cognitively engaged* (η_1)) ($\xi_{3*}\ \eta_1 = \xi_7$) each statistically significantly explain unique variance in *transfer of knowledge* (η_2).

Hypothesis 3 was tested by operationalising each of the latent variables involved via a single indicator variable and fitting the regression model defined by equation 4a on the sample data as an estimate of the parametric regression model defined by equation 4b.

$Y_2=a+b_1X_3+b_2X_4+b_3X_5+e$ ---------- [4a]

$Y_2=\alpha+\beta_1X_3+\beta_2X_4+\beta_3X_5+\varepsilon$ ---------- [4b]

Where:

- Y_2 represents the observed *transfer of knowledge* score
- X_3 refers to the observed *time cognitively engaged* score
- X_4 represents the product of the observed *prior knowledge* and *abstract reasoning capacity* score
- X_5 represents the product of the observed *fluid intelligence* and *time cognitively engaged scores*

Operational hypothesis 3a:

The *time cognitively engaged* score (X_3) statistically significantly explains unique variance in the *transfer of knowledge* observed score (Y_2) that is not explained by the other two effects in the regression model.

$$H_{03a}: \beta[X_3] = 0 | \beta[X_4] \neq 0; \beta[X_5] \neq 0$$

$$H_{a3a}: \beta[X_3] > 0 | \beta[X_4] \neq 0; \beta[X_5] \neq 0$$

Operational hypothesis 3b:

The ordinal interaction between *prior knowledge* and *abstract reasoning capacity* score (X_4) statistically significantly explains unique variance in the *transfer of knowledge* observed score (Y_2) that is not explained by the other two effects in the regression model.

$$H_{03b}: \beta[X_4] = 0 | \beta[X_3] \neq 0; \beta[X_5] \neq 0$$

$$H_{a3b}: \beta[X_4] > 0 | \beta[X_3] \neq 0; \beta[X_5] \neq 0$$

Operational hypothesis 3c:

The ordinal interaction between *fluid intelligence* and *time cognitively engaged* score (X_5) statistically significantly explains unique variance in the *transfer of knowledge* observed score (Y_2) that is not explained by the other two effects in the regression model.

$$H_{03c}: \beta[X_5] = 0 | \beta[X_3] \neq 0; \beta[X_5] \neq 0$$

$$H_{a3c}: \beta[X_5] > 0 | \beta[X_3] \neq 0; \beta[X_5] \neq 0$$

Hypothesis 4:

Learning performance during evaluation (η_6) and *time cognitively engaged* (η_1) each statistically significantly explain unique variance in a*cademic self-efficacy* (η_3).

Hypothesis 4 was tested by operationalising each of the latent variables involved via a single indicator variable and fitting the regression model defined by equation 5a on the sample data as an estimate of the parametric regression model defined by equation 5b.

$$Y_3 = a + b_1X_3 + b_2X_6 + e \text{----------} [5a]$$

$$Y_3 = \alpha + \beta_1X_3 + \beta_2X_6 + \varepsilon \text{----------} [5b]$$

Where:

- Y_3 represents the observed *academic self-efficacy* score
- X_3 refers to the observed *time cognitively engaged* score
- X_6 represents the *learning performance during evaluation* score

Operational hypothesis 4a:

The *time cognitively engaged* score (X_3) statistically significantly explains unique variance in the *academic self-efficacy* observed score (Y_3) that is not explained by *learning performance during evaluation*

$$H_{04a}: \beta[X_3] = 0 | \beta[X_6] \neq 0$$

$$H_{a4a}: \beta[X_3] > 0 | \beta[X_6] \neq 0$$

Operational hypothesis 4b:

The learning performance during evaluation score (X_6) statistically significantly explains unique variance in the *academic self-efficacy* observed score (Y_3) that is not explained by *time cognitively engaged*

$$H_{04b}: \beta[X_6] = 0 | \beta[X_3] \neq 0$$

$$H_{a4b}: \beta[X_6] > 0 | \beta[X_3] \neq 0$$

Hypothesis 5:

Conscientiousness (ξ_1), *learning performance during evaluation* (η_6), *academic self-efficacy* (η_3) and *academic self-leadership* (η_5) each statistically significantly explain unique variance in *learning motivation* (η_4).

Hypothesis 5 was tested by operationalising each of the latent variables involved via a single indicator variable and fitting the regression model defined by equation 6a on the sample data as an estimate of the parametric regression model defined by equation 6b.

$$Y_4 = a + b_1X_1 + b_2X_6 + b_3X_7 + b_4X_8 + e \text{ ---------- } [6a]$$

$$Y_4 = \alpha + \beta_1X_1 + \beta_2X_6 + \beta_3 7_5 + \beta_4X_8 + \varepsilon \text{ ---------- } [6b]$$

Where:

- Y_4 represents the observed *learning motivation* score
- X_1 refers to the observed *conscientiousness* score
- X_6 represents the *learning performance during evaluation* observed score
- X_7 represents the *academic self-efficacy* observed *score*

- X_8 represents the *academic self-leadership* observed score

Operational hypothesis 5a:

The *conscientiousness* score (X_1) statistically significantly explains unique variance in the *learning motivation* observed score (Y_4) that is not explained by the other three effects in the regression model.

$$H_{05a}: \beta[X_1] = 0 | \beta[X_6] \neq 0; \beta[X_7] \neq 0; \beta[X_8] \neq 0$$

$$H_{a5a}: \beta[X_1] > 0 | \beta[X_6] \neq 0; \beta[X_7] \neq 0; \beta[X_8] \neq 0$$

Operational hypothesis 5b:

The *learning performance during evaluation* score (X_6) statistically significantly explains unique variance in the *transfer of knowledge* observed score (Y_2) that is not explained by the other three effects in the regression model.

$$H_{05b}: \beta[X_6] = 0 | \beta[X_1] \neq 0; \beta[X_7] \neq 0; \beta[X_8] \neq 0$$

$$H_{a5b}: \beta[X_6] > 0 | \beta[X_1] \neq 0; \beta[X_7] \neq 0; \beta[X_8] \neq 0$$

Operational hypothesis 5c:

The *academic self-efficacy* score (X_7) statistically significantly explains unique variance in the *transfer of knowledge* observed score (Y_2) that is not explained by the other two effects in the regression model.

$$H_{05c}: \beta[X_7] = 0 | \beta[X_1] \neq 0; \beta[X_6] \neq 0; \beta[X_8] \neq 0$$

$$H_{a5c}: \beta[X_7] > 0 | \beta[X_1] \neq 0; \beta[X_6] \neq 0; \beta[X_8] \neq 0$$

Operational hypothesis 5d:

The *academic self-leadership* score (X_8) statistically significantly explains unique variance in the *transfer of knowledge* observed score (Y_2) that is not explained by the other three effects in the regression model.

$$H_{05d}: \beta[X_8] = 0 | \beta[X_1] \neq 0; \beta[X_6] \neq 0; \beta[X_7] \neq 0$$

$$H_{a5d}: \beta[X_8] > 0 | \beta[X_1] \neq 0; \beta[X_6] \neq 0; \beta[X_7] \neq 0$$

Hypothesis 6:

Academic self-efficacy (η_3) statistically significantly explains variance in *academic self-leadership* (η_5).

Hypothesis 6 was tested by operationalising each of the latent variables involved via a single indicator variable and fitting the regression model defined by equation 7a on the sample data as an estimate of the parametric regression model defined by equation 7b.

$Y_5=a+b_1X_7+e$ ---------- [7a]

$Y_5=\alpha+\beta_1X_7+\varepsilon$ ---------- [7b]

Where:

- Y_5 represents the observed *academic self-leadership* score
- X_7 refers to the observed *academic self-efficacy* score

Operational hypothesis 6a:

The *academic self-efficacy* score (X_7) statistically significantly explains variance in the *academic self-leadership* observed score (Y_5).

$$H_{06a}: \beta[X_7]=0$$

$$H_{a6a}: \beta[X_7]<0$$

Hypothesis 7:

Automisation (η_7) statistically significantly explains variance in *learning performance during evaluation* (η_6).

Hypothesis 7 was tested by operationalising each of the latent variables involved via a single indicator variable and fitting the regression model defined by equation 8a on the sample data as an estimate of the parametric regression model defined by equation 8b.

$Y_6=a+b_1X_9+e$ ---------- [8a]

$Y_6=\alpha+\beta_1X_9+\varepsilon$ ---------- [8b]

Where:

- Y_6 represents the observed *learning performance during evaluation* score

- X_9 refers to the observed *automisation* score

Operational hypothesis 7a:

The *automisation* score (X_9) statistically significantly explains variance in the *learning performance during evaluation* observed score (Y_6).

$$H_{07a}: \beta[X_9] = 0$$

$$H_{a7a}: \beta[X_9] > 0$$

Hypothesis 8:

Transfer of knowledge (η_2) and the interaction between *information processing capacity* and *time cognitively engaged* ($\xi_2 * \eta_1 = \xi_5$) each statistically significantly explain unique variance in automisation (η_7).

Hypothesis 8 was tested by operationalising each of the latent variables involved via a single indicator variable and fitting the regression model defined by equation 10a on the sample data as an estimate of the parametric regression model defined by equation 10b.

$Y_7 = a + b_1X_{10} + b_2X_{11} + e$ ----------[10a]

$Y_7 = \alpha + \beta_1X_{10} + \beta_2X_{11} + \varepsilon$----------[10b]

Where:

- Y_7 represents the observed *automisation* score
- X_{10} refers to the observed *transfer of knowledge* score
- X_{11} represents the product of the *information processing capacity* and *time cognitively engaged* scores

Operational hypothesis 8a:

The *conscientiousness* score (X_1) statistically significantly explains unique variance in the *time cognitively engaged* observed score (Y_1) that is not explained by l*earning motivation*

$$H_{08a}: \beta[X_{10}] = 0 | \beta[X_{11}] \neq 0$$

$$H_{a8a}: \beta[X_{10}] > 0 | \beta[X_{11}] \neq 0$$

Operational hypothesis 8b:

The l*earning motivation* score (X_2) statistically significantly explains unique variance in the *time cognitively engaged* observed score (Y_1) that is not explained by *conscientiousness*.

$$H_{08b}: \beta[X_{11}] = 0 | \beta[X_{10}] \neq 0$$

$$H_{a8b}: \beta[X_{11}] > 0 | \beta[X_{10}] \neq 0$$

4.9.3 Assumptions underlying multiple linear regression analysis

The following assumptions apply to simple and multiple linear regression analysis (Tabachnick & Fidell, 2007):

- Linearity: The relationship between Y and X_i is linear;
- Normality: The residuals (Y-E[Y|Xi]) follow a normal distribution;
- Homoscedasticity: The conditional variance in the residuals should be constant across values of $E[Y|X_i]$.

The following two conditions, although not strictly speaking assumptions, should also be met:

- Absence of collinearity: Predictors are individually and in combination not strongly correlated with each other;
- Absence of highly influential observations: No observations exist that exert excessive influence on the regression parameter estimates.
- Three terms are associated with the process of evaluating the influence that an observation exerts:
- Outliers: Observations/cases with large residuals;
- Leverage: Observations that lie far from the other observations in terms of its levels on the independent variables only;
- Influence: Observations that greatly influence the regression parameter estimates when they are excluded viz included in the analysis.

4.9.4 Testing hypothesis 2: Regressing Time Cognitively Engaged onto Conscientiousness and Learning motivation.

The zero-order correlations between the three observed variables are shown in Table 4.39.

Table 4.39

Zero-order Correlations between Time Cognitively Engaged, Conscientiousness and Learning Motivation

		M_TCE_1_2 [Y_1]	M_CON_1_2 [X_1]	M_LMOT_1_2 [X_2]
M_TCE_1_2 [Y_1]	Pearson Correlation	1	.642**	.668**
	Sig. (1-tailed)		.000	.000
	N	114	114	114
M_CON_1_2 [X_1]	Pearson Correlation	.642**	1	.527**
	Sig. (1-tailed)	.000		.000
	N	114	114	114
M_LMOT_1_2 [X_2]	Pearson Correlation	.668**	.527**	1
	Sig. (1-tailed)	.000	.000	
	N	114	114	114

**. Correlation is significant at the 0.01 level (1-tailed).
Note: M_TCE_1_2 [Y_1] represent the single indicator for *Time Cognitively Engaged* calculated by taking the mean scores of item parcel 1 and item parcel 2 for *Time Cognitively Engaged*, M_CON_1_2 [X_1] represent the single indicator for *Conscientiousness* calculated by taking the mean scores of item parcel 1 and item parcel 2 for *Conscientiousness* and M_LMOT_1_2 [X_2] represent the single indicator calculated for *Learning Motivation*, calculated by taking the mean score of item parcel 1 and item parcel 2 for *Learning Motivation.*

Table 4.39 indicates that both *conscientiousness* and *learning motivation* can be expected to statistically significantly explain unique variance in *time cognitively engaged* when they are both included in a regression model. Both predictor variables statistically significantly ($p<.05$) correlated with the criterion variable but although they statistically significantly correlated with each other ($p<.05$) they explained less variance in each other than they explained in the criterion. Collinearity was therefore not a problem. This conclusion was supported by the collinearity diagnostic statistics reported in Table 4.40 and in Table 4.42. The condition index reported in Table 4.40 expresses the square root of the ratio of the largest eigenvalue to the eigenvalue of interest. If the condition index is above 30, the regression is said to suffer from significant multicollinearity. The tolerance values reported in Table 4.42 reflect the proportion of variance that is not explain in each predictor when regressing it on the remaining predictors in the regression model (i.e. $1-R^2$ where R^2 is the proportion of variance explained in each predictor when regressing it on the remaining predictors). Tolerance values less than .10 are regarded as indicative of multicollinearity (Tabachnick & Fidell, 2007). The variance inflation factor (VIF) is calculated as the inverse of tolerance (1/tolerance). VIF values greater than 10 are considered indicative of multicollinearity (Tabachnick & Fidell, 2007).

Table 4.40

Collinearity Diagnostics for the Regression of Time Cognitively Engaged, Conscientiousness and Learning Motivation

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	M_CON_1_2	M_LMOT_1_2
1	1	2.960	1.000	.00	.00	.00
	2	.024	11.115	.48	.83	.02
	3	.016	13.558	.51	.16	.98

A normal probability plot of the standardised residuals obtained for the fitted regression model defined in equation 3a is shown in Figure 4.5. The fact that the observations tended to reasonably closely hug the 45-degree reference line suggests that the normality assumption has not been seriously violated.

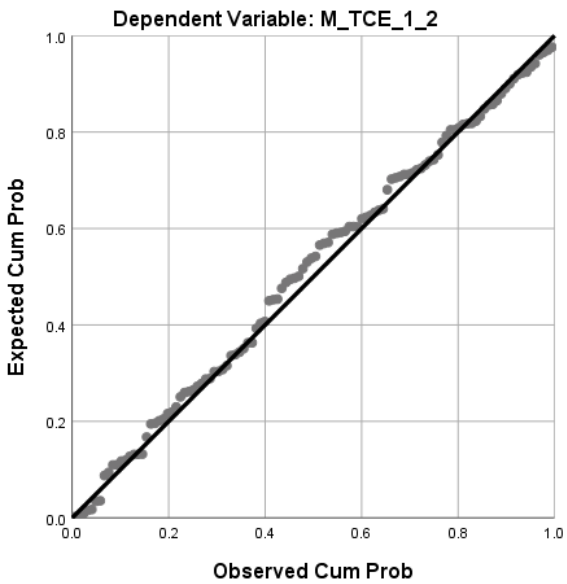


Figure 4.5: ***Normal P-P Plot of Regression Standardised Residual***

The scatterplot plotting the standardised residuals against the standardised predicted values is shown in Figure 4.6. The distribution of the standardised residuals around the horizontal reference line drawn through zero showed no discernible pattern. There was no fan-like pattern indicating that the homoscedasticity assumption had been violated. The reasonably random scatter of the standardised residuals around the horizontal reference line moreover suggested that a linear model is appropriate for the data.

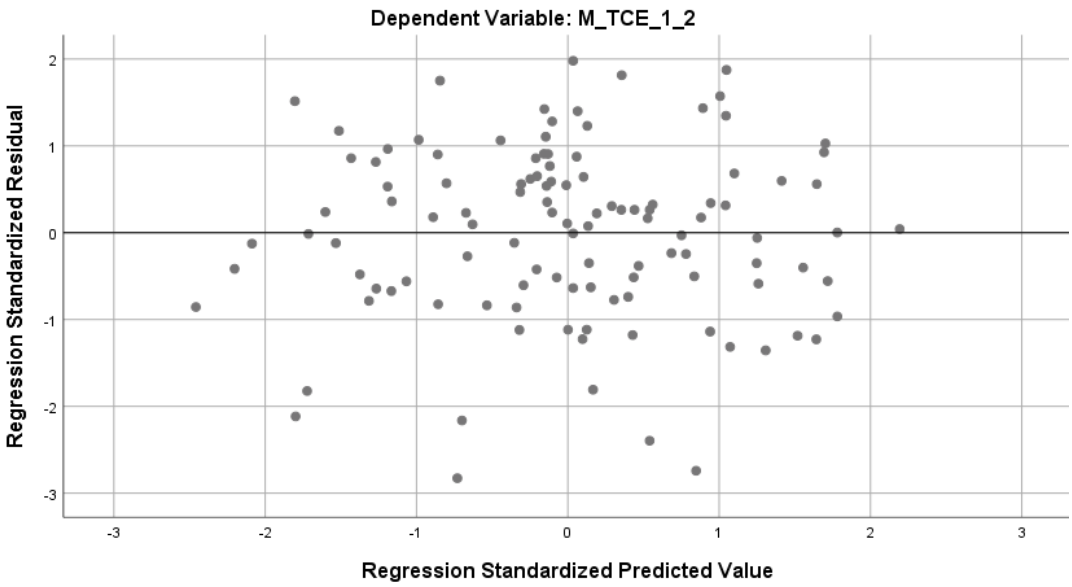


Figure 4.6: ***Scatterplot of the standardised residuals plotted against the standardised predicted values***

Descriptive statistics for the outlier, leverage and influence statistics that were calculated for each observation in the data set are shown in Table 4.41. The descriptive statistics showed no univariate outliers (no |standardised residual|>3.0) and no multivariate outliers (none of the probabilities to observe the Mahalanobis estimate or larger are smaller than .001). Four high leverage cases were however identified (the centred leverage value exceeded [2k+2]/n=6/114=.05263 for observations 74, 81, 82 and 109) and two influential cases as judged by the Cook's distance measure (the Cook's distance exceeded 4/114=.035 for observations 80 and 109). Focus in the current regression analysis centred on the partial regression slope parameter estimates. The critical question to consider is therefore the extent to which the inclusion of suspected influential cases affected these slope parameter estimates. The DFBETA statistics provide an estimate for each observation in the data set of the extent to which the intercepts and slope parameter estimates would be affected by the deletion of a specific observation. The critical cut-off value suggested for DFBETAs is 2/√(n)=2/√114=.18732. However, Hair. Anderson, Tatham and Black (1995) recommend that the former cut-off value should be used in the case of large samples and that a critical DFBETA cut-off value of 1.00 should be used in small and medium sized samples. When judged by the latter criterion Table 4.41 indicates that none of the observations needed to be regarded as highly influential cases that exerted unduly high influence over the regression parameter estimates.

Table 4.41

Outlier, Leverage and Influence Statistics for the Regression of Time Cognitively Engaged on Conscientiousness and Learning Motivation

		Standardised Residual	Mahalanobis Distance	Prob_Mah	Cook's Distance	Centred Leverage Value	Standardised DFFIT	Standardised DFBETA Intercept	Standardised DFBETA M_CON_1_2	Standardised DFBETA M_LMOT_1_2
N	Valid	114	114	114	114	114	114	114	114	114
	Missing	0	0	0	0	0	0	0	0	0
Median		.1010855	1.7020401	.303419	.0035688	.0150623	.0186271	.0057883	.0025275	-.0011299
Minimum		-2.82773	.01936	.0021	.00000	.00017	-.48199	-.39159	-.39307	-.45007
Maximum		1.97950	8.40926	.9862	.07568	.07442	.47977	.34376	.38843	.36930

Table 4.42 indicates that H_{02a}: $\beta[X_1]=0|\ \beta[X_2]\neq 0$ and H_{02b}: $\beta[X_2]=0|\ \beta[X_1]\neq 0$ could be rejected ($p<.05$). Support was therefore obtained for the operational hypothesis 2a that the *conscientious* score (X_1) statistically significantly ($p<.05$) explains variance in the *time cognitively engaged* score (Y_1) that is not explained by *learning motivation* and for operational hypothesis 2b that the l*earning motivation* score (X_2) statistically significantly ($p<.05$) explains unique variance in the *time cognitively engaged* observed score (Y_1) that is not explained by *conscientiousness.*

The R^2 in the model summary section of Table 4.42 indicates that the weighted linear combination of *conscientiousness* and *learning Motivation* explained approximately 56.3% of the variance in *time cognitively engaged*. A closer look at the standardised beta coefficients shows that *learning motivation* had a slightly stronger influence on *time cognitively engaged* than *conscientiousness* did. The unique variance in *conscientiousness* explained $.341^2$.116 (11.6%) of the total variance in *time cognitively engaged* and the unique variance in *learning motivation* explained .151 (15.1%) of the total variance in *time cognitively engaged*.

Table 4.42

Time Cognitively Engaged Regression Analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.750[a]	.563	.555	.63798

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	58.199	2	29.099	71.494	.000[b]
	Residual	45.179	111	.407		
	Total	103.378	113			

Model		Unstandardised Coefficients B	Unstandardised Coefficients Std. Error	Standardised Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	.741	.346		2.140	.035					
	M_CON_1_2	.389	.072	.402	5.438	.000	.642	.459	.341	.722	1.385
	M_LMOT_1_2	.440	.071	.457	6.184	.000	.668	.506	.388	.722	1.385

Note: M_TCE_1_2 [Y_1] represent the single indicator for *Time Cognitively Engaged* calculated by taking the mean scores of item parcel 1 and item parcel 2 for *Time Cognitively Engaged*, M_CON_1_2 [X_1] represent the single indicator for *Conscientiousness* calculated by taking the mean scores of item parcel 1 and item parcel 2 for *Conscientiousness* and M_LMOT_1_2 [X_2] represent the single indicator calculated for *Learning Motivation*, calculated by taking the mean score of item parcel 1 and item parcel 2 for *Learning Motivation.*

4.9.5 Testing hypothesis 3: Regression Of Transfer Of Knowledge onto Abstract Thinking Capacity*Prior Knowledge, Abstract Thinking Capacity*Time Cognitively Engaged and Time Cognitively Engaged

The zero-order correlations between the four observed variables are shown in Table 4.43.

