THE DEVELOPMENT AND EMPIRICAL EVALUATION OF AN EXTENDED LEARNING POTENTIAL STRUCTURAL MODEL

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DECLARATION

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Bright Mahembe   Date: April 2014

ABSTRACT

In South Africa, selection from a diverse population poses a formidable challenge. The challenge lies in subgroup difference in the performance criterion. Protected group members perform systematically lower on the criterion due to systematic, group-related differences in learning and job competency potential latent variables required to succeed in learning and on the job. These subgroup differences are attributable to the unequal development and distribution of intellectual capital across racial-ethnic subgroups due to systemic historical disadvantagement. This scenario has made it difficult for organisations in South Africa to meet equity targets when selecting applicants from a diverse group representative of the South African population, while at the same time maintaining production and efficiency targets. Therefore there is an urgent need for affirmative development. Ensuring that those admitted to affirmative development interventions successfully develop the job competency potential and job competencies required to succeed on the job requires that the appropriate people are selected into these interventions. Selection into affirmative development opportunities represents an attempt to improve the level of *Learning performance during evaluation* of learners admitted to affirmative development opportunities. A valid understanding of the identity of the determinants of learning performance in conjunction with a valid understanding of how they combine to determine the level of learning performance achieved should allow the valid prediction of *Learning performance during evaluation*.

The primary objective of the present study was to integrate and elaborate the De Goede (2007) and the Burger (2012) learning potential models in a manner that circumvents the problems and shortcomings of these models by developing an extended explanatory learning performance structural model that explicates additional cognitive and non-cognitive learning competency potential latent variables that affect learning performance and that describes the manner in which these latent variables combine to affect learning performance.

A total of 213 participants took part in the study. The sample was predominantly made up of students from previously disadvantaged groups on the extended degree programme of a university in the Western Cape Province of South Africa. The proposed De Goede – Burger – Mahembe Learning Potential Structural Model was tested via structural equation modeling after performing item and dimensional analyses. Item and dimensional analyses were performed to identify poor items and ensure uni-dimensionality. Uni-dimensionality is a requirement for item parcel creation. Item parcels were used due to sample size restrictions.

The fit of the measurement and structural models can generally be regarded as reasonable and both models showed close fit. Significant relationships were found between: *Information processing capacity* and *Learning Performance during evaluation; Self-leadership* and *Motivation to learn; Motivation to learn* and *Time-engaged-on-task; Self efficacy* and *Self-leadership; Knowledge about cognition* and *Regulation of cognition; Regulation of cognition* and *Time-cognitively-engaged; Learning goal orientation* and *Motivation to learn; Openness to experience* and *Learning goal orientation.* Support was not found for the relationships between *Conscientiousness* and *Time-cognitively-engaged,* as well as between *Time-cognitively-engaged* and *Learning performance*. The hypothesised moderating effect of Prior learning on the relationship between *Abstract reasoning capacity* and *Learning performance during evaluation* was not supported. The statistical power of the test of close fit for the comprehensive LISREL model was examined. The discriminant validity of the item parcels were ascertained. The limitations of the research and suggestions for future studies have been highlighted. The results of the present study provide some important insights for educators and training and development specialists on how to identify potential students and talent for affirmative development in organisations in South Africa.

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CHAPTER ONE

INTRODUCTION, RESEARCH INITIATING QUESTION AND RESEARCH OBJECTIVE

1.1 INTRODUCTION

The work that we do plays a significant role in our lives. It does not only provide the economic basics of our day-to-day survival but also helps the organisations, which we work for, to meet the needs of, and provide the services required by society. Organisations are man-made entities that exist to satisfy various societal needs. The achievement of organisational success in the provision of the products and services required by society depends to a large extent on the quality of the four factors of production, namely; entrepreneurship, capital, natural resources and labour and the manner in which they are managed. Most models that attempt to explain organisational success are anchored on the availability of human capital (Denison, 1990; Gibson, Ivancevich & Donnelly, 1991; Miles, 1980; Theron & Spangenberg, 2002). Human capital is a vital and indispensable resource for organisational effectiveness.

Human capital is defined as the value resulting from the productive investment in humans, including their skills and health, which are the outcomes of education, healthcare, and on-the-job training (Todaro, 1994). Performance (defined in terms of behaviours and outcomes) depends in a systematic manner on specific person and environmental characteristics. Human capital accumulates if the critical person qualities that affect performance are developed. Some person characteristics can be altered while others are relatively stable dispositions. Those that are not malleable need to be controlled by controlling the characteristics of the people that flow into positions. HR[1]'s ability to professionally regulate the entry of employees into the organisation through sound selection practices is essential for organisational success

[1] Human resource management

as the quality of the human resources that the organisation has at its disposal is likely to affect the efficiency with which organisations produce specific products or services[2].