Table 4.43

Zero-order Correlations between Transfer of Knowledge, Abstract Thinking Capacity* Prior Knowledge, Abstract Thinking Capacity* Time Cognitively Engaged and Time Cognitively Engaged

		M_TCE_1_2 [X_3]	CFT_PRI [X_4]	CFT_TCE [X_5]	M_TK_1_2 [Y_2]
M_TCE_1_2 [X_3]	Pearson Correlation	1	.087	.128	.382**
	Sig. (1-tailed)		.179	.087	.000
	N	114	114	114	114
CFT_PRI [X_4]	Pearson Correlation	.087	1	-.005	.135
	Sig. (1-tailed)	.179		.479	.077
	N	114	114	114	114
CFT_TCE [X_5]	Pearson Correlation	.128	-.005	1	-.026
	Sig. (1-tailed)	.087	.479		.391
	N	114	114	114	114
M_TK_1_2 [Y_2]	Pearson Correlation	.382**	.135	-.026	1
	Sig. (1-tailed)	.000	.077	.391	
	N	114	114	114	114

**. Correlation is significant at the 0.01 level (1-tailed).

Note: M_TCE_1_2 [X_3]represent the single indicator for *Time Cognitively Engaged* calculated by taking the mean scores of item parcel 1 and item parcel 2 for *Time Cognitively Engaged*, CFT_PRIM_CON_1_2 [X_4] represent the single indicator for the *Abstract thinking capacity*Prior* Knowledge interaction effect calculated by taking the product of the mean-centred single indicators of *Abstract thinking capacity* and *Prior Knowledge*, CFT_TCE [X5] represents the single indicator for the *Abstract thinking capacity*Time Cognitively Engaged* interaction effect calculated by taking the taking the product of the mean-centred single indicators of *Abstract thinking capacity* and *Time Cognitively Engaged* interaction effect and M_TK_1_2 [X_2] represent the single indicator calculated for *Transfer of Knowledge*, calculated by taking the mean score of item parcel 1 and item parcel 2 for *Transfer of Knowledge*

Table 4.43 indicates that out of the three independent variables only *time cognitively engaged* can be expected to statistically significantly explain unique variance in *transfer of knowledge* when all three variables are included in a regression model. *Time cognitively engaged* was

the only predictor variable that statistically significantly ($p<.05$) correlated with the criterion variable. There was also no statistically significant correlation between the predictor variables ($p>.05$)[53]. Collinearity was therefore not a problem. This conclusion was supported by the collinearity diagnostic statistics reported in Table 4.44 and in Table 4.46. The condition index reported in Table 4.44 indicates that the condition index is below 30 therefore the regression does not suffer from multicollinearity. The tolerance values reported in Table 4.46 reflect the proportion of variance that is not explained in each predictor when regressing it on the remaining predictors in the regression model (i.e. $1-R^2$ where R^2 is the proportion of variance explained in each predictor when regressing it on the remaining predictors). Tolerance values less than .10 is regarded as indicative of multicollinearity (Tabachnick & Fidell, 2007). The variance inflation factor (VIF) is calculated as the inverse of tolerance (1/tolerance). VIF values greater than 10 are considered indicative of multicollinearity (Tabachnick & Fidell, 2007).

Table 4.44

Collinearity Diagnostics for the Regression of Time Cognitively Engaged, Conscientiousness and Learning Motivation

				Variance Proportions			
Model	Dimension	Eigenvalue	Condition Index	(Constant)	M_TCE_1_2	CFT_PRI	CFT_TCE
1	1	2.045	1.000	.01	.01	.03	.00
	2	.998	1.431	.00	.00	.00	.98
	3	.939	1.476	.00	.00	.97	.00
	4	.019	10.447	.99	.99	.01	.02

A normal probability plot of the standardised residuals obtained for the fitted regression model defined in equation 4a is shown in Figure 4.7. The fact that the observations tend to reasonably closely hug the 45-degree reference line suggests that the normality assumption has not been seriously violated.

[53] The indicator variables involved in the interaction effects were mean-centered before calculating the product terms.

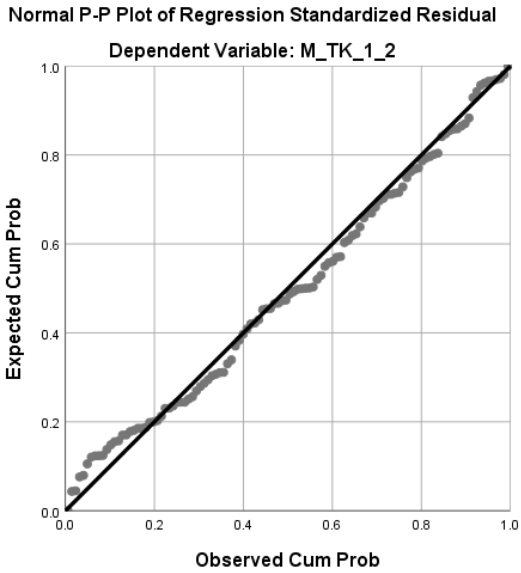


***Figure 4.7*: Normal P-P Plot of Regression Standardised Residual**

The scatterplot plotting the standardised residuals against the standardised predicted values is shown in Figure 4.8. The distribution of the standardised residuals around the horizontal reference line show no discernible pattern. There is no fan-like pattern indicating that the homoscedasticity assumption had been violated. The reasonably random scatter of the standardised residuals around the horizontal reference line moreover suggest that a linear model is appropriate for the data**.**

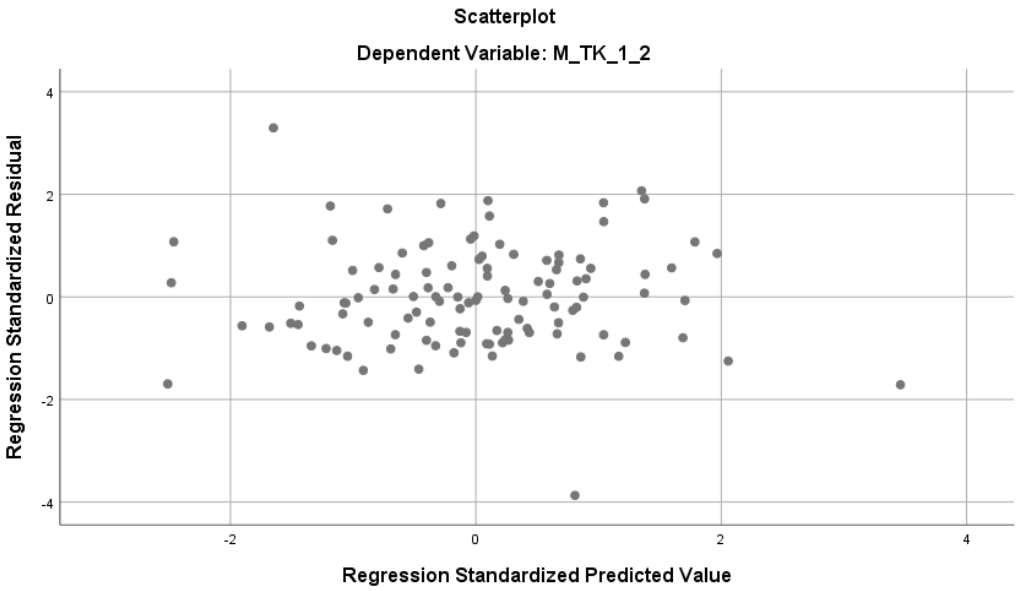


Figure 4.8: ***Scatterplot of the standardised residuals plotted against the standardised predicted values***

Descriptive statistics for the outlier, leverage and influence statistics that were calculated for each observation in the data set are shown in Table 4.45. The descriptive statistics showed no univariate outliers (no |standardised residual|>3.0) and no multivariate outliers (none of the probabilities to observe the Mahalanobis estimate or larger are smaller than .001). Eight high leverage cases were however identified (the centered leverage value exceeded [2k+2]/n=8/114=.070175 for observations 7, 10, 26, 45, 54, 63, 80 and 81) and six influential cases as judged by the Cook's distance measure (the Cook's distance exceeded 4/114=.035 for observations 7, 10, 54, 74, 80 and 108). Focus in the current regression analysis centers on the partial regression slope parameter estimates. The DFBETA statistics provide an estimate for each observation in the data set of the extent to which the intercepts and slope parameter estimates would be affected by the deletion of a specific observation. The critical question to consider is therefore the extent to which the inclusion of suspected influential cases affected these slope parameter estimates. Using the cut-off score of 1.00 proposed by Hair et al. (1995) for small and medium sized samples Table 4.45 indicates that the maximum for DFBETA CFT_TCE fell above the cut-off score of 1.00. The maximum value was identified as observation 54. This observation can be regarded as a highly influential case that exerted unduly high influence over the regression parameter estimates. There were no other observations for DFBETA CFT_TCE that were above the cut-off score off 1.00. The regression analysis was subsequently repeated without observation 54. The results of this regression analysis are shown in Table 4.47.

Table 4.47 indicates that out of H_{03a}: $\beta[X_3]=0|\ \beta[X_4]\neq0;\ \beta[X_5]\neq0$, H_{03b}: $\beta[X_4]=0|\ \beta[X_3]\neq0;\ \beta[X_5]\neq0$ and H_{03c}: $\beta[X_5]=0|\ \beta[X_3]\neq0;\ \beta[X_5]\neq0$, H_{03a}: $\beta[X_3]=0|\ \beta[X_4]\neq0;\ \beta[X_5]\neq0$, H_{03b}: $\beta[X_4]=0|\ \beta[X_3]\neq0;\ \beta[X_5]\neq0$ and H_{03c}: $\beta[X_5]=0|\ \beta[X_3]\neq0;\ \beta[X_5]\neq0$ could be rejected ($p<.05$)[54]. Support was therefore obtained for:

- Operational hypothesis 3a that the *time cognitively engaged* score (X_3) statistically significantly ($p<.05$) explains variance in the *transfer of knowledge* score (Y_1) that is not explained by the interaction effects *abstract thinking capacity*prior knowledge* (X_4) and *abstract thinking capacity*time cognitively engaged* (X_5),

[54] The exceedance probabilities shown in Table 4.47 are those associated with two-tailed test significance tests and non-directional alternative hypothesis. In the current study all alternative hypotheses were formulated as directional hypotheses. The appropriate exceedance probability when deciding on H_{0i} is therefore the printer significance value divided by 2.

Table 4.45

Outlier, Leverage and Influence Statistics for the Regression of Time Cognitively Engaged on Conscientiousness and Learning Motivation

		Standardised Residual	Mahalanobis Distance	Cook's Distance	centred Leverage Value	Standardised DFFIT	Standardised DFBETA Intercept	Standardised DFBETA CFT_PRI	Standardised DFBETA CFT_TCE	Standardised DFBETA M_TCE_1_2	Prob_Mah
N	Valid	114	114	114	114	114	114	114	114	114	114
	Missing	0	0	0	0	0	0	0	0	0	0
Median		-.0488477	1.0069153	.0019844	.0089108	-.0050101	-.0020194	.0019431	-.0005154	.0003670	.7996
Minimum		-3.87054	.00239	.00000	.00002	-2.11648	-.47377	-1.03934	-.95746	-.78899	.00
Maximum		3.29567	49.57887	1.07558	.43875	1.39014	.83000	.29652	1.79783	.44754	1.00

Table 4.46

Transfer of Knowledge Regression Analysis (case 54 still included]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.402[a]	.162	.139	.75580

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.129	3	4.043	7.078	.000[b]
	Residual	62.836	110	.571		
	Total	74.965	113			

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3.248	.367		8.848	.000					
	M_TCE_1_2	.326	.075	.383	4.332	.000	.382	.382	.378	.976	1.025
	CFT_PRI	.002	.001	.101	1.153	.251	.135	.109	.101	.992	1.008
	CFT_TCE	-.025	.029	-.075	-.849	.398	-.026	-.081	-.074	.983	1.017

Note :M_TCE_1_2 represents the single indicator for Time Cognitively Engaged, CTI_PRI represents the single indicator for the *Abstract thinking capacity*Prior* Knowledge interaction effect and CTI_TCE represents the single indicator for the *Abstract thinking capacity*Time Cognitively Engaged* interaction effect

Table 4.47

Transfer of Knowledge Regression Analysis (case 54 excluded]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.449[a]	.202	.180	.74070

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	15.137	3	5.046	9.197	.000[b]
	Residual	59.802	109	.549		
	Total	74.939	112			

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3.031	.371		8.163	.000					
	M_TCE_1_2	.372	.076	.432	4.875	.000	.389	.423	.417	.934	1.071
	CFT_PRI	.003	.002	.172	1.962	.052	.148	.185	.168	.953	1.049
	CFT_TCE	-.076	.036	-.192	-2.117	.037	-.044	-.199	-.181	.892	1.121

Note :M_TCE_1_2 represents the single indicator for Time Cognitively Engaged, CTI_PRI represents the single indicator for the *Abstract thinking capacity*Prior* Knowledge interaction effect and CTI_TCE represents the single indicator for the *Abstract thinking capacity*Time Cognitively Engaged* interaction effect

- Operational hypothesis 3c, that the interaction effect *abstract thinking capacity*time cognitively engaged* (X_5) statistically significantly ($p<.05$) explains variance in the *transfer of knowledge* score (Y_1) that is not explained by *time cognitively engaged* (X_3) and *abstract thinking capacity*prior knowledge* (X_4), and

- Operational hypothesis 3b that the interaction effect *abstract thinking capacity*prior knowledge* (X_4) statistically significantly ($p<.05$) explains variance in the *transfer of knowledge* score (Y_1) that is not explained by *time cognitively engaged* (X_3) and *abstract thinking capacity*time cognitively engaged* (X_5).

The R^2 in the model summary (Table 4.47) indicates that the weighted linear combination of *Abstract Thinking Capacity Prior Knowledge, Abstract Thinking Capacity*Time Cognitively Engaged* and *Time Cognitively Engaged* explains approximately 20.2% of the variance in *Transfer of Knowledge*. The unique variance in *Time Cognitively Engaged* explained $.417^2$ = 0.174 (17.4%) of the total variance in *Time Cognitively Engaged*, whilst *Abstract Thinking Capacity*Time Cognitively Engaged* explained .033 (3.3%) of the total variance in *Time Cognitively Engaged*.

The exclusion of the influential case had a substantial effect on the results. In the initial regression analysis, the effect of the *Abstract Thinking Capacity*Time Cognitively Engaged* interaction effect was statistically insignificant ($p>.05$). the proportion of variance explained by the weighted composite of independent variables also increased markedly.

4.9.6 Testing hypothesis 4: Regression of Academic Self-Efficacy onto Learning Performance and Time Cognitively Engaged

The zero-order correlations between the three observed variables are shown in Table 4.48. Table 4.48 raises concern whether both independent variables, *learning performance* and *time cognitively engaged* can be expected to statistically significantly explain unique variance in *academic self-efficacy* when both predictor variables are included in a regression model. Both predictor variables *learning performance and time cognitively engaged,* statistically significantly ($p<.05$) correlated with the criterion variable. There, however, also was a statistically significant correlation between *time cognitively engaged* and *learning performance* ($p<.05$), which indicates that these two variables share variance.

Table 4.48

Zero-order Correlations between Academic Self-Efficacy, Learning Performance and Time Cognitively Engaged

		M_ASE_1_2 [Y_3]	LP [X_6]	M_TCE_1_2 [X_3]
M_ASE_1_2 [Y_3]	Pearson Correlation	1	.245**	.380**
	Sig. (1-tailed)		.004	.000
	N	114	114	114
LP [X_6]	Pearson Correlation	.245**	1	.403**
	Sig. (1-tailed)	.004		.000
	N	114	114	114
M_TCE_1_2 [X_3]	Pearson Correlation	.380**	.403**	1
	Sig. (1-tailed)	.000	.000	
	N	114	114	114

Note: M_ASE_1_2 represents the single indicator for *Academic Self-efficacy* calculated from its two item parcels, LP represents the single indicator for *Learning Performance* and M_TCE_1_2 represents the single indicator for *Time Cognitively Engaged* calculated from its to item parcels.

The problem was that the two predictors explained more variance in each other than they explain variance in the criterion. This raised the concern that *learning performance* might not statistically significantly explain unique variance in the dependent variable not explained by *time cognitively engaged*. The condition index reported in Table 4.49 indicates that the condition index is below 30 therefore the regression does not suffer from multicollinearity. The tolerance values reported in Table 4.51 serve as an indicator of the absence of multicollinearity. The VIF values also were not greater than 10 serving as a further indicator of the absence of multicollinearity.

Table 4.49

Collinearity Diagnostics for the Regression of Time Cognitively Engaged, Conscientiousness and Learning Motivation

				Variance Proportions		
Model	Dimension	Eigenvalue	Condition Index	(Constant)	M_TCE_1_2	Post Knowledge
1	1	2.961	1.000	.00	.00	.00
	2	.022	11.577	.02	.83	.55
	3	.017	13.070	.98	.16	.45

A normal probability plot of the standardised residuals obtained for the fitted regression model defined in equation 5a is shown in Figure 4.9. The fact that the observations tended to reasonably closely hug the 45-degree reference line suggests that the normality assumption has not been seriously violated.

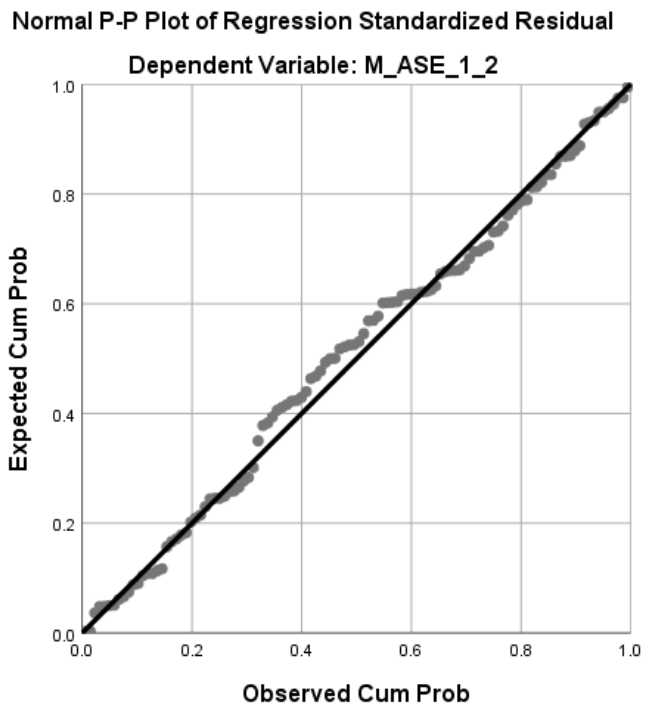


Figure 4.9: ***Normal P-P Plot of Regression Standardised Residual***

The scatterplot plotting the standardised residuals against the standardised predicted values is shown in Figure 4.10.

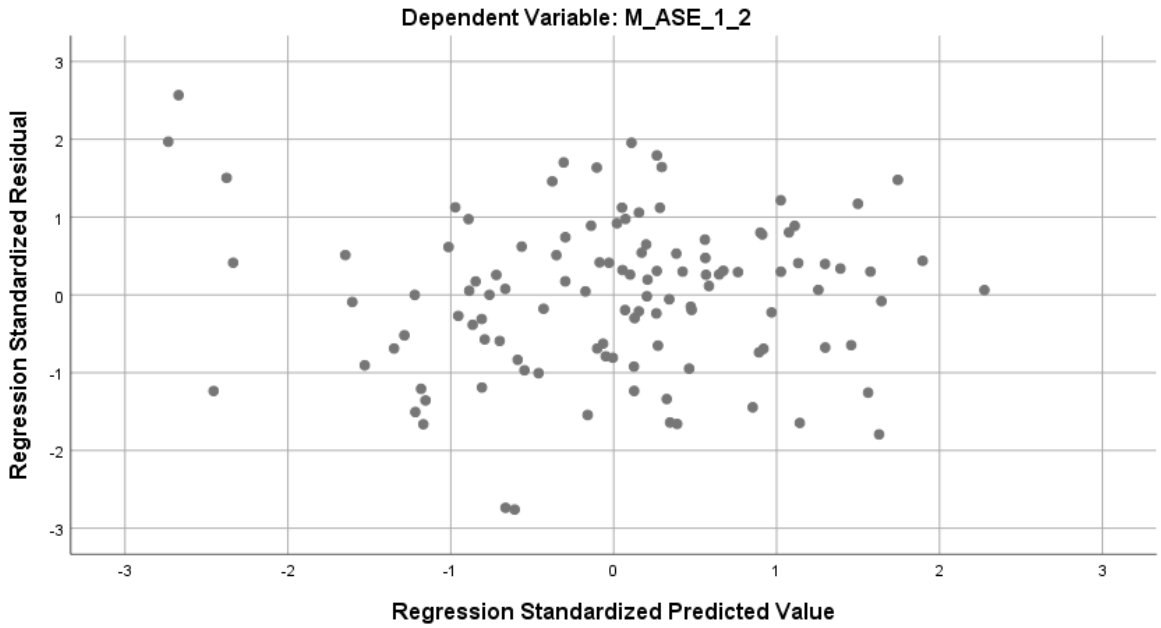


Figure 4.10: ***Scatterplot of the standardised residuals plotted against the standardised predicted values***

The distribution of the standardised residuals around the horizontal reference line drawn through zero showed no discernible pattern. There was no fan-like pattern indicating that the homoscedasticity assumption had been violated. The reasonably random scatter of the standardised residuals around the horizontal reference line moreover suggested that a linear model was appropriate for the data.

Descriptive statistics for the outlier, leverage and influence statistics that were calculated for each observation in the data set are shown in Table 4.50. The descriptive statistics showed no univariate outliers (no |standardised residual|>3.0) and no multivariate outliers (none of the probabilities to observe the Mahalanobis estimate or larger are smaller than .001). Eight high leverage cases were however identified (the centered leverage value exceeded [2k+2]/n=6/114=.05263 for observations 74, 81, 82, 90, 100, 104, 108 and 114) and nine influential cases as judged by the Cook's distance measure (the Cook's distance exceeded 4/114=.035 for observations 10, 74, 80, 81, 82, 89, 108, 109 and 113). Focus in the current regression analysis centered on the partial regression slope parameter estimates. The critical question to consider is therefore the extent to which the inclusion of suspected influential cases affected these slope parameter estimates. The DFBETA statistics provide an estimate for each observation in the data set of the extent to which the intercepts and slope parameter estimates would be affected by the deletion of a specific observation. Using the cut-off score of 1.00 proposed by Hair et al. (1995) for small and medium sized samples Table 4.50 indicates that there are none of the observations that can be regarded as highly influential cases and that exert unduly high influence over the regression parameter estimates.

Table 4.50

Outlier, Leverage and Influence Statistics for the Regression of Time Cognitively Engaged on Conscientiousness and Learning Motivation

		Standardised Residual	Mahalanobis Distance	Cook's Distance	Centred Leverage Value	Standardised DFFIT	Standardised DFBETA Intercept	Standardised DFBETA M_TCE_1_2	Standardised DFBETA LP	Prob_Mah
N	Valid	114	114	114	114	114	114	114	114	114
	Missing	0	0	0	0	0	0	0	0	0
Median		.0703948	1.2763056	.0026531	.0112947	.0146337	-.0018269	.0017221	.0012664	.7348
Minimum		-2.75993	.00627	.00000	.00006	-.41172	-.29242	-.67858	-.60783	.02
Maximum		2.56704	9.52135	.19623	.08426	.78959	.64848	.41412	.29420	1.00

Table 4.51 indicates that out of H_{04a}: $\beta[X_3] = 0 | \beta[X_6] \neq 0$ and H_{04b}: $\beta[X_6] = 0 | \beta[X_3] \neq 0$ only H_{04a}: $\beta[X_3] = 0 | \beta[X_6] \neq 0$ could be rejected ($p<.05$). Support was therefore obtained for the operational hypothesis 4a that the *time cognitively engaged* score (X_3) statistically significantly ($p<.05$) explains variance in the *academic self-efficacy* (Y_2) that is not explained by *learning performance* (X_6). Support for operational hypothesis 4b that *learning performance* (X_6) statistically significantly ($p<.05$) explains variance in the *academic self-efficacy* score (Y_2) that is not explained by *time cognitively engaged* (X_3) was not obtained.

The R^2 in the model summary indicates that the weighted linear combination of *time cognitively engaged* and *learning performance* explained approximately 15.4% of the variance in *academic self-efficacy*. In Table 4.51, it can be seen that the weighted linear combination of *time cognitively engaged* and *learning performance* significantly explained variance in *academic self-efficacy* ($p < .05$). *Learning performance* did not explain any significant ($p > .05$) unique variance in *academic self-efficacy* when controlling for *time cognitively engaged*. *Learning performance* did, however, statistically significantly ($p < .05$) explain variance in *academic self-efficacy* when ignoring the effect of *time cognitively engaged* (see Table 4.48). The unique variance in *time cognitively engaged* explains $.307^2 = .0942$ (9.2%) of the total variance in *academic self-efficacy*.