Selection is one of the fundamental HR functions that have a significant bearing on organisational effectiveness and performance. Jobs constitute collections of tasks that incumbents need to perform (successfully). The extent to which individuals can successfully perform the tasks comprising a job depends on the extent to which they possess the qualities that determine performance in the job, as well as on the extent to which the environmental characteristics are conducive to high performance. Selection attempts to control performance by allowing only those individuals with the (non-malleable) person characteristics required to meet the minimum competence levels for the position.

The personnel selection decision-making process on whether to accept or reject an applicant is complicated by the unavailability of direct information on actual job performance in a particular position at the time when the selection decision is made. Selection decisions are therefore based on expected/predicted work performance, $E[Y|X_i]$ (Ghiselli, 1956; Ghiselli, Campbell & Zedeck, 1981; Schmitt, 1989; Theron, 2007). There are different decision-making strategies[3] available to the decision-maker,

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[2] The fact that the level of competence that employees achieve on the performance dimensions is not only determined by non-malleable person characteristics, but also by malleable person characteristics and malleable situational characteristics makes it impossible to rely only on sound recruitment and selection practices; the manner in which the human resources are utilized and managed also has significant implications for the efficient production of goods and services.

[3] The multiple regression method which is usually expressed in the form $E[Y|X_i] = \mathbf{a} + b_1X_1 + b_2X_i \ldots + b_pX_p$ assuming that p tests are taken. $E[Y|X_i]$ = predicted job performance; X_i represent applicants' scores on p selection tests; b_i represents the partial regression weights for test X_i and **a** indicates a constant or intercept value for the regression hyperplane. The multiple regression method is based on the assumption that (a) the predictors are linearly related to the criterion and (b) since the predicted criterion score is a function of the sum of the weighted predictor scores, the predictors are additive and can compensate for one another (an outstanding performance on one of the predictors can compensate for a poor performance on another predictor. The multiple cut-offs method assumes that (a) a nonlinear relationship exists among the predictors and the criterion, that is, a minimum amount of each important predictor attribute is necessary for successful performance of a job and that (b) predictors are not compensatory. The multiple hurdle approach makes the same assumption as in the

these include a multiple regression strategy, a multiple hurdle strategy, a multiple cutoff strategy and a profile comparison strategy (Gatewood, Feild & Barrick, 2008). The decision-maker in adddition has a choice whether the performance/criterion inferences are derived clinically or mechanically from the available predictor information. Clinical prediction ($E_C[Y|Xi]$) entails combining information from test scores and measures obtained from interviews and observations, covertly, through the use of an implicit combination rule imbedded in the mind of a clinician to arrive at a judgment about the expected criterion performance of the individual being assessed (Gatewood, Feild & Barrick, 2008; Grove & Meehl, 1996; Murphy & Davidshofer, 2005). Mechanical prediction ($E_M[Y|Xi]$) involves using the information overtly in terms of an explicit combination rule to arrive at a judgment about the expected criterion performance of the individual being assessed (Gatewood, Feild & Barrick, 2008; Murphy & Davidshofer, 2005). These criterion/performance inferences need to be valid and unbiased. The selection decision based on the criterion inferences needs to be fair and have positive utility. Utility alludes to the overall usefulness of a selection procedure, its accuracy and the importance of the decisions derived about employees (Dunnette, 1966). The reason for determining selection utility is to show the degree to which the use of a selection procedure improves the quality of individuals selected compared to if the procedure was not used (Gatewood & Feild, 1990). Utility is optimised when maximum gain in performance is achieved at the lowest investment to affect the improvement in performance. If the criterion inferences are biased selection decisions based on such inferences can be considered unfair.

multiple cut-off method that there is a minimum level of each predictor attribute necessary for performance on the job. The two differ in the methods of collecting predictor information. In the multiple cut-off approach the procedure is non-sequential whereas in the multiple hurdle approach the procedure is sequential. In other words, each applicant must meet the minimum cut-off or hurdle for each predictor before going to the next predictor.

According to Cleary (1968, p. 115), "a test is biased[4] for members of a subgroup of the population if, in the prediction of a criterion for which the test was designed, consistently nonzero errors of prediction are made for members of the subgroup. In other words, the test is biased if the criterion score predicted from the common regression line is consistently too high or too low for members of the subgroup. With this definition of bias, there may be a connotation of 'unfair' particularly if the use of the test produces a prediction that is too low. If the test is used for selection, members of a subgroup may be rejected when they were capable of adequate performance." This definition represents the thinking behind the regression model proposed by Cleary (1968) which has become the standard model for fairness decisions in psychological assessment. To explore the difficulties involved when selecting from a diverse applicant group, comprising of a previously disadvantaged group (A) and a previously advantaged group (B), three selection scenarios, which differ in terms of the nature of the predictor and criterion differences across the two groups, can be discerned (Bobko & Bartlett, 1978; Cascio, 2011; Russell, 2000).