Table 4.51

Academic Self-Efficacy Regression Analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.393[a]	.154	.139	.85332

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14.764	2	7.382	10.138	.000[b]
	Residual	80.825	111	.728		
	Total	95.588	113			

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3.037	.495		6.134	.000					
	LP	.008	.007	.110	1.158	.249	.245	.109	.101	.838	1.194
	M_TCE_1_2	.322	.092	.335	3.516	.001	.380	.317	.307	.838	1.194

Note: M_ASE_1_2 represents the single indicator for Academic Self-efficacy calculated from its two item parcels, LP represents the single indicator for Learning Performance and M_TCE_1_2 represents the single indicator for Time Cognitively Engaged calculated from its to item parcels.

4.9.7 Testing hypothesis 5: Regression of Learning Motivation onto Learning Performance, Academic Self-Leadership, Academic Self-Efficacy and Conscientiousness.

The zero-order correlations between the five observed variables are shown in Table 4.52.

Table 4.52

Zero-order Correlations between Learning Motivation, Learning Performance, Academic Self-Leadership, Academics Self-Efficacy and Conscientiousness

		M_LMOT_1_2 [Y_4]	LP [X_6]	M_ASL_1_2 [X_7]	M_ASE_1_2 [X_8]	M_CON_1_2 [X_1]
M_LMOT_1_2 [Y_4]	Pearson Correlation	1	.361**	.399**	.537**	.527**
	Sig. (1-tailed)		.000	.000	.000	.000
	N	114	114	114	114	114
LP [X_6]	Pearson Correlation	.361**	1	.189*	.245**	.193*
	Sig. (1-tailed)	.000		.022	.004	.020
	N	114	114	114	114	114
M_ASL_1_2 [X_2]	Pearson Correlation	.399**	.189*	1	.160*	.386**
	Sig. (1-tailed)	.000	.022		.044	.000
	N	114	114	114	114	114
M_ASE_1_2 [X_3]	Pearson Correlation	.537**	.245**	.160*	1	.416**
	Sig. (1-tailed)	.000	.004	.044		.000
	N	114	114	114	114	114
M_CON_1_2 [X_3]	Pearson Correlation	.527**	.193*	.386**	.416**	1
	Sig. (1-tailed)	.000	.020	.000	.000	
	N	114	114	114	114	114

Note: M_LMOT_1_2 represents the single indicator for *Learning Motivation* calculated from its two item parcels, LP represents the single indicator for *Learning Performance*, M_ASL_1_2 represents the single indicator for *Academic Self-leadership* calculated from its two item parcels, M_ASE_1_2 represents the single indicator for *Academic Self-efficacy* calculated from its two item parcels and M_CON_1_2 represents the single indicator for *Conscientiousness* calculated from its two item parcels.

Table 4.52 indicates that all four independent variables can be expected to statistically significantly explain unique variance in *learning motivation* when all four variables are included in a regression model. Each of the four predictor variables statistically significantly ($p<.05$) correlated with the criterion variable. There were statistically significant correlations between the predictor variables ($p<.05$). Collinearity was, however, not a problem seeing that the predictor variables explained less variance in each other than they did in the criterion. This conclusion is supported by the collinearity diagnostic statistics reported in Table 4.53 and in Table 4.55. The condition index values reported in Table 4.53 indicate that the regression does not suffer from multicollinearity. The tolerance values reported in Table 4.55 also indicated the absence of multicollinearity. None of the VIF values that are reported are greater than 10, which serves as a further indicator of the absence of multicollinearity.

Table 4.53

Collinearity Diagnostics for the Regression of Learning Motivation, Learning Performance, Academic Self-Leadership, Academics Self-Efficacy and Conscientiousness

				Variance Proportions				
Model	Dimension	Eigenvalue	Condition Index	(Constant)	Post Knowledge	M_CON_1_2	M_ASL_1_2	M_ASE_1_2
1	1	4.912	1.000	.00	.00	.00	.00	.00
	2	.034	11.977	.01	.43	.51	.00	.01
	3	.023	14.508	.02	.02	.00	.39	.53
	4	.021	15.272	.08	.50	.44	.08	.25
	5	.010	22.729	.90	.05	.06	.54	.21

A normal probability plot of the standardised residuals obtained for the fitted regression model defined in equation 6a is shown in Figure 4.11. The fact that the observations tend to reasonably closely hug the 45-degree reference line suggests that the normality assumption has not been seriously violated.

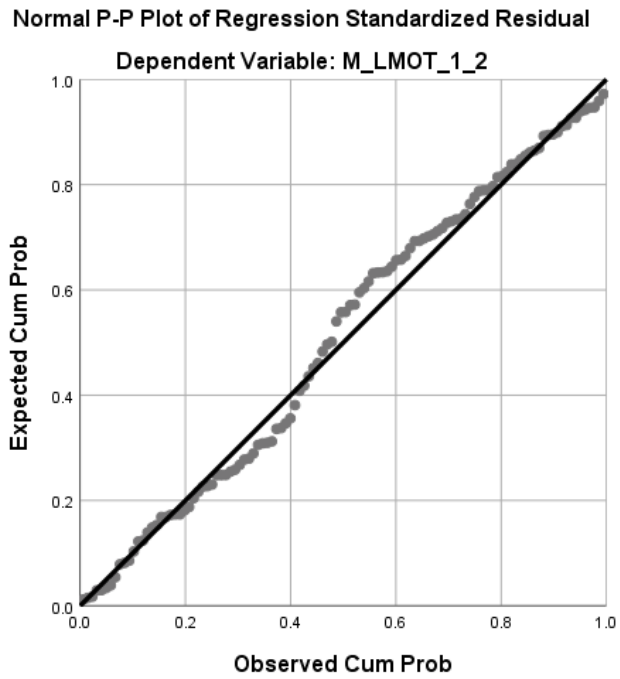


Figure 4.11: ***Normal P-P Plot of Regression Standardised Residual***

The scatterplot plotting the standardised residuals against the standardised predicted values is shown in Figure 4.12. The distribution of the standardised residuals around the horizontal reference line drawn through zero showed no discernible pattern. There was no fan-like pattern indicating that the homoscedasticity assumption had been violated. The reasonably

random scatter of the standardised residuals around the horizontal reference line moreover suggest that a linear model was appropriate for the data.

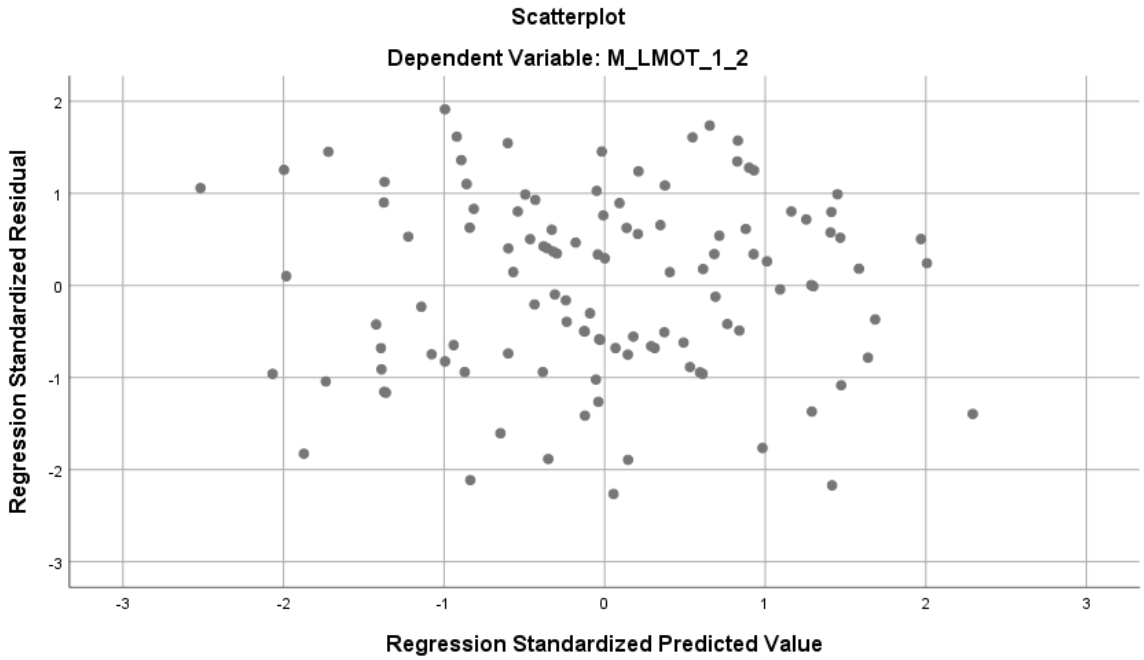


Figure 4.12: ***Scatterplot of the standardised residuals plotted against the standardised predicted values***

Descriptive statistics for the outlier, leverage and influence statistics that were calculated for each observation in the data set are shown in Table 4.54. The descriptive statistics showed no univariate outliers (no |standardised residual|>3.0) and no multivariate outliers (none of the probabilities to observe the Mahalanobis estimate or larger are smaller than .001). Five high leverage cases were, however, identified (the centered leverage value exceeded [2k+2]/n=10/114=.08772 for observations 46, 80, 81, 82 and 108) and seven influential cases as judged by the Cook's distance measure (the Cook's distance exceeded 4/114=.035 for observations 53, 56, 59, 66, 82, 95 and 109). Focus in the current regression analysis centered on the partial regression slope parameter estimates. The critical question to consider is therefore the extent to which the inclusion of suspected influential cases affected these slope parameter estimates. The DFBETA statistics provide an estimate for each observation in the data set of the extent to which the intercepts and slope parameter estimates would be affected by the deletion of a specific observation. Using the cut-off score of 1.00 proposed by Hair et al. (1995) for small and medium sized samples Table 4.54 indicates that there are none of the observations that can be regarded as highly influential cases that exert unduly high influence on the regression parameter estimates.

Table 4.54

Outlier, Leverage and Influence Statistics for the Regression of Learning Motivation on Learning Performance, Academic Self-Leadership, Academics Self-Efficacy and Conscientiousness

		Standardised Residual	Mahalanobis Distance	Cook's Distance	Centred Leverage Value	Standardised DFFIT	Standardised DFBETA Intercept	Standardised DFBETA LP	Standardised DFBETA M_ASL_1_2	Standardised DFBETA M_ASE_1_2	Standardised DFBETA M_CON_1_2	Prob_Mah
N	Valid	114	114	114	114	114	114	114	114	114	114	114
	Missing	0	0	0	0	0	0	0	0	0	0	0
Median		.1450047	3.0572467	.0045102	.0270553	.0267155	-.0057129	.0052035	-.0000619	-.0004202	-.0081842	.3830
Minimum		-2.26473	.20655	.00000	.00183	-.60053	-.35186	-.31186	-.45743	-.25859	-.22560	.00
Maximum		1.91282	24.83844	.07035	.21981	.49577	.31182	.26526	.33128	.52539	.45385	.98

Table 4.55 indicates that H_{05a}: $\beta[X_1] = 0 | \beta[X_6] \neq 0; \beta[X_7] \neq 0; \beta[X_8] \neq 0$, H_{05b}: $\beta[X_6] = 0 | \beta[X_1] \neq 0; \beta[X_7] \neq 0; \beta[X_8] \neq 0$, H_{05c}: $\beta[X_7] = 0 | \beta[X_1] \neq 0; \beta[X_6] \neq 0; \beta[X_8] \neq 0$ and H_{05d}: $\beta[X_8] = 0 | \beta[X_1] \neq 0; \beta[X_6] \neq 0; \beta[X_7] \neq 0$ could all be rejected ($p<.05$). Support was therefore obtained for the operational hypothesis 5a that the *conscientiousness* score (X_1) statistically significantly ($p<.05$) explained variance in the *learning motivation* score (Y_4) that is not explained by the remaining predictor variables (X_6, X_7 and X_8). Support was also found for the operational hypothesis 5b that the *learning performance* score (X_6) statistically significantly ($p<.05$) explained variance in the *learning motivation* score (Y_4) that is not explained by the remaining predictor variables (X_1, X_7 and X_8).

Hypothesis 5c also obtained support, which indicates that the *academic self-efficacy* score (X_7) statistically significantly ($p<.05$) explained variance in the *learning motivation* score (Y_4) that is not explained by the remaining predictor variables (X_1, X_6 and X_8). Lastly, support was obtained for the operational hypothesis 5d that the *academic self-leadership* score (X_8) statistically significantly ($p<.05$) explained variance in the *learning motivation* score (Y_4) that is not explained by the remaining predictor variables (X_1, X_6 and X_7).

The R^2 in the model summary indicates that the weighted linear combination of *Conscientiousness, Academic Self-Efficacy, Academic Self-Leadership* and *Learning Performance* explained approximately 47.6% of the variance in *Learning Motivation*. In Table 4.55, it can be seen that the weighted linear combination of *Conscientiousness, Academic Self-Efficacy, Academic Self-Leadership* and *Learning Performance* significantly explained variance in *Learning Motivation* ($p < .05$). The unique variance in *Conscientiousness* explained $.227^2 = .052$ (5.2%) of the total variance in *Learning Motivation* with the unique variance in *Academic Self-Efficacy* explaining $0.310^2 = 0.096$ (9.6%) of the total variance in *Learning Motivation*. The unique variance in *Academic Self-Leadership* explained $.188^2 = .0353$ (3.53%) of the total variance in *Learning Motivation* with the unique variance in *Learning Performance* explaining $0.177^2 = .031$ (3.1%) of the total variance in *Learning Motivation*.

Table 4.55

Learning Motivation Regression Analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.690[a]	.476	.457	.73050

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	52.941	4	13.235	24.802	.000[b]
	Residual	58.166	109	.534		

		Total		111.107	113						

Model		Unstandardised Coefficients		Standardised Coefficients			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-.078	.587		-.134	.894					
	M_CON_1_2	.269	.082	.267	3.275	.001	.527	.299	.227	.720	1.388
	LP	.015	.006	.185	2.556	.012	.361	.238	.177	.914	1.094
	M_ASL_1_2	.292	.108	.205	2.709	.008	.399	.251	.188	.837	1.195
	M_ASE_1_2	.375	.084	.348	4.479	.000	.537	.394	.310	.798	1.253

Note: M_LMOT_1_2 represents the single indicator for *Learning Motivation* calculated from its two item parcels, LP represents the single indicator for *Learning Performance*, M_ASL_1_2 represents the single indicator for *Academic Self-leadership* calculated from its two item parcels, M_ASE_1_2 represents the single indicator for *Academic Self-efficacy* calculated from its two item parcels and M_CON_1_2 represents the single indicator for *Conscientiousness* calculated from its two item parcels.

4.9.8 Testing hypothesis 6: Regression of Academic Self-Leadership onto Academic Self-efficacy

The zero-order correlation between the two observed variables are shown in Table 4.56.

Table 4.56

Zero-order Correlation between Academic Self-Leadership and Academic Self-Efficacy

		M_ASL_1_2 [Y_5]	M_ASE_1_2 [X_7]
M_ASL_1_2 [Y_5]	Pearson Correlation	1	.160*
	Sig. (1-tailed)		.044
	N	114	114
M_ASE_1_2 [X_7]	Pearson Correlation	.160*	1
	Sig. (1-tailed)	.044	
	N	114	114

Note: M_ASL_1_2 represents the single indicator for *Academic Self-leadership* calculated from its two item parcels and M_ASE_1_2 represents the single indicator for *Academic Self-efficacy* calculated from its two item parcels.

As can be seen in Table 4.56 the independent variable, *academic self-efficacy*, can be expected to statistically significantly explain variance in *academic self-leadership* when included in a regression model. The predictor variable statistically significantly ($p<.05$) correlated with the criterion variable. With regards to the regression of academic self-leadership onto academic self-efficacy multicollinearity was not an issue since the regression model only contained a single predictor.

In Figure 4.13 a normal probability plot of the standardised residuals obtained for the fitted regression model defined in equation 6a can be seen. The fact that the observations tend to

reasonably closely hug the 45-degree reference line suggests that the normality assumption has not been seriously violated.

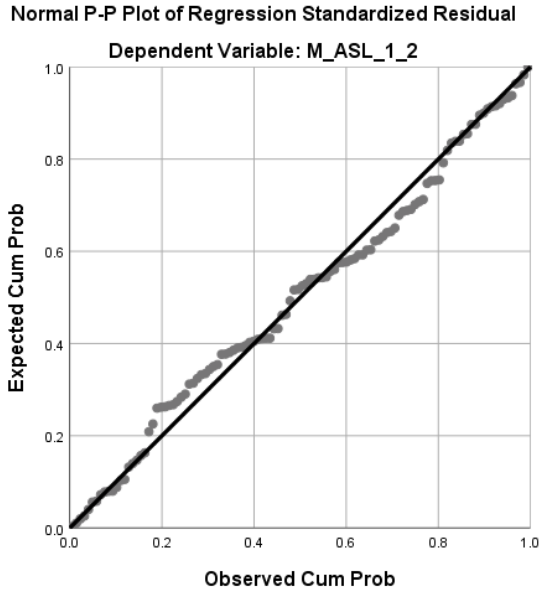


Figure 4.13: ***Normal P-P Plot of Regression Standardised Residual***

The scatterplot plotting the standardised residuals against the standardised predicted values is shown in Figure 4.14.

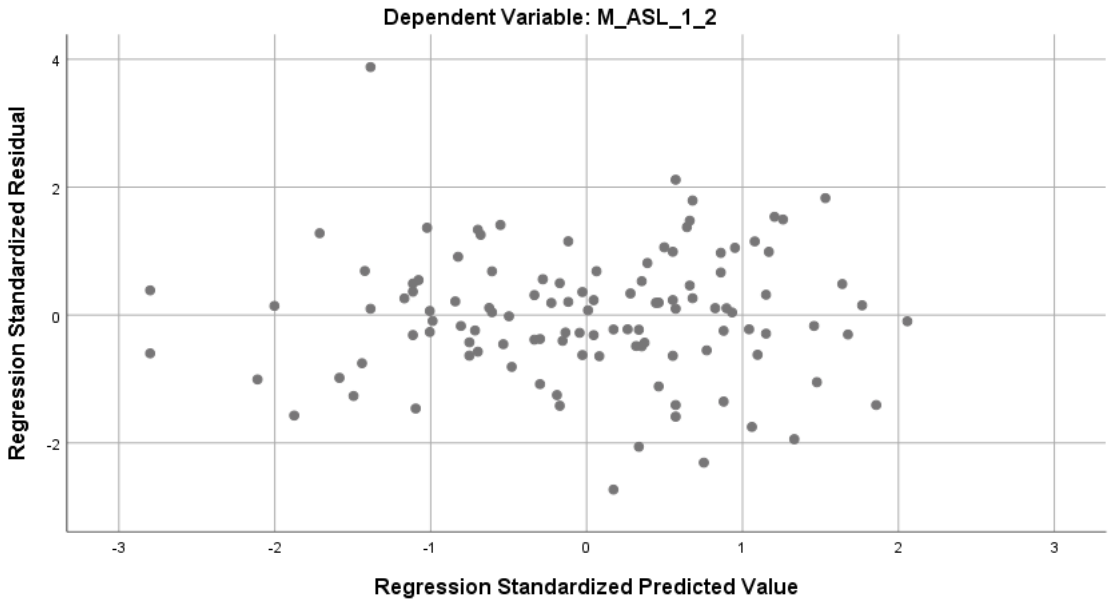


Figure 4.14: ***Scatterplot of the standardised residuals plotted against the standardised predicted values***

No discernible pattern was identified when looking at the distribution of the standardised residuals around the horizontal reference line drawn through zero. There was no fan-like pattern indicating that the homoscedasticity assumption had been violated. It appears that a linear model was appropriate for the data when looking at the reasonably random scatter of the standardised residuals around the horizontal reference line.

Table 4.57 depicts the descriptive statistics for the outlier, leverage and influence statistics that were calculated for each observation in the data set. The descriptive statistics showed no univariate outliers (no |standardised residual|>3.0) and multivariate outliers (the probabilities of observations 49, 87 and 106 to observe the Mahalanobis estimate or larger are smaller than .001). Five high leverage cases were however identified (the centered leverage value exceeded [2k+2]/n=4/114=.035 for observations 10, 13, 74, 89 and 109) and six influential cases as judged by the Cook's distance measure (the Cook's distance exceeded 4/114=.035 for observations 31, 42, 46, 81, 82 and 108). The partial regression slope parameter estimates were the central focus in the current regression analysis. The critical question to consider is therefore the extent to which the inclusion of suspected influential cases affected these slope parameter estimates. The DFBETA statistics provide an estimate for each observation in the data set of the extent to which the intercepts and slope parameter estimates would be affected by the deletion of a specific observation. Using the cut-off score of 1.00 proposed by Hair et al. (1995) for small and medium sized samples Table 4.57 indicates that there are none of the observations that can be regarded as highly influential cases and that exert unduly high influence over the regression parameter estimates.

Table 4.57

Outlier, Leverage and Influence Statistics for the Regression of Academic Self-Leadership onto Academic Self-Efficacy

		Standardised Residual	Mahalanobis Distance	Cook's Distance	Centred Leverage Value	Standardised DFFIT	Standardised DFBETA Intercept	Standardised DFBETA M_ASE_1_2	Prob_Mah
N	Valid	114	114	114	114	114	114	114	114
	Missing	0	0	0	0	0	0	0	0
Median		.0533627	.4867342	.0019836	.0043074	.0061652	-.0022672	.0009329	.9218
Minimum		-2.72954	.00008	.00000	.00000	-.32921	-.31345	-.55667	.05
Maximum		3.87868	7.83840	.20430	.06937	.68537	.61848	.29078	1.00

Table 4.58 indicates that H_{06a}: $\beta[X_7] = 0$ could be rejected ($p<.05$)[55]. Although the regression slope estimate was statistically significant when evaluated in a one-tailed test the sign of the regression slope estimate did not conform to the position held under the alternative hypothesis. The path-specific hypothesis postulated that *academic self-efficacy* would negatively affect *academic self-leadership*. An increase in *academic self-efficacy* was hypothesised to lower the extent to which affirmative development learners display *academic self-leadership*. Support was therefore not obtained for the operational hypothesis 6a that the *academic self-efficacy* score (X_7) statistically significantly ($p<.05$) explains variance in *academic self-leadership* (Y_5).

The R^2 in the model summary indicates that *academic self-leadership* explains only approximately 2.6% of the variance in *academic self-leadership*.

Table 4.58

Academic Self-Leadership Regression Analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.160[a]	.026	.017	.69128

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.411	1	1.411	2.953	.088[b]
	Residual	53.521	112	.478		
	Total	54.932	113			

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Correlations		
		B	Std. Error	Beta			Zero-order	Partial	Part
1	(Constant)	3.853	.367		10.500	.000			
	M_ASE_1_2	.122	.071	.160	1.719	.088	.160	.160	.160

Note: M_ASL_1_2 represents the single indicator for Academic Self-leadership calculated from its two item parcels and M_ASE_1_2 represents the single indicator for Academic Self-efficacy calculated from its two item parcels.

4.9.9 Testing Hypothesis 7: Regression of Learning Performance onto Automisation

The zero-order correlation between the two observed variables are shown in Table 4.59.

[55] The regression analysis output depicts the exceedance probability associated with a two-tailed test and a non-directional alternative hypothesis. In the current study all alternative hypotheses were formulated as directional hypotheses. The appropriate exceedance probability when deciding on H_{0i} is therefore the printer significance value divided by 2.

Table 4.59

Zero-order Correlation between Learning Performance and Automisation

		M_AUTO_1_2 [X_9]	LP [Y_6]
M_AUTO_1_2 [X_9]	Pearson Correlation	1	.463**
	Sig. (1-tailed)		.000
	N	114	114
LP [Y_6]	Pearson Correlation	.463**	1
	Sig. (1-tailed)	.000	
	N	114	114

Note: M_AUTO_1_2 represents the single indicator for *Automisation* calculated from its two item parcels and LP represents the single indicator for *Learning Performance*

Table 4.59 indicates that the independent variable, *automisation*, can be expected to statistically significantly explain variance in *learning performance* when included in a regression model. The predictor variable statistically significantly ($p<.05$) correlated with the criterion variable. A normal probability plot of the standardised residuals obtained for the fitted regression model defined in equation 7a is shown in Figure 4.15. The fact that the observations tend to reasonably closely hug the 45-degree reference line suggests that the normality assumption has not been seriously violated.

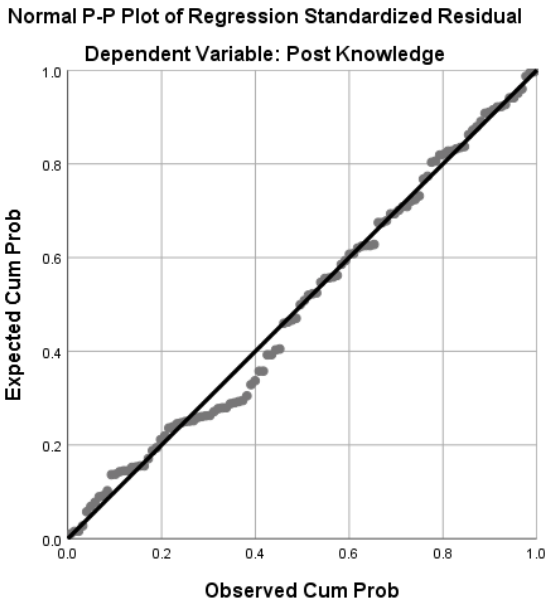


Figure 4.15: ***Normal P-P Plot of Regression Standardised Residual***

In Figure 4.16 the scatterplot plotting the standardised residuals against the standardised predicted values can be seen. The distribution of the standardised residuals around the horizontal reference line drawn through zero showed no discernible pattern. No fan-like pattern was identified, which would have indicated that the homoscedasticity assumption had been

violated. The reasonably random scatter of the standardised residuals around the horizontal reference line moreover suggest that a linear model was appropriate for the data.

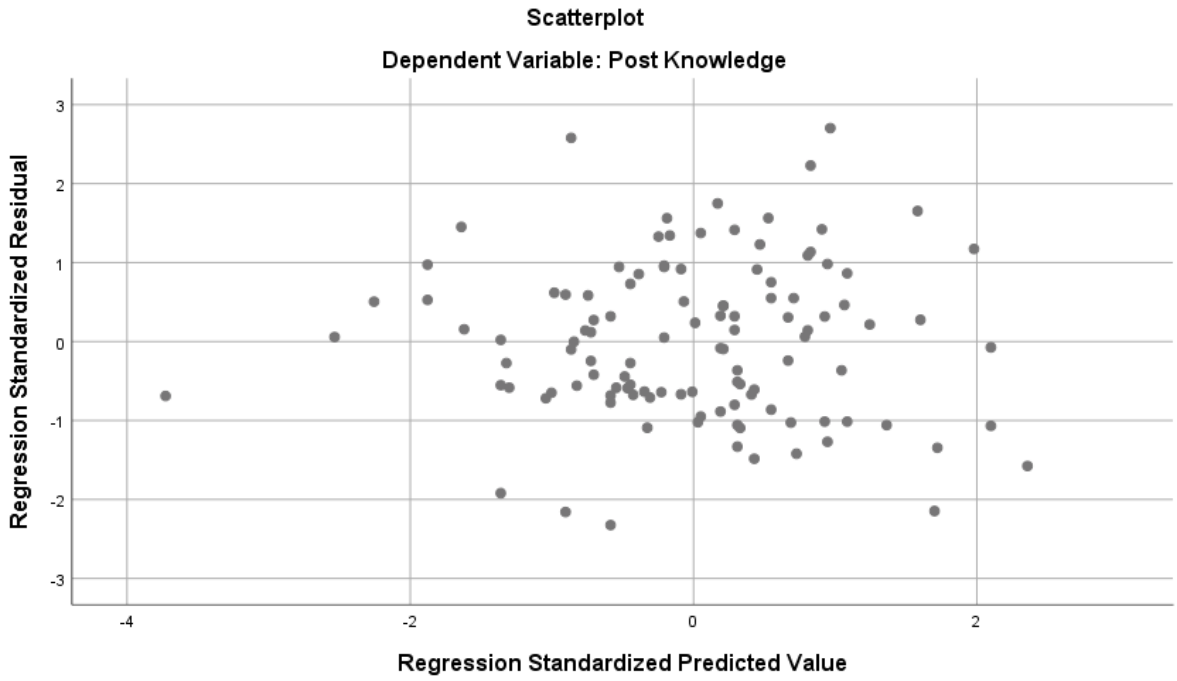


Figure 4.16: ***Scatterplot of the standardised residuals plotted against the standardised predicted values***

Descriptive statistics for the outlier, leverage and influence statistics that were calculated for each observation in the data set are shown in Table 4.60. The descriptive statistics showed no univariate outliers (no |standardised residual|>3.0), however multivariate outliers were detected (the probabilities for observations 32, 37 and 39 to observe the Mahalanobis estimate or larger are smaller than .001). Six high leverage cases were moreover identified (the centered leverage value exceeded [2k+2]/n=4/114=.035 for observations 10, 13, 68, 74, 85, and 108) and ten influential cases as judged by the Cook's distance measure (the Cook's distance exceeded 4/114=.035 for observations 20, 60, 68, 80, 82, 87, 90, 100, 104 and 108). Focus in the current regression analysis centered on the partial regression slope parameter estimates. The critical question to consider is therefore the extent to which the inclusion of suspected influential cases affected these slope parameter estimates. The DFBETA statistics provide an estimate for each observation in the data set of the extent to which the intercepts and slope parameter estimates would be affected by the deletion of a specific observation. Using the cut-off score of 1.00 proposed by Hair et al. (1995) for small and medium sized samples Table 4.60 indicates that there are none of the observations that can be regarded as highly influential cases and that exert unduly high influence over the regression parameter

estimates. The cases flagged as outliers were therefore not considered for deletion/exclusion from the regression analysis.

Table 4.60

Outlier, Leverage and Influence Statistics for the Regression of Learning Performance on Automisation

		Standardised Residual	Mahalanobis Distance	Cook's Distance	Centred Leverage Value	Standardised DFFIT	Standardised DFBETA Intercept	Standardised DFBETA M_AUTO_1_2	Prob_Mah
N	Valid	114	114	114	114	114	114	114	114
	Missing	0	0	0	0	0	0	0	0
Median		.0098077	.3940815	.0033611	.0034874	.0016198	-.0014518	.0003946	.9413
Minimum		-2.32392	.00008	.00000	.00000	-.41933	-.28598	-.37380	.00
Maximum		2.70331	13.89760	.08493	.12299	.36965	.34505	.27787	1.00

Table 4.61 indicates that H_{07a}: $\beta[X_9] = 0$ could be rejected ($p<.05$), therefore support was obtained for the operational hypothesis 6a that the *automisation* score (X_9) statistically significantly ($p<.05$) explains variance in *learning performance* (Y_6). The R^2 in Table 4.61 indicates that the *automisation* score (X_9) explained 21.4% of the variance in *learning Performance*.

Table 4.61

Learning Performance Regression Analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.463[a]	.214	.207	10.96988

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3679.856	1	3679.856	30.579	.000[b]
	Residual	13477.887	112	120.338		
	Total	17157.743	113			

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Correlations		
		B	Std. Error	Beta			Zero-order	Partial	Part
1	(Constant)	27.355	6.677		4.097	.000			
	M_AUTO_1_2	9.533	1.724	.463	5.530	.000	.463	.463	.463

Note: M_AUTO_1_2 represents the single indicator for *Automisation* calculated from its two item parcels and LP represents the single indicator for *Learning Performance*

4.9.10 Testing Hypothesis 8: Regression of Automisation onto Information Processing Capacity*Time Cognitively Engaged and Transfer Of Knowledge

The zero-order correlations between the three observed variables are shown in Table 4.62.

Table 4.62

Zero-order Correlations between Automisation, Information Processing Capacity* Time Cognitively Engaged and Transfer of Knowledge

		M_AUTO_1_2 [Y_7]	FAST_TCE [X_{11}]	M_TK_1_2 [X_{10}]
M_AUTO_1_2 [Y_7]	Pearson Correlation	1	.072	.834**
	Sig. (1-tailed)		.225	.000
	N	114	114	114
FAST_TCE [X_{11}]	Pearson Correlation	.072	1	.038
	Sig. (1-tailed)	.225		.345
	N	114	114	114
M_TK_1_2 [X_{10}]	Pearson Correlation	.834**	.038	1
	Sig. (1-tailed)	.000	.345	
	N	114	114	114

Note: M_AUTO_1_2 represents the single indicator for *Automisation* calculated from its two item parcels, M_TK_1_2 represents the single indicator for *Transfer of Knowledge* calculated from its two item parcels and

FAST_TCE represents the single indicator variable for *the Information Processing Capacity* Time Cognitively Engaged* interaction effect

Table 4.62 indicates that of the two independent variables only *transfer of knowledge* can be expected to statistically significantly explain unique variance in *automisation* when both predictor variables are included in a regression model. Of the two predictor variables only *transfer of knowledge* statistically significantly (p<.05) correlated with the criterion variable. There is also no statistically significant correlation between the predictor variables. The condition index reported in Table 4.63 indicates that the condition index values are below 30 therefore the regression does not suffer from multicollinearity. The tolerance values reported in Table 4.65 reflect the absence of multicollinearity. The VIF values also are not greater than 10 serving as a further indicator of the absence of multicollinearity.

Table 4.63

Collinearity Diagnostics for the Regression of Automisation, Information Processing Capacity*Time Cognitively Engaged and Transfer of Knowledge

				Variance Proportions		
Model	Dimension	Eigenvalue	Condition Index	(Constant)	FAST_TCE	M_TK_1_2
1	1	2.013	1.000	.01	.01	.01
	2	.973	1.438	.00	.99	.00
	3	.014	12.083	.99	.00	.99

A normal probability plot of the standardised residuals obtained for the fitted regression model defined in equation 7a is shown in Figure 4.17.

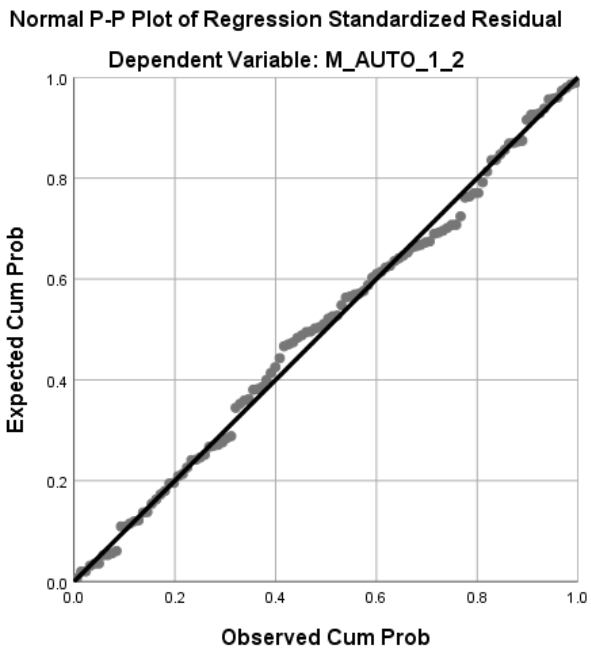


Figure 4.17: ***Normal P-P Plot of Regression Standardised Residual***

The observations tend to reasonably closely hug the 45-degree reference line, which suggests that the normality assumption had not been seriously violated.

The scatterplot plotting the standardised residuals against the standardised predicted values is shown in Figure 4.18. The distribution of the standardised residuals around the horizontal reference line drawn through zero showed no discernible pattern. There was no fan-like pattern indicating that the homoscedasticity assumption had been violated. The reasonably random scatter of the standardised residuals around the horizontal reference line that are reasonably randomly scattered suggest that a linear model was appropriate for the data.

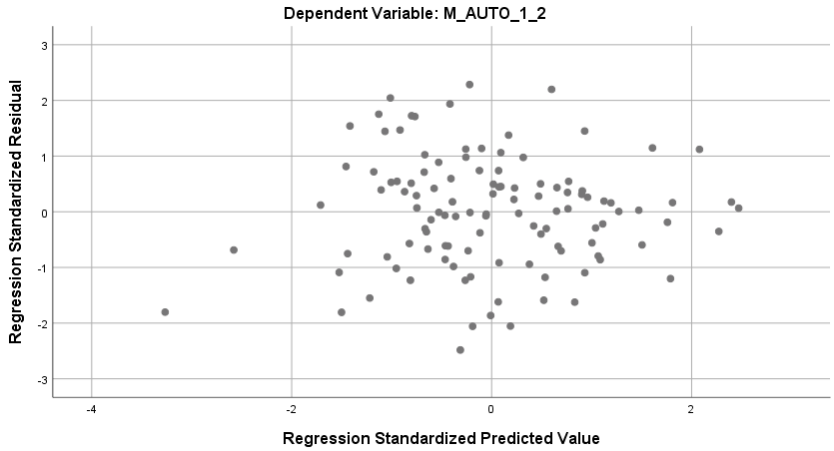


Figure 4.18: ***Scatterplot of the standardised residuals plotted against the standardised predicted values***

Descriptive statistics for the outlier, leverage and influence statistics that were calculated for each observation in the data set are shown in Table 4.64. The descriptive statistics showed no univariate outliers (no |standardised residual|>3.0) and no multivariate outliers (none of the probabilities to observe the Mahalanobis estimate or larger are smaller than .001). Fourteen high leverage cases were however identified (the centered leverage value exceeded [2k+2]/n=6/114=.05263 for observations 10, 26, 32, 45, 54, 68, 74, 77, 80, 82, 85, 104, 108 and 114) and five influential cases as judged by the Cook's distance measure (the Cook's distance exceeded 4/114=.035 for observations 26, 32, 54, 82 and 108). Using the cut-off score of 1.00 proposed by Hair et al. (1995) for small and medium sized samples Table 4.64 indicates that there are none of the observations that can be regarded as highly influential cases and that exerted unduly high influence over the regression parameter estimates.

Table 4.65 indicates that H_{08a}: $\beta[X_{10}]=0|\ \beta[X_{11}]\neq 0$ could be rejected ($p<.05$), but H_{08b}: $\beta[X_{11}]=0|\ \beta[X_{10}]\neq 0$ could not be rejected ($p>.05$). Support was therefore obtained for the operational hypothesis 8a that the *transfer of knowledge* score (X_{10}) statistically significantly ($p<.05$)

explains variance in the *automisation* score (Y_7) that is not explained by the *information processing capacity time cognitively engaged* interaction effect score (X_{11}). Support was not obtained for operational hypothesis 8b that the *information processing capacity*time cognitively engaged* interaction effect (X_{11}) statistically significantly ($p<.05$) explains variance in the *automisation* score (Y_7) that is not explained by the *transfer of knowledge* score (X_{10}).

Table 4.64

Outlier, Leverage and Influence Statistics for the Regression of Time Cognitively Engaged on Conscientiousness and Learning Motivation

Statistics

		Standardised Residual	Mahalanobis Distance	Cook's Distance	Centred Leverage Value	Standardised DFFIT	Standardised DFBETA Intercept	Standardised DFBETA FAST_TCE	Standardised DFBETA M_TK_1_2	Prob_Mah
N	Valid	114	114	114	114	114	114	114	114	114
	Missing	0	0	0	0	0	0	0	0	0
Median		.0405126	.7196694	.0022314	.0063688	.0071132	-.0004244	.0017784	.0002468	.8686
Minimum		-2.48220	.00643	.00000	.00006	-.65387	-.64661	-1.05226	-.22707	.00
Maximum		2.28491	20.98379	.37438	.18570	1.07783	.25929	.51812	.62451	1.00

The R^2 in the model summary in Table 4.65 indicates that the weighted linear combination of *information processing capacity*time cognitively engaged* and *transfer of knowledge* explained approximately 69.7% of the variance in *automisation*. In Table 4.65, it can be seen that the weighted linear combination of *information processing capacity*time cognitively engaged* and *transfer of knowledge* significantly explained variance in *automisation* ($p < .05$). The unique variance in *transfer of knowledge* explained $.834^2 = 0.691$ (69.1%) of the total variance in *automisation.*

Table 4.65

Automisation Regression Analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.835[a]	.697	.692	.33240

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	28.229	2	14.114	127.744	.000[b]
	Residual	12.264	111	.110		
	Total	40.493	113			

Model		Unstandardised Coefficients		Standardised Coefficients			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.876	.188		4.655	.000					
	FAST_TCE	.001	.001	.040	.768	.444	.072	.073	.040	.999	1.001
	M_TK_1_2	.612	.038	.832	15.925	.000	.834	.834	.832	.999	1.001

Note: M_AUTO_1_2 represents the single indicator for *Automisation* calculated from its two item parcels, M_TK_1_2 represents the single indicator for *Transfer of Knowledge* calculated from its two item parcels and FAST_TCE represents the single indicator variable for *the Information Processing Capacity* Time Cognitively Engaged* interaction effect

CHAPTER 5

DISCUSSION OF RESULTS, RECOMMENDATIONS FOR FUTURE RESEARCH AND PRACTICAL RECOMMENDATIONS

5.1. INTRODUCTION

Selection in South Africa poses a unique challenge for human resource managers. Organisations have an obligation towards stakeholders to select employees that will maximise stakeholder economic value but organisations also have a moral and legislative obligation to diversify their workforce. This creates a paradoxical situation brought about by the implementation of legislation by the Apartheid regime that led to certain people not getting access to proper education and not getting the opportunity to develop their intellectual capital simply because they belonged to specific population groups. Companies have an obligation towards stakeholders to select employees with the necessary skills that will maximise organisational performance. However, selection procedures designed to select the cream of the crop in terms of skills will lead to adverse impact against previously disadvantaged groups. Adverse impact refers to the situation where a specific selection strategy implemented by an organisation leads to members of a specific group having a lower likelihood of selection in comparison to another group (Theron, 2009).

The Employment Equity Act 55 of 1998 was implemented to give previously disadvantaged groups the opportunity to share in the economic wealth of South Africa. The overall objective of the Act is to ensure fair treatment and achieve equity in employment, through promoting equal opportunities and implementing affirmative action measures to redress disadvantages of the past experienced by people from designated groups (Finnemore, 2013).

However, the current study harbours concerns about the manner in which affirmative action is implemented in many South African public- and private-sector organisations. Exemplary examples most likely exist. The concern is though that they are a small minority. The current study's concern is that affirmative action as it is currently implemented requires companies to employ a certain number of previously disadvantaged employees just so that companies can comply with legislative requirements, without sufficient consideration of the question whether they possess the necessary skills to do the specific job they are being selected for. The absence to a thorough descriptive diagnostic study on South African private- and public-sector organisations' interpretation, implementation and management of affirmative action interventions was experienced as frustrating. According to the current study the core reason

for the implementation of affirmative action should be to address in an intellectually honest manner the reasons for the under-representation of previously disadvantaged South Africans in South African public- and especially private sector organisations, and in this intellectually honest manner, to promote equal opportunities for previously disadvantaged groups. However, placing members of previously disadvantaged groups in jobs that they do not poses the necessary skills for does not promote equal opportunity; it only sets them up for failure and tends to do more harm than good. When approached from a developmental perspective, affirmative action creates a platform to tap into the vast source of underdeveloped human resources in South Africa and increase competitiveness on a global scale. Seeing that businesses are by law required to diversify their work force it only makes sense to support the aims of affirmative action when approached from a developmental perspective. Businesses can embrace affirmative action by using their human resources function to help train and develop the untapped human capital in South Africa.

Affirmative development will be effective when human resource managers select learners that will most benefit from affirmative action programs. The human resources manager should therefore take up the responsibility of making him-/herself knowledgeable in the area of affirmative development and develop an understanding of the factors that will determine the extent to which a learner will benefit from taking part in affirmative action skills development programs or not. To effectively select candidates into an affirmative development programme, especially the non-malleable determinants of learning performance need to be validly understood.

Effective selection as described above is of critical importance but effective selection on its own is not enough to ensure successful affirmative development. Learning performance also depends on malleable learner characteristics as well as malleable situational characteristics. Human resource interventions should therefore also be initiated, prior to development or running concurrently with the development programme, aimed at optimising these malleable determinants of learning performance. Both selection into the affirmative programme and interventions aimed at equipping the learner for developmental success will require that the identity of the factors underlying affirmative development learning performance be understood as well as the manner in which these factors combine to determine learning performance. It is therefore necessary to first get clarity on the fundamental nature of the key behavioural performance areas that forms the learning task. Only if the learning competencies that constitute learning are clear can one attempt to explicate the nomological network of latent variables that characterises the learners and the perception learners have of the learning environment (Burger, 2012) that determine the level of competence that learners will achieve

on these learning competencies. What is required, therefore, is the development of a comprehensive learning potential structural model. Such a learning potential structural model, if validated, will not only assist in the selection of candidates into the affirmative development programme but also in other human resource interventions that precede the development programme and/or that run concurrently with the programme aimed at enhancing the learning performance of those candidates admitted onto the programme. The use of such a learning potential structural model will help human resource managers implement affirmative action development interventions that will be able to help identify and develop individuals that will actually benefit from these interventions.

Previous studies have attempted to develop such a learning potential structural model. De Goede (2007) explicated and empirically tested the learning potential structural model implied by the APIL test battery, that was developed by Taylor (1989,1992,1994,1997), to measure learning potential in the South African context. The original structural model that was proposed by De Goede (2007) focused only on the cognitive aspects of learning potential. Later studies made arguments that the non-cognitive factors of learning potential should also be explored. Burger (2012) argued that focusing purely on cognitive factors that influence learning potential is too restrictive a view to have, and that to truly understand learning potential the structural model should be elaborated to include non-cognitive factors as well. All the studies that directly or indirectly elaborated on the De Goede (2007) model acknowledged in one way or another that *classroom learning performance* and *learning performance during evaluation* in part is comprised of cognitive learning competencies and that the level of competence that is achieved is influentially determined by cognitive learning competency potential latent variables. During the empirical testing of these elaborated learning potential structural models, however, the cognitive competencies and the cognitive learning competency potential latent variables were deleted because of problems associated with the appropriate operationalisation of the two learning competencies, *transfer of knowledge* and *automisation* (De Goede & Theron, 2010).

The current study argued that although the elaboration of the original De Goede (2007) learning potential structural model through the inclusion of the non-cognitive factors proposed by Burger (2012), Du Toit (2014), Mahembe (2014), Pretorius (2014), Prinsloo (2013) and Van Heerden (2013) are of definite value, it was nonetheless seen as imperative that the cognitive competencies and the cognitive learning potential latent variables were returned to the elaborated learning potential structural model and that this extended model is then further elaborated on so as to more accurately reflect the intricate manner in which the cognitive part of the psychological mechanism underpinning learning performance operates. The critical

problem that needed to be solved in order to allow the return of the cognitive competencies and the cognitive learning competency potential latent variables to the learning potential model was the measurability of the cognitive learning competencies of *transfer* and *automisation*.

Although previous studies (Burger, 2012; Du Toit, 2014; Mahembe, 2014; Pretorius, 2014; Prinsloo, 2013; Van Heerden, 2013) have contributed to a more comprehensive and penetrating understanding of the nomological net underlying *classroom learning performance* and *learning performance during evaluation* further research on learning potential was still deemed necessary. More specifically further research on the cognitive hub of *classroom learning performance* was deemed necessary. The fact that all of the post-De Goede (2007) learning potential research excluded the cognitive learning competencies of *transfer* and *automisation* from the structural models that were empirically tested inhibited theorising from developing a more penetrating and detailed understanding of the manner in which the cognitive learning competencies of *transfer* and *automisation* create new knowledge that is available for transfer in *learning performance during evaluation.* Therefore, instead of starting with a new model to explain variance in *learning performance during evaluation*, it was subsequently decided a more a fruitful option was to continue with the cumulative process and further elaborate on one or more of the aforementioned elaborations on the De Goede (2007) model by returning the focus to the nucleus of *classroom learning performance* and *learning performance during evaluation.*

The primary objective of this study was to integrate the De Goede (2007) and Burger (2012) learning potential structural models and to expand and modify the integrated De Goede-Burger model. More specifically the objective of the research was to:

- Identify additional cognitive latent variables and paths that were not included in the integrated De Goede- Burger learning potential structural model in order to obtain a more penetrating and detailed understanding of the manner in which the cognitive learning competencies of *transfer* and *automisation* create new knowledge through *classroom learning performance* and how this new knowledge affects *learning performance during evaluation*;
- Develop hypotheses on the manner in which these additional latent variables were embedded in the integrated De Goede- Burger learning potential structural model;
- Empirically test the expanded De Goede- Burger learning potential structural model by evaluating the model's absolute fit and testing the statistical significance of the estimated path coefficient for the hypothesised paths in the model.

5.2 RESULTS

5.2.1 Evaluation of the Measurement Model

The overall goodness-of-fit of the measurement model was tested through structural equation modelling. It needs to be acknowledged that due to the length of the survey the researchers encountered some practical limitations with regards to gathering a sufficient number of observations in-order to be able to use Structural Equation Modelling (SEM) as the chosen method to analyse the data. According to Kelloway (1998) the number of observations in terms of sample sizes that is deemed as satisfactory for most SEM applications are 200 observations or more. In the first attempt to run the analysis the model failed to converge. The researchers recognised this as a potential problem before the data analysis was undertaken. Due to the length of the survey and the reluctance of people to fill in surveys, only 114 complete responses were obtained. The total number of freed parameters in the measurement model was 114. There was no point in fitting a just-identified measurement model.

In-order to still use SEM as an analysis technique and obtain model fit the researchers considered various alternatives that would allow them to reduce the number of freed measurement model parameters in the proposed model, which in turn would reduce the required number of observations that would be needed to run the data and obtain model fit. The alternatives that were considered were; the classically parallel model, the tau-equivalent model, the essentially tau-equivalent model and the congeneric model. These various measurement models define the options in terms of which the number of freed measurement model parameters could be reduced.

The tau-equivalent model was considered first. Fixing the factor loadings to be equal within subscales and the intercepts to be equal and equal to zero reduced the number of freed parameters from 114 to 100. The ratio of observations to freed parameters was still considered problematic. The classically parallel model that constrains the elements of $\boldsymbol{\tau}$, $\boldsymbol{\Lambda}^{\mathbf{x}}$, and $\boldsymbol{\Theta}_{\boldsymbol{\delta}}$ to be equal across the indicators of each latent variable was therefore subsequently considered. Constraining the error variances of each latent variable to be equal further reduced the number of freed parameters down to 86. The possibility of also constraining the elements of $\boldsymbol{\Phi}$ to be equal was considered. Doing so would reduce the number of freed measurement model parameters by a further 54 to only 32 which would have solved the problem that the number of freed parameters exceed the number of observations in the sample. Very little any theoretical justification could, however, be offered when viewed from the perspective of measurement theory to defend such a step.

The attempt to converge the model was successful, however, the solution was inadmissible although the model did obtain reasonable fit. The use of starting values did not solve the problem. The initial model was fitted utilising maximum likelihood estimation. Subsequently the model was fitted using diagonally weighted least squares estimation. The model converged with close fit but $\theta_{\delta 15,15}$ had an inadmissible negative value (albeit now only marginal negative). Setting a starting value of .50 for $\lambda_{15,8}$ under robust diagonally least squares estimation resulted in a model that converged without any inadmissible values. The goodness of fit statistics in Table 4.38 showed that the model obtained a RMSEA value of 00 thus indicating exact fit in the sample. Table 4.38 also showed the Satorra-Bentler scaled chi-square obtained a value of 824.782 (p=.00) with the null hypothesis of exact fit of the measurement model (H_{01a}: RMSEA = 0) being rejected, which implied that the measurement model didn't have the ability to reproduce the observed co-variance matrix to a degree of accuracy not only explainable in terms of sampling error[56]. In addition, the probability of observing the sample estimate of the root mean square error of approximation (RMSEA = 00) under the close fit null hypothesis (H_{01b}: RMSEA $\leq$ .05) was sufficiently large (p = 1.00) to not reject the close fit null hypothesis. The remaining fit statistics in Table 4.38 only indicated reasonable model fit. The majority of the measurement error variance estimates were statistically insignificant (p>.05). Considering the fact that:

- Under robust maximum likelihood estimation the model only fitted reasonably (RMSEA=.074, p<.05) and returned an inadmissible solution;
- Under diagonally weighted least squares estimation with the use of starting values the fit statistics returned inexplicably contradictory results;
- The majority of the measurement error variances were statistically insignificant (p>.05)

This forced the researchers to conclude that the fitted measurement model therefore did not provide a sufficiently credible description of the process that generated the observed inter-item parcel covariance matrix to have faith in the measurement model parameter estimates or the item parcels. There was therefore no justification in interpreting the measurement model parameters. Moreover, there was no justification in proceeding with the fit of the structural model via structural equation modelling.

Seeing that the attempt to obtain measurement model fit was unfruitful and there was no justification in proceeding with the fit of the structural model via structural equation modelling

[56] The small exceedance probability associated with the test of the exact fit null hypothesis came as a surprise and formed part of the uneasiness with the results that lead the researchers not to interpret the measurement model parameter estimates.

it was decided to take a more robust approach by evaluating the path specific substantive hypotheses via multiple regression analysis.

5.2.2 Regression Analysis

Evaluating the path specific substantive hypotheses via multiple regression analysis meant dissecting the structural model into 7 regression models, fitting each of these via multiple linear regression analysis and testing the path-specific substantive hypotheses by testing the significance of the partial regression slope coefficient estimates.

The zero-order correlation analysis that preceded the regression of *time cognitively engaged* onto *conscientiousness* and *learning motivation* indicated that both *conscientiousness* and *learning motivation* can be expected to statistically significantly explain unique variance in *time cognitively engaged* when they are both included in a regression model. The tolerance values and the variance inflation factor indicated multicollinearity was absent in the regression model. No multivariate outliers were detected with the probabilities for none of the observations to observe the Mahalanobis estimate or larger were found smaller than .001. Two high leverage cases were identified with the centred leverage value for each of these observations exceeding .035. Four influential cases, as judged by Cook's distance measure, was also identified with each of these observations exceeding the critical cut-off value of .035. The DFBETA statistics indicated that there were no highly influential cases that exerted unduly high influence over the regression parameter estimates. The analyses corroborated the inference derived from the correlation matrix that both indicator variables (*conscientiousness* and *learning motivation*) statistically significantly ($p<.05$) explained unique variance in the criterion, variance that was not explained by the other indicator variable. Support was therefore obtained for the path-specific substantive research hypotheses that *conscientiousness* and *learning motivation* each exert a unique positive influence on *time cognitively engaged*.

The intention of the current study was to contribute to the insight developed into affirmative development learning potential via the Stellenbosch University learning potential research niche area. The findings on of the current study on the path-specific substantive hypotheses have therefore been interpreted from the perspective of the Stellenbosch University learning potential research niche area. The finding that *conscientiousness* and *learning motivation* each exert a unique positive influence on *time cognitively engaged* agrees with the findings of

Burger (2012), Du Toit (2014), Mahembe (2014)[57] and Prinsloo (2013)[58]. Van Heerden (2013) also found support for the effect of *learning motivation* on *time cognitively engaged* but she did not hypothesise a direct path from *conscientiousness* to *time cognitively engaged*. In her model the effect of *conscientiousness* on *time cognitively engaged* was mediated by *learning motivation*. She found support for this mediated path. Du Toit (2014) did not include *conscientiousness* in her model. Pretorius (2014), in contrast, somewhat surprisingly failed to find support for the effect of *learning motivation* and *conscientiousness* on *time cognitively engaged*. Strong, consistent empirical evidence in support of the role of *conscientiousness* and *learning motivation* in time cognitively engaged therefore exists. It needs to be said though that the Pretorius (2014) model also included environmental unfavourableness, an *environmental unfavourableness x tenacit*y interaction effect and *environmental unfavourableness x parental quality* interaction effect as effects that influence *time cognitively engaged*. Pretorius' (2014) finding should therefore be seen that *learning motivation* and *conscientiousness* do not significantly affect *time cognitively engaged* when controlling for environmental unfavourableness, an *environmental unfavourableness x tenacit*y interaction effect and *environmental unfavourableness x parental quality* interaction effect. These generally positive findings are extremely gratifying since these two effects make convincing substantive theoretical sense. *Conscientiousness* represents the second-order trait characterised by being persistent, planful, careful, responsible, and hardworking which are important attributes for accomplishing work tasks in all jobs (Barrick & Mount, 1991). *Learning motivation* represents the desire on the part of learners to learn the learning material (Burger, 2012).

The zero-order correlation analysis that preceded the regression of *transfer of knowledge* onto *abstract thinking capacity*prior knowledge, abstract thinking capacity time cognitively engaged* and *time cognitively engaged* indicated that out of the three independent variables only *time cognitively engaged* can be expected to statistically significantly explain unique variance in *transfer of knowledge* when all three variables are included in a regression model. The tolerance values and the variance inflation factor indicated multicollinearity was absent in the regression model. No multivariate outliers were detected with the probabilities for none of

[57] It is acknowledged that Mahembe (2014) concluded that the effect of conscientiousness on time cognitively engaged was statistically insignificant ($p>.05$). Mahembe (2014), however incorrectly used a two-tailed test to evaluate the significance of the parameter estimate given the fact that he formulated a directional alternative hypothesis. When using a more appropriate one-tailed test the estimate is found to be statistically significant ($p<.05$).

[58] It is acknowledged that the current study's findings are strictly speaking not directly comparable to the findings of Burger (2012), Mahembe (2014), Prinsloo (2013) and van Heerden (2013). They tested the significance of the relationship between the latent variables whereas in the current study tested the relationship between the observed variables.

the observations to observe the Mahalanobis estimate or larger were found smaller than .001. Eight high leverage cases were identified with the centred leverage value for each of these observations exceeding .035. Six influential cases as judged by Cook's distance measure was also identified with each of these observations exceeding the critical cut-off value of .035. The DFBETA statistics indicated that observation 54 can be regarded as highly influential cases that exerts unduly high influence over the regression parameter estimates. The regression analyses with observation 54 included corroborated the inference derived from the correlation matrix that *time cognitively engaged w*as the only indicator variable that statistically significantly ($p<.05$) explained unique variance, variance that was not explained by the other indicator variable, in the dependant variable. However, when the highly influential case 54 was removed from the regression analysis *time cognitively engaged* score (X_3), the *abstract thinking capacity*prior knowledge interaction effect* (X_4) and the *abstract thinking capacity*time cognitively engaged interaction effect* (X_5) statistically significantly ($p<.05$) explained unique variance in *transfer of knowledge.* Support was therefore obtained for the path-specific substantive research hypotheses that *time cognitively engaged,* the *abstract thinking capacity*time cognitively engaged interaction effect* and the *abstract thinking capacity*prior knowledge interaction effect* each exert a unique positive influence on *transfer of knowledge.*

This hypothesis had not been tested by any other researcher involved in the Stellenbosch University learning potential research niche area. Their failure to do so is what motivated the current research study. De Goede (2007) tested the hypothesis that *abstract thinking capacity* positively affects *transfer of knowledge*. De Goede (2007) concluded that the effect of *abstract thinking capacity* on *transfer of knowledge* was statistically insignificant ($p>.05$). De Goede (2007), however incorrectly used a two-tailed test to evaluate the significance of the parameter estimate given the fact that he formulated a directional alternative hypothesis. When using a more appropriate one-tailed test the estimate is found to be statistically significant ($p<.05$). *Fluid* intelligence cannot operate in a vacuum. *Transfer of knowledge* cannot occur in the absence of *prior knowledge*. The less *prior knowledge* a learner has the longer the "distance" over which the *abstract thinking capacity* needs to "stretch" to find a solution to a novel problem and consequently the stronger the *abstract thinking capacity* needs to be. De Goede (2007) and Taylor (1994) implicitly acknowledged this. Taylor's (1994) decision to measure *transfer of knowledge* in the APIL via test stimulus material that was equally unfamiliar to advantaged and disadvantaged learners implicitly acknowledges the crucial role that prior knowledge plays in real-life transfer. Neither, however, failed to explicitly acknowledge an *abstract thinking capacity*prior knowledge interaction effect*. Moreover, how long *fluid intelligence* needs to

grapple with a novel problem before an aha-insight is derived depends on the strength of the abstract thinking capacity. Hence an *abstract thinking capacity*time cognitively engaged* interaction effect made substantive theoretical sense. The support the current study obtained for all three components of the hypothesis that *time cognitively engaged,* the *abstract thinking capacity*time cognitively engaged interaction effect* and the *abstract thinking capacity*prior knowledge interaction effect* each exert a unique positive influence on *transfer of knowledge* was extremely gratifying. This effect constitutes part of the cognitive core of the psychological mechanism regulating learning performance[59].

The zero-order correlation analysis that preceded the regression of *academic self-efficacy* onto *learning performance* and *time cognitively engaged* raised the concern that both independent variables cannot be expected to statistically significantly explain unique variance in *academic self-efficacy* when they are both included in a regression model. The tolerance values and the variance inflation factor indicated multicollinearity was absent in the regression model. No multivariate outliers were detected with the probabilities for none of the observations to observe the Mahalanobis estimate or larger were found smaller than .001. Eight high leverage cases were identified with the centred leverage value for each of these observations exceeding .035. Nine influential cases as judged by Cook's distance measure was also identified with each of these observations exceeding the critical cut-off value of .035. The DFBETA statistics indicated that there were no highly influential cases that exerted unduly high influence over the regression parameter estimates. The analyses corroborated the inference derived from the correlation matrix that of the two indicator variables only *time cognitively engaged* statistically significantly ($p<.05$) explained unique variance, variance that was not explained by the other indicator variable, in the dependant variable (*academic self-efficacy*). Support was therefore obtained for the path-specific substantive research hypotheses that *time cognitively engaged,* exerts a unique positive influence on *academic self-efficacy.*

The current study's failure to find support for the hypothesis that *learning performance* positively feeds back on *academic self-efficacy* (when controlling for *time cognitively engaged*) disagrees with the finding of Burger (2012) and van Heerden (2013) who did find support for this hypothesis. Burger (2012) found no support for the hypotheses that *time cognitively engaged* positively influences *academic self-efficacy* with the estimated path coefficient not being statistically significant ($p > .05$). Van Heerden (2013) did not control for the direct effect

[59] The other part of the cognitive core is the role that *automisation*, *information processing capacity*, *post-knowledge* and *time cognitively engaged* play in *learning performance*. Unfortunately due to the omission of the post-knowledge measure the current study's position on this part of the core of the psychological mechanism could not be empirically tested.

of *time cognitively engaged* on *academic self-efficacy*. Du Toit (2014) found support for the effect of *learning performance* on *academic self-efficacy* but did not investigate the effect of *time cognitive engaged* on *academic self-efficacy*. Pretorius (2014) did not test the effect of these two latent variables on *academic self-efficacy*. The omission of a *post-knowledge* scale from the composite research questionnaire necessitated the removal of *post-knowledge* as a latent variable from the hypotheses that were empirically tested. This prevented *time cognitively engaged* from playing the role in the mechanism as was originally theorised, namely that it would moderate the effect of *information processing capacity* on *automisation*. Moreover, it seems theoretically reasonable to argue that not only would the effect of *post-knowledge* on *learning performance* be moderated by *abstract thinking capacity* as originally hypothesised but *time cognitively engaged* would also moderate this relationship. When these effects are returned to the model it would make more theoretical sense to argue like Burger (2012) and van Heerden (2013), and in agreement with Bandura's (1977) theory on self-efficacy, that *learning performance* is (directly and indirectly) affected by *time cognitively engaged* and *learning performance* feeds back onto *academic self-efficacy*.

The zero-order correlation analysis that preceded the regression of *learning motivation* onto *learning performance, academic self-leadership, academic self-efficacy* and *conscientiousness* indicated that all four independent variables can be expected to statistically significantly explain unique variance in *learning motivation* when all four variables are included in a regression model. The tolerance values and the variance inflation factor indicated multicollinearity was absent in the regression model. No multivariate outliers were detected with the probabilities for none of the observations to observe the Mahalanobis estimate or larger were found smaller than .001. Five high leverage cases were identified with the centred leverage value for each of these observations exceeding .035. Seven influential cases, as judged by Cook's distance measure, were also identified with each of these observations exceeding the critical cut-off value of .035.The DFBETA statistics indicated that there were no highly influential cases that exerted unduly high influence over the regression parameter estimates. The analyses corroborated the inference derived from the correlation matrix that all four indicator variables statistically significantly ($p<.05$) explained unique variance, variance that was not explained by the other indicator variables, in the dependant variable (*learning motivation*). Support was therefore obtained for the path-specific substantive research hypotheses that *learning performance, academic self-leadership, academic self-efficacy* and *conscientiousness* each exert a unique positive influence on *learning motivation.*

The current study's finding corresponds to the findings of Prinsloo (2013) who found support for the finding that *academic self-efficacy*, *learning performance* and *conscientiousness*

positively affected *learning motivation*. Prinsloo (2013) did not hypothesise an *academic self-leadership* direct effect on *learning motivation*. Burger (2012) tested the same hypothesis as in the current study and found support for the effect of all four hypothesised effects. Van Heerden (2013) found support for the effect of *academic self-efficacy* and *conscientiousness* on *learning motivation*. She, however, did not examine the feedback effect of *learning motivation* and the effect of *academic self-leadership* on *learning motivation*. Mahembe (2014) found support for the effect of *academic self-leadership* but did not test the other effects hypothesised in the current research study. Du Toit (2014) found support for the effect of *self-efficacy* on *learning motivation* when controlling for *mastery learning goal orientation*. She did not examine the remaining effects that the current study hypothesised to affect *learning motivation*. The general support found across various studies in the Stellenbosch University learning potential research niche area for this hypothesis is gratifying and bolsters confidence in the position that *learning performance, academic self-leadership, academic self-efficacy* and *conscientiousness* each exert a unique positive influence on *learning motivation.*

The zero-order correlation analysis that preceded the regression of *academic self-leadership* onto *academic self-efficacy* indicated the independent variable can be expected to statistically significantly explain unique variance in *academic self-leadership* when included in a regression model. Five high leverage cases were identified with the centred leverage value for each of these observations exceeding .035. Six influential cases as judged by Cook's distance measure was also identified with each of these observations exceeding the critical cut-off value of .035. The DFBETA statistics indicated that there were no highly influential cases that exerted unduly high influence over the regression parameter estimates. The analyses corroborated the inference derived from the correlation matrix that *academic self-efficacy* statistically significantly ($p<.05$) explained unique variance in the dependant variable. Support was, however not obtained for the path-specific substantive research hypothesis that *academic self-efficacy* exerts a negative influence on *academic self-leadership*.

The hypothesised negative effect of *academic self-efficacy* on *academic self-leadership* was right from the start contentious. Burger (2012) originally hypothesised a positive relationship. Her argument was that learners who believed in their learning ability would more assertively self-lead their own learning performance. Although she obtained a statistically significant ($p<.05$) estimate for the hypothesised path the estimate was negative. This prompted the Burger (2012) to *post hoc* argue that a negative relationship might make substantive theoretical sense in the sense that learners who believe that they are capable of succeeding in learning tasks, would tend not to see the need to aggressively implement academic self-leadership strategies as the learner may feel that he/she is capable of performing successfully

without the implementation of these self-leadership strategies (Burger 2012). Prinsloo (2013), in her originally hypothesised model found a statistically significant negative relationship between *academic self-efficacy* and *academic self-leadership*. She originally hypothesised a positive relationship. The fascinating and frustrating finding though was that when she modified her model by deleted two insignificant direct effects (p>.05) that were linked to *academic self-leadership* (*hope* and *optimism*) while maintaining the significant effect of *conscientiousness*, the path from *academic self-efficacy* to *academic self-leadership* become statistically significantly (p<.05) negative (like Burger (2012)). Du Toit (2014) found the effect of *academic self-efficacy* on *academic self-leadership* to be statistically insignificant (p>.05) when controlling for the effect of *learning motivation*. The current study did not hypothesise that *conscientiousness* would affect *academic self-leadership* (and found a positive relationship between *academic self-efficacy* and *academic self-leadership*). In theorising about the relationship between *academic self-efficacy* and *academic self-leadership* the fact that in the Burger (2012) and Prinsloo (2013) studies *academic self-efficacy* was negatively related to *academic self-leadership* when statistically controlling for *conscientiousness* (i.e. when removing the variance in *academic self-leadership* explained by *conscientiousness*). A part of the differences between learners in the extent to which they display academic self-leadership is due to differences in *conscientiousness*. The question is therefore, when those difference in *academic self-leadership* due to differences in *conscientiousness* are removed, how would differences in *academic self-efficacy* (not related to differences in conscientiousness) affect the left-over differences in *academic self-leadership*? The findings of Burger (2012) and Prinsloo (2013) suggest a negative effect. Equally conscientious learners who believe that they are capable of succeeding in learning tasks, would tend not to aggressively implement academic self-leadership strategies as they may feel that they are capable of performing successfully without the aggressive implementation of these self-leadership strategies. The current study strengthens confidence in this argument in that it obtained a positive relationship when not controlling for *conscientiousness*.

The zero-order correlation analysis that preceded the regression of *learning performance* onto *automisation* indicated that the independent variable can be expected to statistically significantly explain unique variance in *learning performance* when included in a regression model. Multivariate outliers were detected with the probabilities for three observations to observe the Mahalanobis estimate or larger were found smaller than .001. Six high leverage cases were identified with the centred leverage value for each of these observations exceeding .035. Ten influential cases as judged by Cook's distance measure was also identified with each of these observations exceeding the critical cut-off value of .035. The

DFBETA statistics, however indicated that there are none of the observations that can be regarded as highly influential cases and that exert unduly high influence over the regression parameter estimates. The analyses corroborated the inference derived from the correlation matrix that the *automisation* statistically significantly (p<.05) *explained* unique variance in the dependant variable (*learning performance*). Support was therefore obtained for the path-specific substantive research hypotheses that *automisation,* exerts a positive influence on *learning performance.*

The current study's finding agrees with the find of de Goede (2007). No other study in the Stellenbosch University learning potential research niche area examined the effect of *automisation* on *learning performance*. De Goede (2007) concluded that the effect of *automisation* on *learning performance* was statistically insignificant (p>.05). De Goede (2007), however incorrectly used a two-tailed test to evaluate the significance of the parameter estimate given the fact that he formulated a directional alternative hypothesis. When using a more appropriate one-tailed test the estimate is found to be statistically significant (p<.05). The hypothesis that the current study tested did not accurately reflect the original hypothesis. Originally it was hypothesised that the effect of *automisation* on *learning performance* is mediated by *post-knowledge* and that the effect of *post-knowledge* on *learning performance* is moderated by *abstract thinking capacity*. The fact that no measure of post-knowledge was available prevented the testing of this hypothesis

The zero-order correlation analysis that preceded the regression of *automisation* onto *information processing capacity*time cognitively engaged* and *transfer of knowledge* indicated that only *transfer of knowledge* can be expected to statistically significantly explain unique variance in *automisation* when included in a regression model. The tolerance values and the variance inflation factor indicated multicollinearity was absent in the regression model. Multivariate outliers were detected with the probabilities for three observations to observe the Mahalanobis estimate or larger were found smaller than .001. Fourteen high leverage cases were identified with the centred leverage value for each of these observations exceeding .035. Five influential cases as judged by Cook's distance measure was also identified with each of these observations exceeding the critical cut-off value of .035. The DFBETA statistics indicated that none of the observations can be regarded as highly influential cases that exert unduly high influence over the regression parameter estimates. The analyses corroborated the inference derived from the correlation matrix that of the two indicator variables only *transfer of knowledge* statistically significantly (p<.05) explained unique variance in the dependant variables. Support was therefore obtained for the path-specific substantive research hypotheses that *transfer of knowledge,* exerts a unique positive influence on *automisation.*

The hypothesis tested in the current study differs from Taylor's (1994) theorising that *automisation* affects *transfer of knowledge*. De Goede (2007) consequently in his attempt to model Taylor's theorising on learning potential also hypothesised a direct effect of *automisation* on *transfer of knowledge*. Taylor's (1994) argument was the faster newly developed insight is automated the faster cognitive capacity is released for further transfer. His argument, however, ignored the fact that in terms of his own theorising different cognitive facets drive *transfer of knowledge* (*abstract thinking capacity*) and *automisation* (*information processing capacity*). De Goede (2007) found support for the hypothesised effect of *automisation* on *transfer of knowledge.* The current study argued that through transfer of post-knowledge on novel problems new insight is obtained. However, unless that insight is automated it does not become crystallised knowledge but rather only a fleeting understanding. Only if the insight derived through transfer of prior knowledge is automated does it become available for further transfer. The current study's failure to find support for the *information processing capacity*time cognitively engaged* interaction effect was disappointing. The current study possibly erred by not also hypothesising an *information processing capacity* main effect in as argued by Taylor (1994) and de Goede (2007) along with the *information processing capacity*time cognitively engaged* interaction effect.

The results obtained via the seven regression analyses are summarised in Figure 5.1.

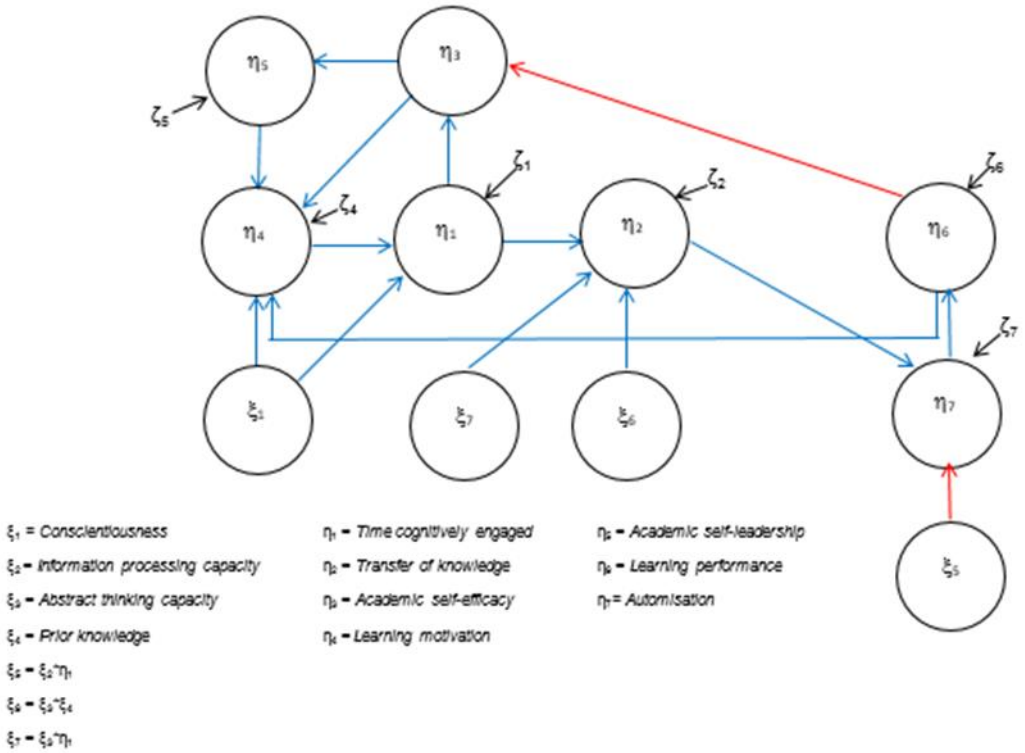


Figure 5.1: ***Summary of the regression analyses results***

It is acknowledged that depicting the results in this manner fails to reflect the fact that the regression analyses dissected the structural model and tested the hypothesised relationships in an isolated manner that ignored the manner in which the relationships are embedded in the larger network.

5.3. PRACTICAL IMPLICATIONS

Burger (2012) acknowledged in her study that the non-cognitive factors proposed in her study should be supplemented by the cognitive factors that were proposed by De Goede (2007). The learning potential structural model proposed in this study included the reduced learning potential model that was proposed by Burger (2012) combined with the cognitive factors that were proposed by De Goede (2007). The cognitive factors that were proposed by De Goede (2007) were elaborated on by hypothesising prior knowledge and post knowledge as possible latent variables that would provide a richer and more integrated insight into the role that cognitive factors play in learning potential. The purpose of the proposed learning potential model was to gain a holistic understanding of the nomological network of factors that underpins learning performance with the aim of addressing shortcomings in affirmative action within South Africa.

The concern is that aggressive affirmative action hurts the people it is meant to help through the gradual systematic implosion of organisations due to the lack of motivated and competent personnel and a loss of institutional memory (Du Toit, 2014; Esterhuyse, 2008). It can be assumed that the lack of motivated and competent personnel can be a cause of frustration and concern for organisations. Another factor that adds to the frustration of affirmative action, as it is currently applied, is the fact that the majority of learners who register for skills development programs, do not complete these programmes. Letsoalo (2007a; 2007b) stated that in 2007 the Department of Labour's implementation report on skills development stated that almost 80% of learners registered for SETA learnerships did not complete their training. This is problematic because the skills development programmes that are designed to provide skilled labourers from previously disadvantaged groups are failing.

To reduce frustration currently experienced with the traditional interpretation of affirmative action and with many current learnerships to the extent that such frustration exists, an affirmative development approach is needed where people from previously disadvantaged groups with the necessary learning potential will be identified for affirmative development programmes, as well as people who will actually successfully complete the programmes. By

obtaining the expected results for the proposed learning potential structural model in this study a broader understanding can be gained of the underlying factors that constitute learning performance. This understanding will allow for the development of a selection battery that is theoretically well-grounded and, allows for valid criterion inferences[60] and is practically viable and will help identify learners with the necessary learning potential to complete the affirmative development programme. This selection battery will also enable companies to use the limited resources that they have optimally by selecting learners that are more likely to succeed in an affirmative development programme. In designing such a selection battery, a choice will have to be made between a construct-orientated and a content-orientated approach to selection (Binning & Barret, 1989). Under the latter approach a series of small learning exercises taken from the content of the development programme will have to be developed where insights developed during the initial exercises are needed gain insight into the later exercises. This will allow assessment of the learning competencies. Under the former approach learning competency potential latent variables like *conscientiousness*, *learning motivation*, *abstract thinking capacity*, *information processing capacity* and *prior knowledge* will have to be assessed. The ideal would be to develop an actuarial prediction model. The manner in which the latent competency potential latent variable measures are combined in the experimental actuarial prediction model should acknowledge the manner in which the latent variables have been found to affect *learning performance during evaluation*.

The hypothesised effects hypothesised in the reduced learning potential structural model, for which support was obtained via the multiple regression analyses, can be used to address the current lack of success that skills development programmes are experiencing. The underlying factors proposed in the learning potential structural model should be used to inform HR interventions aimed at enhancing learning performance. These latent variables firstly indicate which variables can be included in an experimental selection battery aimed at selecting candidates into an affirmative development programme and secondly what can be done once selected candidates are on the programme (or what can be done with selected candidates after they have been selected but before they go on the programme). All the predictor latent variables (i.e., excluding *learning performance during evaluation*) in the reduced learning potential structural model for which support was found (i,e, excluding the *information processing capacity*time cognitively engaged* interaction effect). It would then have to be

[60] The criterion in this case will be post-development learning performance during evaluation. It therefore needs to reflect the extent to which learners are able to transfer their newly derived crystallised knowledge onto novel job-relevant problems.

empirically determined which of these predictor variables explain unique variance in the criterion *learning performance during evaluation* when included in a single regression model.

Selecting the best candidates into a development programme is not enough to ensure success. Emphasis can be placed on the non-cognitive factors proposed in the learning potential structural model when compiling courses. HR should zoom in on the malleable non-cognitive determinants of learning potential (like academic self-efficacy, learning motivation, prior knowledge, academic self-leadership) and develop these after selection, but before training as well as during training via the trainer

In the final analysis the current study was aimed at reducing adverse impact. In this study it was argued that there is currently a misperception about the fundamental cause of adverse impact as far as HR practitioners are too often advised to use psychometric tests that reduce adverse impact as per the Employment Equity Act. This requirement appears to be misplaced seeing that no matter how valid, reliable and unbiased a psychometric measurement is, and even if the information from such a measure is used fairly to make criterion inferences, it will not be able to lessen adverse impact if the location of the group-specific criterion distributions differ (Theron, 2007; 2009). This is because the scores that are obtained from psychometric measurements in themselves do not cause adverse impact. It is differences in the means of group-specific criterion distributions about which inferences are made from these test scores that lead to adverse impact. The psychometric measurement that is used in the selection procedure is merely the messenger that points out that groups differ in abilities required for the specific job. It is due to past injustices and historical events that groups in South Africa differ in ability, and adverse impact follows as a logical consequence of those differences during selection. Another advantage of making use of a selection battery that will assist in selecting learners for development that will maximally benefit from the development and most likely complete the development programmes, is that the root of adverse impact will be addressed. The selection of learners who possess the necessary learning potential and who will complete affirmative development programmes will lead to an increase in the pool of employees who have the necessary abilities to do what is required in specific jobs.

5.4 POSSIBLE LIMITATIONS OF THIS STUDY

To provide a representative sample of previously disadvantaged groups within the South African context is something that is not easily practically attainable. This is in itself a regrettable and unfortunate state of affairs as it suggests that affirmative development is not something that is a general and widespread phenomenon. Therefore, a group of undergraduate

engineering students at Stellenbosch University was subjected to this study. This decision was made following the argument that the psychological processes underpinning learning is the same regardless of an advantaged or disadvantaged background.

Due to an insufficient number of observations the analysis of the proposed structural model via structural equation modelling had to be simplified to a multiple regression analysis. This is acknowledged as a methodological limitation. The explanation lies spread over the whole of the psychological mechanism regulating the level of learning performance achieved by learners. Taking the mechanism apart invariably results in a loss of meaning. Moreover, the use of multiple regression unavoidably requires the testing of the path-specific substantive hypotheses indirectly by testing path-specific operational hypotheses. Theoretical interest resides in the overall substantive research hypothesis and the path-specific substantive hypotheses. The use of linear multiple regression did not allow for the substantive research hypothesis and the path-specific substantive hypotheses to be tested directly.

An unfortunate oversight by the researchers forced them to remove *post-knowledge* from the structural model that was eventually empirically tested. This was regrettable as *post-knowled*ge was hypothesised to play a pivotal role in the section of the learning psychological mechanism that links *classroom learning performance* to *learning performance during evaluation*. Learning is a never-ending human activity. It is not restricted to the classroom. Learning at its core is *transfer* of existing crystallised knowledge onto novel problems and the *automisation* of the insights/solutions derived through transfer to expand and elaborate the crystallised knowledge. The expanded and elaborated crystallised knowledge is transferred unto novel problems and the insights/solutions derived through transfer is *automised* to expand and elaborate the crystallised knowledge. *Prior knowledge* is expanded and elaborated into *post-knowledge* via transfer and automisation. It is therefore becomes very difficult to claim that a valid description of the psychological mechanism that underpins learning had be attained if *post knowledge* is not included in the learning potential structural model.

5.5. SUGGESTIONS FOR FUTURE RESEARCH

It would be fruitful if future research could analyse the proposed learning potential structural model or an elaborated version of the model via structural equation modelling as initially proposed in this study. Seeing that the theoretical interest resides in the overall substantive research hypothesis and the path-specific substantive hypotheses of the proposed learning potential model, it is proposed that future research be conducted that allows for the exploration

of the richness of the overall substantive research hypothesis and the path-specific substantive hypotheses. In-order to explore the overall substantive research hypothesis and the path-specific substantive hypotheses future researchers would need to ensure that they have enough observations, which would allow them to analyse the proposed learning potential structural model via structural equation modelling.

In-order to ensure a sufficient number of observations future researchers would have to come to some sort of an agreement with a large enough institution or organisation where the members of the institution or organisation are subjected to the learning potential survey over a period of one or two days. An alternative that could be considered is the use of planned missing designs as a data collection method. Planned missing data designs is a method that allows researchers to collect incomplete data from participants (Little & Rhemtulla, 2013). According to Little and Rhemtulla (2013), this can be done by randomly assigning participants to have missing items, missing measurement occasions or missing measures. Some of the benefits of this method are: the shortening of surveys, which reduces the burden on participants leading to higher quality data; the shortening of surveys allows for more items in a study, increasing the breadth of constructs; and a reduction in the cost of data collection (Little & Rhemtulla, 2013). The researcher would have to determine what planned missing design would be relevant based on the purpose of his/her study as well as on the design of his/her survey.

The argument that the psychological mechanism underpinning *classroom learning performance* and *learning performance during evaluation* of advantaged and disadvantaged learner is the same (although the levels of the latent variables most likely will differ) should be put to empirical test. Multi-group structural equation modelling can be used to formally test whether the structural model proposed in the current study (assuming that the proposed model achieves at least close fit) is invariant across advantaged and disadvantaged learner groups, and if so, whether the strength of the structural relations is invariant across groups.

The current study argued that it is due to past injustices and historical events that groups in South Africa differ in job competency potential. The learning potential structural model proposed in the current study should be elaborated in future research by formally modelling the mechanism that determines the level of *prior knowledge*. Cottrell, Newman and Roisman (2015) embarked on a study to determine possible factors that could explain the black-white gap in cognitive test scores with the aim of better understanding the phenomenon of adverse impact. In their study they identified a number of socio-demographic latent variables that are proposed to be possible explanations for the black-white gap in cognitive test scores. Some

of the factors they identified in past research are birth order, maternal verbal ability/knowledge, learning materials, parenting factors and birth weight. These socio-demographic latent variables should be considered for inclusion in an elaborated model that aims to explain the mechanism that determines the level of an individual's *prior knowledge*.

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APPENDIX A

COMPOSITE LEARNING POTENTIAL RESEARCH QUESTIONNAIRE

UNIVERSITEIT·STELLENBOSCH·UNIVERSITY
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CONSENT TO PARTICIPATE IN RESEARCH

Collaboration and Elaboration of learning potential structural models proposed by De Goede (2007) and Burger (2012).

You are asked to participate in a research study conducted by Braam Venter (Masters student, MCom, from the Department of Industrial Psychology at Stellenbosch University. The results of this study will contribute to my master's thesis. You were selected as a possible participant in this study because you have completed your grade 12 studies in mathematics and decided to study engineering at Stellenbosch University.

1. PURPOSE OF THE STUDY

The purpose of this study is to integrate and elaborate existing theoretical models developed by De Goede (2007) and Burger (2012) with regards to differences in learning performance. The aim is therefore to elaborate on previous research in-order to see how cognitive and non-cognitive variables play a role in learning.

2. PROCEDURES

If you volunteer to participate in this study, we would ask you to do the following things: If you agree to participate in the study will be asked to complete a 1h 30min survey. You will also be asked for permission to access to your grade 12 mathematics - and first semester engineering mathematics marks. Marks will only be accessed if you have given the necessary consent. By providing me with the necessary consent you will allow me to obtain access to your marks via the official university data archive to use as part of this research. Once you have given the researcher consent to access your marks, the researcher will come in contact with the university and request access to your grade 12 mathematics mark and your first year first semester engineering mark, by providing the university with proof of your informed consent.

3. POTENTIAL RISKS AND DISCOMFORTS

There exist no serious foreseeable risks associated with participation in the research study. You will be asked to provide your student numbers, and therefore the completion of the survey

will not be completely anonymous. You will also be asked for access to your grade 12 mathematics – and first semester , engineering mathematics mark which may cause a feeling of vulnerability and emotional discomfort . Your student number will be used to match the survey that you have completed with your grade 12 math and first year engineering math marks. The data collected will be kept strictly confidential, and no single participant's results will be discussed in the final report. Participation in the research might in addition create some discomforts and inconvenience for you in that you have to set aside some time to complete the online questionnaire.

4. POTENTIAL BENEFITS TO SUBJECTS AND/OR TO SOCIETY

There exist no direct benefits for you, the participant. However, the development of this learning potential structural model will assist in the development of a more penetrating understanding of the determinants of learning performance and in the development of interventions aimed at promoting successful learning. The proposed structural model that the study will empirically test is specifically aimed at identifying and eliciting learning potential amongst South Africans. Thus, this research will be of value to the participants' community and South African society as a whole.

5. PAYMENT FOR PARTICIPATION

One lucky participant will receive a prize. The winner of the prize will be picked at random. All participants' student numbers will go into a lucky draw. Your student number will be drawn via a random number generator to ensure that selection is random. The lucky winner will be contacted through his/her student e-mail (@sun.ac.za) to inform him/her that he/she has won.

6. CONFIDENTIALITY

Any information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission or as required by law. Confidentiality will be maintained by means of restricting access to the data to the researchers (Braam Venter and Prof Callie Theron), 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 the form of an unrestricted open source electronic thesis, as well as in an article published in an accredited scientific journal. Not one of these publications will reveal the identity of any research participant (learner), or the academic marks of any learner.

7. PARTICIPATION AND WITHDRAWAL

You can choose whether to be in this study or not. If you volunteer to be in this study, you may withdraw at any time without consequences of any kind. You may also refuse to answer any

questions you don't want to answer and still remain in the study. The investigator may withdraw you from this research if circumstances arise which warrant doing so.

8. IDENTIFICATION OF INVESTIGATORS

If you have any questions or concerns about the research, please feel free to contact Braam Venter (072 784 5339 or janabventer@gmail.com) or Prof Callie Theron (021 808 3009 or ccth@sun.ac.za).

9. RIGHTS OF RESEARCH SUBJECTS

You may withdraw your consent at any time and discontinue participation without penalty. You are not waiving any legal claims, rights or remedies because of your participation in this research study. If you have questions regarding your rights as a research subject, contact Ms Maléne Fouché [mfouche@sun.ac.za; 021 808 4622] at the Division for Research Development at Stellenbosch University.

10. PROVIDING INFORMED CONSENT

I hereby voluntarily consent to participate in this study under the stipulated conditions:

- ❍ Yes
- ❍ No

I hereby voluntarily consent to that the researcher may access my matric mathematics mark and my first year first semester engineering mark via the data archive of Stellenbosch University for the purpose of this research study

- ❍ Yes
- ❍ No

Only the scales in the Composite Learning Potential Research Questionnaire that are available in the public domain and that are not subject to copywrite or that were developed by the researchers are reproduced here. All the scales in Section A were subject to copywrite

SECTION B

Time Cognitively Engaged

Engaged learners exhibit sustained involvement in learning activities; these learners initiate action when given the opportunity and exert intense effort and concentration in the application of learning tasks (Burger, 2012). Student engagement can therefore be seen as a student's willingness to engage in routine learning activities such as attending class.

You will be given certain statements that relate to a the extent to which you cognitively engage with your academic learning material You will rate each statement on a given scale in terms of how relevant you feel the statement is to you. A seven point Likert-scale is used that ranges from Never - Always.

	Never	Almost Never	Rarely	Sometimes	Often	Very Often	Always
1. I spent enough time on my academic work to reach my learning/academic goals at the end of the first semester.	❍	❍	❍	❍	❍	❍	❍
2. I exerted enough cognitive effort on my engineering math learning/academic work to reach my goals at the end of the first semester.	❍	❍	❍	❍	❍	❍	❍
3. In my first semester engineering math module I actively listened and engaged with my lecturer.	❍	❍	❍	❍	❍	❍	❍
4. In my first semester engineering math module I exerted effort to concentrate and understand what my lecturer is saying.	❍	❍	❍	❍	❍	❍	❍
5. I was intellectually/mentally engaged with what my lecturer was saying in my first semester engineering math module.	❍	❍	❍	❍	❍	❍	❍
6. I was intellectually/mentally engaged with my first semester engineering math study material outside of compulsory class times.	❍	❍	❍	❍	❍	❍	❍
7. I made sure that when I set time aside to study I used my time efficiently and exerted effort to learn the material.	❍	❍	❍	❍	❍	❍	❍
8. When I got down to work with regards to my first semester engineering math module, I worked hard.	❍	❍	❍	❍	❍	❍	❍

9. I forced myself to focus if my mind drifted off while I was studying	❍	❍	❍	❍	❍	❍	❍
10. This past semester I put enough time and effort into my engineering math module to reach my first semester goal.	❍	❍	❍	❍	❍	❍	❍
11. I was an active member in my first semester engineering math module	❍	❍	❍	❍	❍	❍	❍
12. I listened intensively/deeply in my first semester engineering math module.	❍	❍	❍	❍	❍	❍	❍
13. I concentrated in my first semester engineering math module.	❍	❍	❍	❍	❍	❍	❍
14. I actively participated in first semester engineering academic group activities.	❍	❍	❍	❍	❍	❍	❍
15. I kept myself focused when I studied for engineering math.	❍	❍	❍	❍	❍	❍	❍
16. When I studied, I was really engaged with my engineering math modules' study material.	❍	❍	❍	❍	❍	❍	❍
17. I tried not to get distracted in class.	❍	❍	❍	❍	❍	❍	❍

Academic Self-Leadership

Academic self-leadership is the process through which individuals influence themselves to achieve the necessary self-direction and motivation to perform well in a learning task. This empowers individuals to be in control of their own behaviour by influencing and leading themselves through the use of specific behavioural and cognitive strategies.

You will be given certain statements that relate to a the extent to which you display academic self-leadership regarding your academic studies You will rate each statement on a given scale in terms of how relevant you feel the statement is to you. A seven point Likert-scale is used that ranges from Never - Always.

	Never	Almost Never	Rarely (3)	Sometimes (4)	Often (5)	Very Often (6)	Always (7)
1. I used my imagination to picture myself performing well on important first semester engineering math learning tasks before I actually did them.	❍	❍	❍	❍	❍	❍	❍
2. I visualised myself successfully performing a first	❍	❍	❍	❍	❍	❍	❍

semester engineering math learning task before I did it.							
3. I mentally rehearsed the way I planned to deal with a first semester engineering math learning challenge before I actually faced the challenge.	❍	❍	❍	❍	❍	❍	❍
4. I wrote down specific learning goals for first semester engineering maths.	❍	❍	❍	❍	❍	❍	❍
5. I consciously had my first semester engineering math learning goals in mind when I studied.	❍	❍	❍	❍	❍	❍	❍
6. I talked to myself (out loud or in my head) to work through difficult learning/academic problems in my first semester engineering math module.	❍	❍	❍	❍	❍	❍	❍
7. I found I was talking to myself (out loud or in my head) to work through difficult learning/academic problems in my first semester engineering math module.	❍	❍	❍	❍	❍	❍	❍
8. When I did a learning/academic assignment especially well, I treated myself to something I liked or activity I especially enjoyed.	❍	❍	❍	❍	❍	❍	❍
9. When I successfully completed a first semester engineering math task, I often rewarded myself with something I like or activity I especially enjoyed.	❍	❍	❍	❍	❍	❍	❍
10. I evaluated/assessed the correctness of my beliefs and assumptions when I was in difficult situations.	❍	❍	❍	❍	❍	❍	❍
11. I evaluated/assessed my beliefs and assumptions when I had a disagreement with someone else.	❍	❍	❍	❍	❍	❍	❍
12. I was tough on myself in my thinking when I did not do a first semester engineering math task well.	❍	❍	❍	❍	❍	❍	❍
13. I got down on myself when I performed first semester engineering tasks poorly.	❍	❍	❍	❍	❍	❍	❍
14. I felt guilty when I performed first semester engineering math tasks poorly.	❍	❍	❍	❍	❍	❍	❍

15. I made a point of keeping on track as to how well I was doing in my first semester engineering math work.	❍	❍	❍	❍	❍	❍	❍
16. I was aware of how well I was performing my first semester engineering math activities.	❍	❍	❍	❍	❍	❍	❍
17. I kept track of my progress on first semester engineering math work	❍	❍	❍	❍	❍	❍	❍
18. I focused my thinking on the pleasant rather than the unpleasant aspects of my first semester engineering math learning/academic work.	❍	❍	❍	❍	❍	❍	❍
19. I surrounded myself with objects and people that bring out the learning behaviours I wanted in myself in-order to help me learn.	❍	❍	❍	❍	❍	❍	❍
20. I tried to find activities in my work that I enjoyed doing in order to get my work done.	❍	❍	❍	❍	❍	❍	❍
21. I found my own favourite way to get my work done.	❍	❍	❍	❍	❍	❍	❍
22. I used written notes to remind myself of the things I needed to get done.	❍	❍	❍	❍	❍	❍	❍
23. I made lists to remind me of the things I needed to get done.	❍	❍	❍	❍	❍	❍	❍

Academic self-efficacy

Academic self-efficacy is the belief of a learner in his/her academic capabilities. It is this belief rather than his/her actual academic performances, that tends to shape the course of his/her developmental trajectories (Bandura et al. 2001).

You will be given certain statements that relate to a the extent to which you display academic self-leadership regarding your academic studies You will rate each statement on a given scale in terms of how relevant you feel the statement is to you. A seven point Likert-scale is used that ranges from Never - Always.

	Never	Almost Never	Rarely	Sometimes	Often	Very Often	Always
1. I felt that I was able to deal with my first semester first year engineering work.	❍	❍	❍	❍	❍	❍	❍

2. I believed if I tried hard enough I could solve difficult problems in my first year engineering course.	❍	❍	❍	❍	❍	❍	❍
3. I needed reassurance during the first half of my first year engineering course with regards to the academic work.	❍	❍	❍	❍	❍	❍	❍
4. I believed I could handle anything in the first half of my first year engineering course.	❍	❍	❍	❍	❍	❍	❍
5. I was confident that I could cope efficiently with the first half of my first year engineering course.	❍	❍	❍	❍	❍	❍	❍
6. I believed I could solve most problems with regards to my first year engineering course if I put in the necessary effort.	❍	❍	❍	❍	❍	❍	❍
7. I believed I could handle my first year engineering course well.	❍	❍	❍	❍	❍	❍	❍
8. I felt certain that I could achieve the academic goals I set out for myself in my first semester of my first year of engineering.	❍	❍	❍	❍	❍	❍	❍
9. I believed I was capable of reaching the goals I set for my first semester of my first year of engineering even when times were tough.	❍	❍	❍	❍	❍	❍	❍
10. I felt secure about my ability to reach the goals I set for my first semester of my first year of engineering.	❍	❍	❍	❍	❍	❍	❍
11. I felt capable of dealing with most problems that came up in my first semester of first year engineering.	❍	❍	❍	❍	❍	❍	❍
12. I felt I would get good grades in my first semester of first year engineering if I tried hard enough.	❍	❍	❍	❍	❍	❍	❍

Conscientiousness

Conscientious individuals are characterised as being organised, reliable, self-directed, punctual, scrupulous, persevering, self-disciplined, productive, systematic, dutiful, high on achievement striving and hardworking (Nijhuis, Segers & Gijselaers, 2007). According to Eilam, Zeidner and Aharon (2009) this dimension includes features such as ambition, energy, control of inclinations, diligence, carefulness and being practical. Conscientiousness refers to, for the purpose of this study, individuals who are prepared, diligent, make plans and stick to them, thorough in their work, self-disciplined, organised. This dimension is also termed 'the will to succeed,' which expresses intentional goal-driven behaviour.

You will be given certain statements that relate to a the extent to which you act conscientiously regarding your academic studies You will rate each statement on a given scale in terms of how relevant you feel the statement is to you. A seven point Likert-scale is used that ranges from Never - Always.

	Never	Almost Never	Rarely	Sometimes	Often	Very Often	Always
1. I was always prepared in my first semester of first year engineering.	❍	❍	❍	❍	❍	❍	❍
2. I paid attention to details.	❍	❍	❍	❍	❍	❍	❍
3. My parents and/or lecturers needed to check upon me in order for me to get started with my work in my first year of engineering.	❍	❍	❍	❍	❍	❍	❍
4. I got my first semester first year engineering tasks done efficiently and effectively.	❍	❍	❍	❍	❍	❍	❍
5. I successfully completed my first semester first year engineering tasks in the manner I planned to.	❍	❍	❍	❍	❍	❍	❍
6. When I made plans with regards to the first half of first year engineering I stuck to them.	❍	❍	❍	❍	❍	❍	❍
7. I planned my study time.	❍	❍	❍	❍	❍	❍	❍

8. I was thorough in my academic work.	❍	❍	❍	❍	❍	❍	❍
9. I got my academic work completed on time.	❍	❍	❍	❍	❍	❍	❍
10. I developed a study timetable to guide my studying.	❍	❍	❍	❍	❍	❍	❍
11. I stuck to my developed study timetable.	❍	❍	❍	❍	❍	❍	❍
12. The study timetable that I set up was well organised.	❍	❍	❍	❍	❍	❍	❍

Learning Motivation

According to Nunes (2003), motivation involves a choice, by the individual, to expend energy towards one particular set of behaviours. More specifically, Learning Motivation can be defined as the desire on the part of learners to learn the learning material (Ryman & Biersner, 1975).

You will be given certain statements that relate to a the extent to which you display learning motivation regarding your academic studies. You will rate each statement on a given scale in terms of how relevant you feel the statement is to you. A seven point Likert-scale is used that ranges from Never - Always.

	Never (1)	Almost Never (2)	Rarely (3)	Sometimes (4)	Often (5)	Very Often (6)	Always (7)
1. I intended to increase my knowledge during my first semester of first year engineering	❍	❍	❍	❍	❍	❍	❍
2. When I didn't understand some part of the first semester of the first year engineering course I tried harder for example by asking questions.	❍	❍	❍	❍	❍	❍	❍
3. I was willing to exert considerable effort in order to enhance my knowledge and understanding during my first semester of first year engineering	❍	❍	❍	❍	❍	❍	❍
4. I wanted to learn as much as I could during	❍	❍	❍	❍	❍	❍	❍

the first half of first year engineering (4)							
5. I was motivated to learn the work covered in the first semester of first year engineering	❍	❍	❍	❍	❍	❍	❍
6. I intended to do my best in first semester of first year engineering	❍	❍	❍	❍	❍	❍	❍

Transfer of Knowledge

The transfer process refers to the manner through which crystallised abilities develop from the interaction between fluid intelligence/abstract thinking capacity (Cattell, 1971) and novel stimuli (Taylor, 1994) (De Goede, 2007). In essence transfer refers to the influence that previously attained knowledge has on the performance of new learning tasks.

You will be given certain statements that relate to a the extent to which you display transfer of knowledge in your academic studies. You will rate each statement on a given scale in terms of how relevant you feel the statement is to you. A seven point Likert-scale is used that ranges from Never - Always.

	Never	Almost Never	Rarely	Sometimes	Often	Very Often	Always
1. When I encountered unfamiliar learning material in my first semester engineering math module, I struggled to make sense of the learning material.	❍	❍	❍	❍	❍	❍	❍
2. When I encountered unfamiliar learning material in my first semester engineering math module, I compared aspects of the unfamiliar learning material to similar aspects in previous learning material that I have obtained.	❍	❍	❍	❍	❍	❍	❍
3. I was able to make sense of new learning material that was covered in my first semester engineering math module reasonably quickly.	❍	❍	❍	❍	❍	❍	❍
4. I found that my background in mathematics helped me to make sense of the work that was covered during my first semester engineering math module.	❍	❍	❍	❍	❍	❍	❍
5. I acquire new knowledge/ skills in unfamiliar situations/problems through transferring other	❍	❍	❍	❍	❍	❍	❍

skills/knowledge that I have previously obtained.							
6. When I found myself in a situation where I did not have specific knowledge/experience that would help me to make sense of a problem in my first semester engineering math module, I was still effective in solving the problem by making use of general knowledge that I have previously obtained.	❍	❍	❍	❍	❍	❍	❍
7. When I encountered unfamiliar course material in my first semester engineering math module, I had the ability to understand what responses were appropriate in a given situation and what responses weren't.	❍	❍	❍	❍	❍	❍	❍
8. I required assistance when I was introduced to new engineering math course material, in-order to make sense of the material.	❍	❍	❍	❍	❍	❍	❍
9. I required assistance when I was faced with a new engineering math problem, in-order to solve the problem.	❍	❍	❍	❍	❍	❍	❍
10. I found that instructions/information needed to be repeated multiple times when I was working through unfamiliar first semester engineering math material in-order for it to make sense.	❍	❍	❍	❍	❍	❍	❍
11. I found that when making sense of new engineering math course material that it was the similarity of the course material with previous academic course material that I have worked through that allowed me to make sense of the material.	❍	❍	❍	❍	❍	❍	❍
12. I was good at making sense of unfamiliar work covered during the semester.	❍	❍	❍	❍	❍	❍	❍
13. I was –able to recognize the elements of a new engineering math problem that were relevant for solving the problem and the elements that were not relevant.	❍	❍	❍	❍	❍	❍	❍
14. I was able to combine the elements of the new engineering math problem in order to solve the problem.	❍	❍	❍	❍	❍	❍	❍

15. I was able to figure out how new information covered in class related to old information that I have encountered.	❍	❍	❍	❍	❍	❍	❍
16. I was able to create meaningful structure in the learning material covered in my engineering math module.	❍	❍	❍	❍	❍	❍	❍
17. I was able to make sense of the learning material covered in my first semester engineering math module.	❍	❍	❍	❍	❍	❍	❍
18. I memorised my first semester engineering math module's learning material without really understanding what it is all about.	❍	❍	❍	❍	❍	❍	❍
19. I struggled to make sense of what was said in class.	❍	❍	❍	❍	❍	❍	❍
20. I did not understand the lecturer.	❍	❍	❍	❍	❍	❍	❍
21. I understood how different parts of the first semester engineering math module's learning material fit together.	❍	❍	❍	❍	❍	❍	❍
22. I managed to attain a feeling of aha (truly understood) by reflecting on the work that was covered in class for a while.	❍	❍	❍	❍	❍	❍	❍
23. I had to reflect for a very long time before I attained aha (truly understood) on the work that was covered in class.	❍	❍	❍	❍	❍	❍	❍
24. I found it difficult to understand how I would use the first semester engineering math learning material covered in class.	❍	❍	❍	❍	❍	❍	❍
25. Even after going over the work covered in class it still did not really make sense to me.	❍	❍	❍	❍	❍	❍	❍
26. My background in academics allowed me to make sense of the work covered during my first semester engineering math module. (26)	❍	❍	❍	❍	❍	❍	❍
27. I explained the work covered in class to my friends.	❍	❍	❍	❍	❍	❍	❍

Automisation

Automisation refers to an individual's ability to become more effective and efficient in the execution of a task. The extent to which one develops expertise in a certain domain or task depends on the ability of the individual to automate new information.

You will be given certain statements that relate to a the extent to which you display transfer of knowledge in your academic studies. You will rate each statement on a given scale in terms of how relevant you feel the statement is to you. A seven point Likert-scale is used that ranges from Strongly disagree – Strongly agree.

	Strongly Disagree	Disagree	Neither Yes or No	Agree	Strongly Agree
1. The more time I spent on my first semester engineering math learning material the more the learning material became part of me.	❍	❍	❍	❍	❍
2. I found that the level of attention that I had to pay decreased the more I encountered my first semester engineering math learning material.	❍	❍	❍	❍	❍
3. I found that my expertise in mathematics allowed me to better handle unfamiliar first semester engineering math learning material/ solve new engineering math problems that I encountered.	❍	❍	❍	❍	❍
4. I found that I was able to execute complex engineering math tasks, because of previous knowledge/experiences that I have obtained that share similar operations.	❍	❍	❍	❍	❍
5. I found that a lack of knowledge/experience hindered me from making sense of – and solving unfamiliar first semester engineering math problems.	❍	❍	❍	❍	❍
6. Once I had made sense of/solved an unfamiliar engineering math problem I was able to transfer the newly obtained knowledge to make sense of the next new engineering math problem that I encountered.	❍	❍	❍	❍	❍
7. Previously learnt knowledge allowed me to form strategies that helped me to make sense of/ solve unfamiliar engineering math learning material/ new engineering math problems.	❍	❍	❍	❍	❍
8. I have internalised the engineering math learning material covered during the first semester.	❍	❍	❍	❍	❍
9. I can discuss the engineering math learning material covered during the semester at any point.	❍	❍	❍	❍	❍

10. After I have written a test I cannot recall much of the first semester engineering math learning material that the test was written on.	❍	❍	❍	❍	❍
11. The insights I have attained during the semester have become part of me.	❍	❍	❍	❍	❍
12. I feel I am in control of the engineering math learning material covered during the first semester.	❍	❍	❍	❍	❍
13. I feel confident that I will be able to use the engineering math learning material covered during the first semester to solve unfamiliar situations/new problems.	❍	❍	❍	❍	❍
14. I can recall and use the work covered during the first semester of engineering maths to provide meaningful answers to questions I have not seen before.	❍	❍	❍	❍	❍
15. I did understand the engineering math work covered during the first semester at some point but I can no longer recall most of it.	❍	❍	❍	❍	❍
16. I feel confident that I will be able to explain the engineering math work covered during the first semester without requiring any significant preparation. (16)	❍	❍	❍	❍	❍
17. I do not feel confident in the area of my first semester engineering math module.	❍	❍	❍	❍	❍
18. I can recall the engineering math work we covered this semester without much effort.	❍	❍	❍	❍	❍

Thank you for completing the questionnaire

If you wish to participate in the competition for the prize please follow the link below to enter your cell phone number

APPENDIX B

LEARNING POTENTIAL MEASUREMENT MODEL LISREL 8.8 SYNTAX

```
FITTING THE REDUCED BRAAM VENTER LP MEASUREMENT MODEL WITH
FACTOR LOADINGS AND ERROR VARIANCES CONSTRAINED TO BE THE SAME WITHIN EACH LATENT
VARIABLE
SYSTEM FILE from file 'C:\LISREL88_BRAAM\BRAAMVN.dsf'
!Asymptotic Covariance Matrix From File 'C:\LISREL88_BRAAM\BRAAMVN.ACM'
Sample Size = 113
Latent Variables  TCE ASE CON LMOT TK AUTO ASL LP FAST_TCE PK_CFT CFT_TCE
Relationships
!ZCFT_1 = CFT
!ZCFT_2 = CFT
ZTCE_P1 = TCE
ZTCE_P2 = TCE
ZASE_P1 = ASE
ZASE_P2 = ASE
ZCON_P1 = CON
ZCON_P2 = CON
ZLMOT_P1 = LMOT
ZLMOT_P2 = LMOT
ZTK_P1 = TK
ZTK_P2 = TK
ZAUTO_P1 = AUTO
ZAUTO_P2 = AUTO
ZASL_P1 = ASL
ZASL_P2 = ASL
!ZFAST_1 = FAST
!ZFAST_2 = FAST
!ZPRIOR = PRIOR
ZLP = LP
RES_1 = FAST_TCE
RES_2 = FAST_TCE
RES_3 = FAST_TCE
RES_4 = FAST_TCE
RES_5 = PK_CFT
RES_6 = PK_CFT
RES_7 = CFT_TCE
RES_8 = CFT_TCE
RES_9 = CFT_TCE
RES_10 = CFT_TCE
SET COVARIANCE OF RES_1 AND RES_2 FREE
SET COVARIANCE OF RES_3 AND RES_4 FREE
SET COVARIANCE OF RES_1 AND RES_3 FREE
SET COVARIANCE OF RES_2 AND RES_4 FREE
SET COVARIANCE OF RES_5 AND RES_6 FREE
SET COVARIANCE OF RES_7 AND RES_8 FREE
SET COVARIANCE OF RES_9 AND RES_10 FREE
SET COVARIANCE OF RES_7 AND RES_9 FREE
SET COVARIANCE OF RES_8 AND RES_10 FREE
!SET PATH FROM CFT TO ZCFT_1 EQ TO PATH FROM CFT TO ZCFT_2
SET PATH FROM TCE TO ZTCE_P1 EQ TO PATH FROM TCE TO ZTCE_P2
SET PATH FOM ASE TO ZASE_P1 EQ TO PATH FROM ASE TO ZASE_P2
SET PATH FROM CON TO ZCON_P1 EQ TO PATH FROM CON TO ZCON_P2
SET PATH FROM LMOT TO ZLMOT_P1 EQ TO PATH FROM LMOT TO ZLMOT_P2
SET PATH FROM TK TO ZTK_P1 EQ TO PATH FROM TK TO ZTK_P2
SET PATH FROM AUTO TO ZAUTO_P1 EQ TO PATH FROM AUTO TO ZAUTO_P2
SET PATH FROM ASL TO ZASL_P1 EQ TO PATH FROM ASL TO ZASL_P2
!SET PATH FROM FAST TO ZFAST_1 EQ TO PATH FROM FAST TO ZFAST_2
SET PATH FROM FAST_TCE TO RES_1 EQ TO PATH FROM FAST_TCE TO RES_2
SET PATH FROM FAST_TCE TO RES_2 EQ TO PATH FROM FAST_TCE TO RES_3
SET PATH FROM FAST_TCE TO RES_3 EQ TO PATH FROM FAST_TCE TO RES_4
SET PATH FROM PK_CFT TO RES_5 EQ TO PATH FROM PK_CFT TO RES_6
```

```
SET PATH FTOM CFT_TCE TO RES_7 EQ TO PATH FROM CFT_TCE TO RES_8
SET PATH FROM CFT_TCE TO RES_8 EQ TO PATH FROM CFT_TCE TO RES_9
SET PATH FROM CFT_TCE TO RES_9 EQ TO PATH FROM CFT_TCE TO RES_10
!SET ERROR VARIANCE OF ZCFT_1 EQ TO ERROR VARIANCE OF ZCFT_2
SET ERROR VARIANCE OF ZTCE_P1 EQ TO ERROR VARIANCE OF ZTCE_P2
SET ERROR VARIANCE OF ZASE_P1 EQ TO ERROR VARIANCE OF ZASE_P2
SET ERROR VARIANCE OF ZCON_P1 EQ TO ERROR VARIANCE OF ZCON_P2
SET ERROR VARIANCE OF ZLMOT_P1 EQ TO ERROR VARIANCE OF ZLMOT_P2
SET ERROR VARIANCE OF ZTK_P1 EQ TO ERROR VARIANCE OF ZTK_P2
SET ERROR VARIANCE OF ZAUTO_P1 EQ TO ERROR VARIANCE OF ZAUTO_P2
SET ERROR VARIANCE OF ZASL_P1 EQ TO ERROR VARIANCE OF ZASL_P2
!SET ERROR VARIANCE OF ZFAST_1 EQ TO ERROR VARIANCE OF ZFAST_2
SET ERROR VARIANCE OF RES_1 EQ TO ERROR VARIANCE OF RES_2
SET ERROR VARIANCE OF RES_2 EQ TO ERROR VARIANCE OF RES_3
SET ERROR VARIANCE OF RES_3 EQ TO ERROR VARIANCE OF RES_4
SET ERROR VARIANCE OF RES_5 EQ TO ERROR VARIANCE OF RES_6
SET ERROR VARIANCE OF RES_7 EQ TO ERROR VARIANCE OF RES_8
SET ERROR VARIANCE OF RES_8 EQ TO ERROR VARIANCE OF RES_9
SET ERROR VARIANCE OF RES_9 EQ TO ERROR VARIANCE OF RES_10
Path Diagram
LISREL OUTPUT: SS SC MI RS AD=9000 IT=9000 ND=3
End of Problem
```

APPENDIX C

Table 4.1: ***Distribution of missing values across items.***

	N	Mean	Std. Deviation	Missing Count	Missing Percent	No. of Extremes[a,b] Low	No. of Extremes[a,b] High
Q1_1.0	113	9.94	.487	1	.9	.	.
Q1_2.0	113	14.94	.385	1	.9	.	.
Q1_3.0	113	1.05	.564	1	.9	.	.
Q1_4.0	113	4.50	2.327	1	.9	.	.
Q1_5.0	110	3.23	1.612	4	3.5	.	.
Q2_1	114	1.08	.680	0	.0	.	.
Q2_2	114	14.33	2.237	0	.0	.	.
Q2_3	114	4.09	1.141	0	.0	.	.
Q2_4	114	13.04	.245	0	.0	.	.
Q2_5	113	10.02	.298	1	.9	.	.
Q3_1	114	11.01	.210	0	.0	.	.
Q3_2	114	5.06	.466	0	.0	.	.
Q3_3	113	6.78	1.033	1	.9	.	.
Q3_4	113	6.01	.094	1	.9	.	.
Q3_5	113	13.78	1.033	1	.9	.	.
Q4_1	112	1.99	.094	2	1.8	.	.
Q4_2	111	7.04	.380	3	2.6	.	.
Q4_3	111	12.98	.190	3	2.6	.	.
Q4_4	111	15.88	1.059	3	2.6	.	.
Q4_5	110	14.90	1.049	4	3.5	.	.
Q5_1	110	12.99	.095	4	3.5	.	.
Q5_2	110	7.00	.000	4	3.5	.	.
Q5_3	109	15.95	.285	5	4.4	.	.
Q5_4	107	5.11	.816	7	6.1	.	.
Q5_5	107	14.00	.000	7	6.1	.	.
Q6_1	103	2.98	.197	11	9.6	.	.
Q6_2	102	9.00	.000	12	10.5	.	.
Q6_3	97	11.19	1.044	17	14.9	.	.
Q6_4	95	9.94	.848	19	16.7	.	.
Q6_5	92	6.05	.521	22	19.3	.	.
Q7_1	89	11.98	.768	25	21.9	.	.
Q7_2	86	12.91	.625	28	24.6	.	.
Q7_3	83	3.12	.993	31	27.2	.	.
Q7_4	79	2.30	1.904	35	30.7	.	.
Q7_5	78	1.17	1.362	36	31.6	.	.
Q8_1	71	3.07	.425	43	37.7	.	.
Q8_2	67	12.67	1.804	47	41.2	.	.
Q8_3	64	2.03	.397	50	43.9	.	.
Q8_4	62	14.56	2.085	52	45.6	.	.
Q8_5	60	4.23	1.382	54	47.4	.	.
Q9_1	54	14.72	1.785	60	52.6	.	.
Q9_2	52	1.08	.555	62	54.4	.	.
Q9_3	47	9.85	1.021	67	58.8	.	.
Q9_4	42	3.10	.617	72	63.2	.	.
Q9_5	39	14.92	.480	75	65.8	.	.
Q10_1	34	1.15	.857	80	70.2	.	.
Q10_2	31	12.35	2.026	83	72.8	.	.
Q10_3	28	4.18	1.389	86	75.4	.	.
Q10_4	23	10.83	.834	91	79.8	.	.
Q10_5	21	10.05	.218	93	81.6	.	.
Q11_1	20	6.75	1.118	94	82.5	.	.
Q11_2	19	5.42	1.017	95	83.3	.	.
Q11_3	15	12.87	.516	99	86.8	.	.
Q11_4	15	2.80	.561	99	86.8	.	.
Q11_5	14	15.71	1.069	100	87.7	.	.
Q12_1	12	5.58	2.021	102	89.5	.	.
Q12_2	11	13.91	.302	103	90.4	.	.
Q12_3	8	8.00	2.828	106	93.0	.	.
Q12_4	7	6.29	.756	107	93.9	.	.

Q12_5	6	12.33	3.615	108	94.7	1	0
Q13_1	6	14.00	4.899	108	94.7	.	.
Q13_2	6	8.00	2.449	108	94.7	.	.
Q13_3	6	13.00	.000	108	94.7	.	.
Q13_4	6	2.50	.837	108	94.7	0	0
Q13_5	6	15.00	.632	108	94.7	.	.
Q1_1.2	114	13.82	1.280	0	.0	.	.
Q1_2.2	114	11.44	2.358	0	.0	.	.
Q1_3.2	114	4.04	.429	0	.0	.	.
Q1_4.2	114	5.11	.733	0	.0	.	.
Q1_5.2	114	14.87	1.093	0	.0	.	.
Q2_1.0	114	10.60	2.008	0	.0	.	.
Q2_2.0	114	12.97	.281	0	.0	.	.
Q2_3.0	114	10.96	.630	0	.0	.	.
Q2_4.0	114	2.86	2.617	0	.0	.	.
Q2_5.0	114	7.04	.295	0	.0	.	.
Q3_1.0	114	12.89	.880	0	.0	.	.
Q3_2.0	114	6.86	.763	0	.0	.	.
Q3_3.0	113	6.00	.916	1	.9	.	.
Q3_4.0	113	1.24	1.365	1	.9	.	.
Q3_5.0	113	11.84	1.014	1	.9	.	.
Q4_1.0	113	5.96	.376	1	.9	.	.
Q4_2.0	112	4.47	2.266	2	1.8	.	.
Q4_3.0	110	15.88	1.056	4	3.5	.	.
Q4_4.0	112	8.98	.553	2	1.8	.	.
Q4_5.0	112	7.03	.390	2	1.8	.	.
Q5_1.0	112	3.48	2.181	2	1.8	.	.
Q5_2.0	112	5.01	.094	2	1.8	.	.
Q5_3.0	112	3.22	1.541	2	1.8	.	.
Q5_4.0	111	13.75	1.510	3	2.6	.	.
Q5_5.0	110	10.94	.512	4	3.5	.	.
Q6_1.0	108	5.01	.348	6	5.3	.	.
Q6_2.0	107	10.93	.683	7	6.1	.	.
Q6_3.0	106	9.96	.412	8	7.0	.	.
Q6_4.0	105	12.90	.838	9	7.9	.	.
Q6_5.0	103	4.29	1.861	11	9.6	.	.
Q7_1.0	101	6.92	.578	13	11.4	.	.
Q7_2.0	98	10.03	1.418	16	14.0	.	.
Q7_3.0	96	2.14	1.139	18	15.8	.	.
Q7_4.0	95	7.15	1.052	19	16.7	.	.
Q7_5.0	92	13.00	.646	22	19.3	.	.
Q8_1.0	84	8.63	1.748	30	26.3	.	.
Q8_2.0	76	14.83	1.380	38	33.3	.	.
Q8_3.0	70	9.04	.494	44	38.6	.	.
Q8_4.0	67	5.07	2.819	47	41.2	.	.
Q9_1.0	61	6.03	.930	53	46.5	.	.
Q9_2.0	57	7.09	1.106	57	50.0	.	.
Q9_3.0	55	12.62	1.995	59	51.8	.	.
Q9_4.0	50	7.28	1.526	64	56.1	.	.
Q9_5.0	43	2.67	2.244	71	62.3	.	.
Q10_1.0	37	10.78	1.493	77	67.5	.	.
Q10_2.0	32	12.37	2.459	82	71.9	.	.
Q10_3.0	26	10.42	2.043	88	77.2	.	.
Q10_4.0	26	14.85	.784	88	77.2	.	.
Q10_5.0	24	5.25	1.225	90	78.9	.	.
Q11_1.0	18	4.39	1.650	96	84.2	.	.
Q11_2.0	16	11.63	1.258	98	86.0	.	.
Q11_3.0	15	13.33	2.320	99	86.8	.	.
Q11_4.0	12	8.58	1.443	102	89.5	.	.
Q11_5.0	12	5.83	2.125	102	89.5	.	.
Q12_1.0	12	3.42	1.443	102	89.5	.	.
Q12_2.0	9	12.67	3.640	105	92.1	.	.
Q12_3.0	8	10.88	.354	106	93.0	.	.
Q12_4.0	8	4.13	.354	106	93.0	.	.
Q12_5.0	7	1.57	1.512	107	93.9	.	.

Q13_1.0	7	9.71	4.271	107	93.9	0	0
Q13_2.0	7	6.71	1.890	107	93.9	.	.
Q13_3.0	7	3.71	1.890	107	93.9	.	.
Q13_4.0	6	14.33	4.082	108	94.7	.	.
Q13_5.0	6	5.00	.000	108	94.7	.	.
Q13_6	5	6.80	.447	109	95.6	.	.
Q1_1.4	114	13.60	3.834	0	.0	.	.
Q1_2.4	113	14.16	2.840	1	.9	.	.
Q1_3.4	112	8.10	1.548	2	1.8	.	.
Q1_4.4	112	13.40	2.276	2	1.8	.	.
Q1_5.4	113	8.25	1.264	1	.9	.	.
Q2_1.1	113	14.45	2.507	1	.9	.	.
Q2_2.1	113	10.10	1.458	1	.9	.	.
Q2_3.1	113	11.59	1.678	1	.9	.	.
Q2_4.1	113	4.65	2.645	1	.9	.	.
Q2_5.1	111	13.54	2.017	3	2.6	.	.
Q3_1.1	113	12.64	1.964	1	.9	.	.
Q3_2.1	113	8.87	1.013	1	.9	.	.
Q3_3.1	111	3.41	2.064	3	2.6	.	.
Q3_4.1	113	1.99	3.130	1	.9	.	.
Q3_5.1	113	4.53	2.143	1	.9	.	.
Q4_1.1	113	6.96	1.270	1	.9	.	.
Q4_2.1	113	6.92	1.070	1	.9	.	.
Q4_3.1	112	11.61	1.778	2	1.8	.	.
Q4_4.1	113	5.21	1.655	1	.9	.	.
Q4_5.1	112	10.37	3.569	2	1.8	.	.
Q5_1.1	113	6.98	.551	1	.9	.	.
Q5_2.1	112	2.40	1.727	2	1.8	.	.
Q5_3.1	112	4.13	1.305	2	1.8	.	.
Q5_4.1	111	13.56	2.021	3	2.6	.	.
Q5_5.1	108	6.19	1.115	6	5.3	.	.
Q6_1.1	108	4.97	.483	6	5.3	.	.
Q6_2.1	108	1.17	1.019	6	5.3	.	.
Q6_3.1	106	12.38	2.664	8	7.0	.	.
Q6_4.1	35	10.69	3.350	79	69.3	0	0
Q6_5.1	92	13.27	2.372	22	19.3	.	.
Q7_1.1	92	12.67	1.704	22	19.3	.	.
Q7_2.1	89	12.93	.927	25	21.9	.	.
Q7_3.1	84	6.14	1.300	30	26.3	.	.
Q7_4.1	81	14.63	1.561	33	28.9	.	.
Q7_5.1	80	6.19	1.527	34	29.8	.	.
Q8_1.1	74	12.68	1.776	40	35.1	.	.
Q8_2.1	72	11.83	1.138	42	36.8	.	.
Q8_3.1	70	9.94	.832	44	38.6	.	.
Q8_4.1	68	2.47	2.195	46	40.4	.	.
Q8_5.0	63	14.75	1.231	51	44.7	.	.
Q9_1.1	61	14.44	2.202	53	46.5	.	.
Q9_2.1	57	7.72	1.556	57	50.0	.	.
Q9_3.1	51	3.61	2.237	63	55.3	.	.
Q9_4.1	47	8.19	1.135	67	58.8	.	.
Q9_5.1	45	14.62	1.386	69	60.5	.	.
Q10_1.1	43	9.77	1.250	71	62.3	.	.
Q10_2.1	39	8.64	1.495	75	65.8	.	.
Q10_3.1	34	5.00	3.025	80	70.2	.	.
Q10_4.1	30	13.17	.592	84	73.7	.	.
Q10_5.1	27	13.07	2.526	87	76.3	.	.
Q10_6	40	9.63	1.659	74	64.9	.	.
Q11_1.1	27	11.15	2.931	87	76.3	.	.
Q11_2.1	27	12.78	3.555	87	76.3	.	.
Q11_3.1	24	6.75	.847	90	78.9	.	.
Q11_4.1	23	5.70	2.382	91	79.8	.	.
Q11_5.1	21	4.90	2.625	93	81.6	.	.
Q12_1.1	20	3.70	.801	94	82.5	.	.
Q12_2.1	17	6.12	2.759	97	85.1	.	.
Q12_3.1	15	5.20	2.396	99	86.8	.	.

Q12_4.1	15	3.47	4.138	99	86.8	0	2
Q12_5.1	13	14.31	3.966	101	88.6	.	.
Q13_1.1	10	6.00	2.000	104	91.2	2	0
Q13_2.1	10	6.90	1.197	104	91.2	.	.
Q13_3.1	10	9.00	3.771	104	91.2	0	0
Q13_4.1	10	5.20	5.514	104	91.2	0	0
Q13_5.1	10	12.40	1.897	104	91.2	.	.
Q1.0	114	1.00	.000	0	.0	.	.
Q1_1.5	113	2.58	2.580	1	.9	.	.
Q1_2.5	113	4.65	2.251	1	.9	.	.
Q1_3.5	114	9.92	.970	0	.0	.	.
Q1_4.5	113	14.60	2.016	1	.9	.	.
Q1_5.5	114	9.05	.967	0	.0	.	.
Q2_1.2	112	11.81	1.270	2	1.8	.	.
Q2_2.2	114	14.76	1.404	0	.0	.	.
Q2_3.2	113	2.12	1.321	1	.9	.	.
Q2_4.2	113	12.61	2.161	1	.9	.	.
Q2_5.2	114	8.97	1.215	0	.0	.	.
Q3_1.2	113	12.50	2.500	1	.9	.	.
Q3_2.2	113	3.35	1.505	1	.9	.	.
Q3_3.2	113	6.21	1.312	1	.9	.	.
Q3_4.2	114	12.94	.943	0	.0	.	.
Q3_5.2	111	14.48	2.335	3	2.6	.	.
Q4_1.2	111	1.18	.993	3	2.6	.	.
Q4_2.2	113	6.99	.675	1	.9	.	.
Q4_3.2	112	2.29	1.528	2	1.8	.	.
Q4_4.2	112	6.28	1.561	2	1.8	.	.
Q4_5.2	112	12.88	1.186	2	1.8	.	.
Q5_1.2	112	3.03	.283	2	1.8	.	.
Q5_2.2	113	2.12	.825	1	.9	.	.
Q5_3.2	111	12.97	.680	3	2.6	.	.
Q5_4.2	113	9.85	.947	1	.9	.	.
Q5_5.2	113	6.96	.930	1	.9	.	.
Q6_1.2	111	11.42	1.871	3	2.6	.	.
Q6_2.2	111	12.77	1.291	3	2.6	.	.
Q6_3.2	110	15.65	2.038	4	3.5	.	.
Q6_4.2	111	6.14	.745	3	2.6	.	.
Q6_5.2	111	4.20	1.334	3	2.6	.	.
Q7_1.2	110	12.63	1.642	4	3.5	.	.
Q7_2.2	110	9.47	1.712	4	3.5	.	.
Q7_3.2	110	12.80	1.373	4	3.5	.	.
Q7_4.2	110	9.93	.821	4	3.5	.	.
Q7_5.2	109	14.29	2.664	5	4.4	.	.
Q8_1.2	108	10.99	1.476	6	5.3	.	.
Q8_2.2	107	8.93	1.147	7	6.1	.	.
Q8_3.2	107	1.62	2.281	7	6.1	.	.
Q8_4.2	107	10.90	.890	7	6.1	.	.
Q8_5.1	103	5.48	2.062	11	9.6	.	.
Q9_1.2	104	3.16	.698	10	8.8	.	.
Q9_2.2	103	13.49	2.326	11	9.6	.	.
Q9_3.2	104	5.06	.912	10	8.8	.	.
Q9_4.2	102	6.26	1.495	12	10.5	.	.
Q9_5.2	102	10.91	.976	12	10.5	.	.
Q10_1.2	98	5.09	.985	16	14.0	.	.
Q10_2.2	97	13.54	2.146	17	14.9	.	.
Q10_3.2	92	15.40	2.598	22	19.3	.	.
Q10_4.2	94	15.83	1.179	20	17.5	.	.
Q10_5.2	93	7.15	1.351	21	18.4	.	.
Q11_1.2	93	4.05	1.297	21	18.4	.	.
Q11_2.2	91	3.32	1.705	23	20.2	.	.
Q11_3.2	91	5.30	1.643	23	20.2	.	.
Q11_4.2	91	2.66	2.596	23	20.2	.	.
Q11_5.2	90	12.76	1.248	24	21.1	.	.
Q12_1.2	84	3.11	.581	30	26.3	.	.
Q12_2.2	82	14.43	2.558	32	28.1	.	.
Q12_3.2	81	7.19	1.305	33	28.9	.	.

Q12_4.2	79	11.49	2.075	35	30.7	.	.
Q12_5.2	76	15.49	2.266	38	33.3	.	.
Q13_1.2	75	7.12	1.090	39	34.2	.	.
Q13_2.2	72	8.94	.886	42	36.8	.	.
Q13_3.2	71	12.76	1.599	43	37.7	.	.
Q13_4.2	63	5.29	1.313	51	44.7	.	.
Q13_5.2	63	11.68	1.740	51	44.7	.	.
Q14_1.2	56	15.61	1.988	58	50.9	.	.
Q14_2.2	53	6.96	.275	61	53.5	.	.
Q14_3.2	45	7.00	.213	69	60.5	.	.
Q14_4.2	45	4.02	.336	69	60.5	.	.
Q14_5	40	7.30	1.604	74	64.9	.	.
Q15_1	38	3.97	4.258	76	66.7	.	.
Q15_2	33	13.61	1.197	81	71.1	.	.
Q15_3	30	4.20	.925	84	73.7	.	.
Q15_4	31	6.16	.523	83	72.8	.	.
Q15_5	31	11.74	.999	83	72.8	.	.
Q16_1	29	1.83	2.740	85	74.6	.	.
Q16_2	28	1.68	2.776	86	75.4	.	.
Q16_3	27	6.74	2.536	87	76.3	.	.
Q16_4	26	2.92	3.006	88	77.2	.	.
Q16_5	24	14.42	1.840	90	78.9	.	.
Q17_1	21	8.71	1.309	93	81.6	.	.
Q17_2	21	12.19	2.713	93	81.6	.	.
Q17_3	20	3.40	1.392	94	82.5	.	.
Q17_4	19	6.63	2.140	95	83.3	.	.
Q17_5	19	11.74	1.695	95	83.3	.	.
Q17_1.0	16	4.44	1.459	98	86.0	.	.
Q17_2.0	15	10.07	.258	99	86.8	.	.
Q17_3.0	13	11.38	3.686	101	88.6	.	.
Q17_4.0	13	8.69	.855	101	88.6	.	.
Q17_5.0	12	2.83	1.850	102	89.5	0	2
Q17_6	12	14.50	1.732	102	89.5	.	.
Q1.1	114	1.00	.000	0	.0	.	.
Q1.2	114	2.98	.352	0	.0	.	.
Q2.3	114	2.09	.508	0	.0	.	.
Q3.0	114	5.91	.603	0	.0	.	.
Q4	113	3.70	1.017	1	.9	.	.
Q5	113	3.20	.709	1	.9	.	.
Q6	114	1.21	.781	0	.0	.	.
Q7	114	4.87	.710	0	.0	.	.
Q8	106	4.91	1.583	8	7.0	0	0
Q9	113	4.01	.762	1	.9	.	.
Q10	114	2.24	.802	0	.0	.	.
Q11	114	4.94	.520	0	.0	.	.
Q12	114	3.21	.836	0	.0	.	.
Q13	114	3.90	1.867	0	.0	0	0
Q14	114	5.92	.402	0	.0	.	.
Q15	114	1.39	1.156	0	.0	.	.
Q16	110	1.35	1.062	4	3.5	.	.
Q17	111	3.90	.632	3	2.6	.	.
Q18	111	4.87	.574	3	2.6	.	.
Q19	112	2.38	.883	2	1.8	.	.
Q20	111	5.35	1.165	3	2.6	8	0
Q21	111	3.99	.757	3	2.6	.	.
Q22	110	4.95	.437	4	3.5	.	.
Q23	111	1.89	1.467	3	2.6	0	5
Q24	111	3.88	.817	3	2.6	.	.
Q25	110	3.82	.815	4	3.5	.	.
Q26	111	5.79	.676	3	2.6	.	.
Q27	107	5.02	1.523	7	6.1	5	0
Q28	109	2.99	.776	5	4.4	.	.
Q29	109	4.45	1.198	5	4.4	9	0
Q30	110	4.35	1.385	4	3.5	16	0
TCE_1	114	4.73	1.359	0	.0	2	0

TCE_2	114	4.84	1.314	0	.0	2	0
TCE_3	114	4.46	1.483	0	.0	0	0
TCE_4	114	5.03	1.347	0	.0	1	0
TCE_5	114	4.71	1.394	0	.0	2	0
TCE_6	114	4.55	1.234	0	.0	7	4
TCE_7	114	4.70	1.282	0	.0	1	0
TCE_8	114	5.33	1.118	0	.0	7	0
TCE_9	114	4.94	1.123	0	.0	0	0
TCE_10	114	4.50	1.592	0	.0	0	0
TCE_11	114	4.45	1.529	0	.0	0	0
TCE_12	114	4.55	1.512	0	.0	3	0
TCE_13	114	4.85	1.422	0	.0	3	0
TCE_14	114	4.39	1.701	0	.0	0	0
TCE_15	114	5.22	1.143	0	.0	10	0
TCE_16	114	5.13	1.164	0	.0	6	0
TCE_17	114	4.77	1.458	0	.0	2	0
ASL_1	114	3.82	1.489	0	.0	0	0
ASL_2	114	3.78	1.309	0	.0	0	0
ASL_3	114	4.05	1.419	0	.0	0	0
ASL_4	114	3.17	1.651	0	.0	0	4
ASL_5	114	4.08	1.541	0	.0	0	0
ASL_6	114	4.65	1.624	0	.0	6	0
ASL_7	114	4.69	1.603	0	.0	7	0
ASL_8	114	4.30	1.734	0	.0	0	0
ASL_9	114	4.38	1.610	0	.0	0	0
ASL_10	114	4.57	1.382	0	.0	9	7
ASL_11	114	4.68	1.286	0	.0	5	7
ASL_12	114	4.99	1.436	0	.0	2	0
ASL_13	114	4.76	1.410	0	.0	3	0
ASL_14	114	5.02	1.540	0	.0	2	0
ASL_15	114	4.56	1.511	0	.0	2	0
ASL_16	114	5.12	1.277	0	.0	0	0
ASL_17	114	4.71	1.329	0	.0	1	0
ASL_18	114	4.39	1.361	0	.0	11	6
ASL_19	114	4.49	1.434	0	.0	12	8
ASL_20	114	4.66	1.268	0	.0	6	7
ASL_21	114	4.77	1.317	0	.0	2	0
ASL_22	114	4.66	1.764	0	.0	9	0
ASL_23	114	4.58	1.739	0	.0	8	0
ASE_1	114	5.10	1.097	0	.0	1	0
ASE_2	114	5.69	1.138	0	.0	0	0
ASE_3	114	4.21	1.340	0	.0	0	0
ASE_4	114	4.89	1.326	0	.0	1	0
ASE_5	114	5.01	1.279	0	.0	0	0
ASE_6	114	5.63	1.243	0	.0	1	0
ASE_7	114	5.27	1.192	0	.0	0	0
ASE_8	114	5.00	1.304	0	.0	2	0
ASE_9	114	4.54	1.345	0	.0	8	8
ASE_10	114	4.75	1.322	0	.0	1	0
ASE_11	114	4.91	1.266	0	.0	1	0
ASE_12	114	5.54	1.345	0	.0	4	0
CON_1	114	4.30	1.233	0	.0	0	0
CON_2	114	4.80	1.235	0	.0	1	0
CON_3	114	2.48	1.603	0	.0	0	8
CON_4	114	4.60	1.203	0	.0	7	5
CON_5	114	4.61	1.266	0	.0	2	0
CON_6	114	4.55	1.263	0	.0	5	9
CON_7	114	4.24	1.609	0	.0	0	0
CON_8	114	4.68	1.379	0	.0	2	0
CON_9	114	5.49	1.409	0	.0	5	0
CON_10	114	3.82	1.897	0	.0	0	0
CON_11	114	3.62	1.737	0	.0	0	0
CON_12	114	4.02	1.809	0	.0	0	0
LMOT_1	114	5.70	1.113	0	.0	1	0
LMOT_2	114	5.07	1.387	0	.0	1	0

LMOT_3	114	5.11	1.279	0	.0	0	0
LMOT_4	114	5.23	1.212	0	.0	0	0
LMOT_5	114	5.12	1.364	0	.0	1	0
LMOT_6	114	5.47	1.221	0	.0	0	0
TK_1	114	4.13	1.171	0	.0	0	0
TK_2	114	4.94	1.170	0	.0	1	0
TK_3	114	4.82	1.250	0	.0	1	0
TK_4	114	5.30	1.463	0	.0	13	0
TK_5	114	5.30	1.152	0	.0	7	0
TK_6	114	4.93	1.173	0	.0	1	0
TK_7	114	4.95	1.143	0	.0	1	0
TK_8	114	3.99	1.442	0	.0	0	0
TK_9	114	4.15	1.428	0	.0	0	0
TK_10	114	3.85	1.512	0	.0	0	0
TK_11	114	4.78	1.173	0	.0	1	0
TK_12	114	4.79	1.201	0	.0	4	11
TK_13	114	4.90	1.004	0	.0	1	0
TK_14	114	4.95	1.038	0	.0	1	0
TK_15	114	5.24	1.058	0	.0	6	0
TK_16	114	4.96	1.170	0	.0	1	0
TK_17	114	5.17	1.144	0	.0	1	0
TK_18	114	3.11	1.582	0	.0	0	2
TK_19	114	3.52	1.495	0	.0	0	5
TK_20	114	3.12	1.535	0	.0	0	4
TK_21	114	5.05	1.275	0	.0	2	0
TK_22	114	5.04	1.170	0	.0	2	0
TK_23	114	3.94	1.365	0	.0	0	0
TK_24	114	3.16	1.473	0	.0	0	1
TK_25	114	3.18	1.428	0	.0	0	2
TK_26	114	5.02	1.197	0	.0	1	0
TK_27	114	4.51	1.345	0	.0	12	6
AUTO_1	114	4.02	.652	0	.0	.	.
AUTO_2	114	3.23	1.031	0	.0	0	0
AUTO_3	114	3.89	.849	0	.0	.	.
AUTO_4	114	4.03	.734	0	.0	.	.
AUTO_5	114	3.19	1.151	0	.0	0	0
AUTO_6	114	4.05	.622	0	.0	.	.
AUTO_7	114	3.96	.703	0	.0	.	.
AUTO_8	114	3.33	.879	0	.0	1	0
AUTO_9	114	3.20	.997	0	.0	6	0
AUTO_10	114	2.84	1.118	0	.0	0	0
AUTO_11	114	3.61	.804	0	.0	1	0
AUTO_12	114	3.29	1.062	0	.0	7	0
AUTO_13	114	3.68	.876	0	.0	4	0
AUTO_14	114	3.64	.811	0	.0	1	0
AUTO_15	114	2.95	1.003	0	.0	0	0
AUTO_16	114	2.89	1.062	0	.0	0	0
AUTO_17	114	2.68	1.147	0	.0	0	9
AUTO_18	114	3.22	1.002	0	.0	7	0
LP	114	62.0439	15.89604	0	.0	3	0
PriorKnowledge	114			0	.0		