The first scenario describes a situation in which (1) both groups A and B employees perform equally well on the job; (2) group A employees perform significantly lower on the personnel selection test relative to group B employees. For any "cut-off score" C (i.e., a vertical line drawn from the X axis upwards signifying the minimum X score needed to receive a job offer), more group B applicants will receive job offers than group A applicants. Stated differently, if the combined regression equation describing the regression of the criterion on the predictor would be mechanically used to predict applicants' expected criterion performance the criterion performance of group B would be systematically underestimated. Members of group B will be unfairly disadvantaged if the decision to hire is based on the rank-ordered $E[Y|X_i]$ and the required number of applicants are selected top-down[5]. As a consequence of

[4] Cleary's use of the phrase "a test is biased" should be described as unfortunate in as far as it is biased with respect to the inferences that are derived from the test scores that unfairly disadvantage members of specific groups rather than biased in the test per se.

[5] Provided $E[Y|X_i] > Y_k$.

the prediction bias the selection procedure will create adverse impact against members of group A. Figure 1.1 is typically cited as a classic example of an "unfair" or "biased" test. It is, however not the test that is unfair. It is the criterion inferences derived by the decision-maker that are unfair. The systematic group-related error in the mechanical predictions can, however, be corrected by incorporating the appropriate group effect/effects in the regression model. If the systematic group-related error in the mechanical prediction model is corrected by making provision for the differences in intercept through the inclusion of a group main effect, the selection procedure will no longer create adverse impact against members of group A.

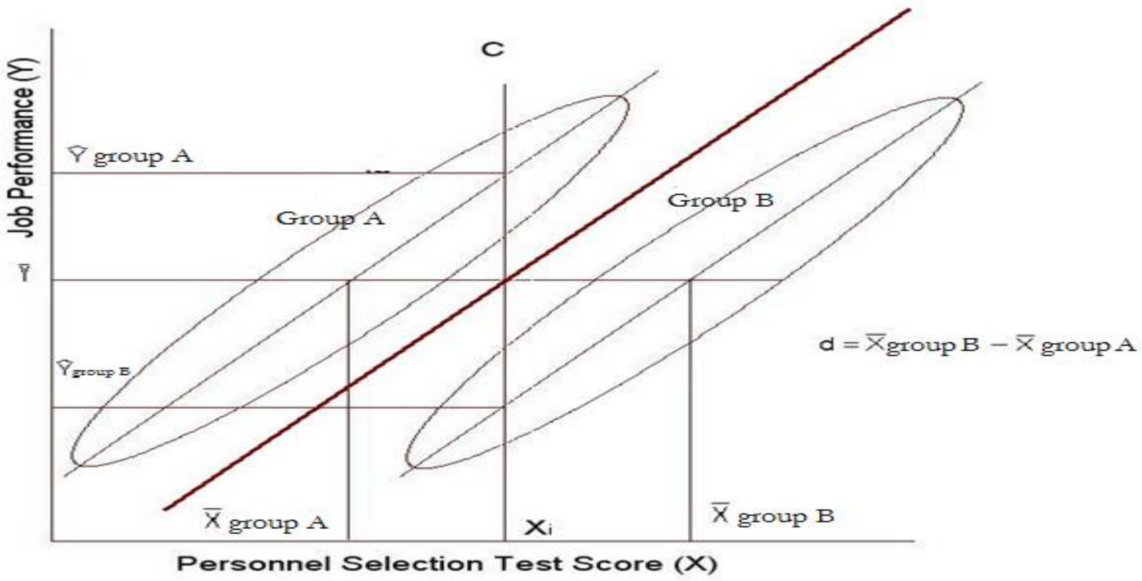

Figure 1.1. Predictive bias scenario 1. Adapted from "The Cleary model: Test bias as defined by the EEOC Uniform Guidelines on employment selection procedures," by J. Russell (2000). Retrieved from http://www.ou.edu/russell/whitepapers/Cleary_model.pdf

The second scenario describes a situation where the mechanical use of a common regression model will not result in systematic group-related prediction error, yet the selection strategy still causes adverse impact. In this case (1) group A and B applicants do not have the same average on the personnel selection test or subsequent job performance; (2) group A and B applicants with the same personnel selection test score X_i will be expected to generate the same level of job performance Y_i; and (3) for any "cut-off score" C (i.e., a vertical line drawn from the X axis upwards signifying the minimum X score needed to receive a job offer), more group B applicants will receive job offers than group A applicants. Stated differently, if the combined regression equation describing the regression of the criterion on the predictor would be mechanically used to predict applicants expected criterion performance the criterion performance of neither group would be systematically underestimated. Members of group A will be disadvantaged, but they will not be unfairly disadvantaged if the decision to hire is based on the rank-ordered $E[Y|X_i]$ and the required number of applicants are selected top-down. Hence, even though the criterion inferences are derived fairly in the Cleary (1968) sense of the term, the use of this mechanical selection strategy will still have adverse impact against group A applicants (Bobko & Bartlett, 1978; Cascio& Aguinis, 2011; Russell, 2000). This is depicted in Figure 1.2.

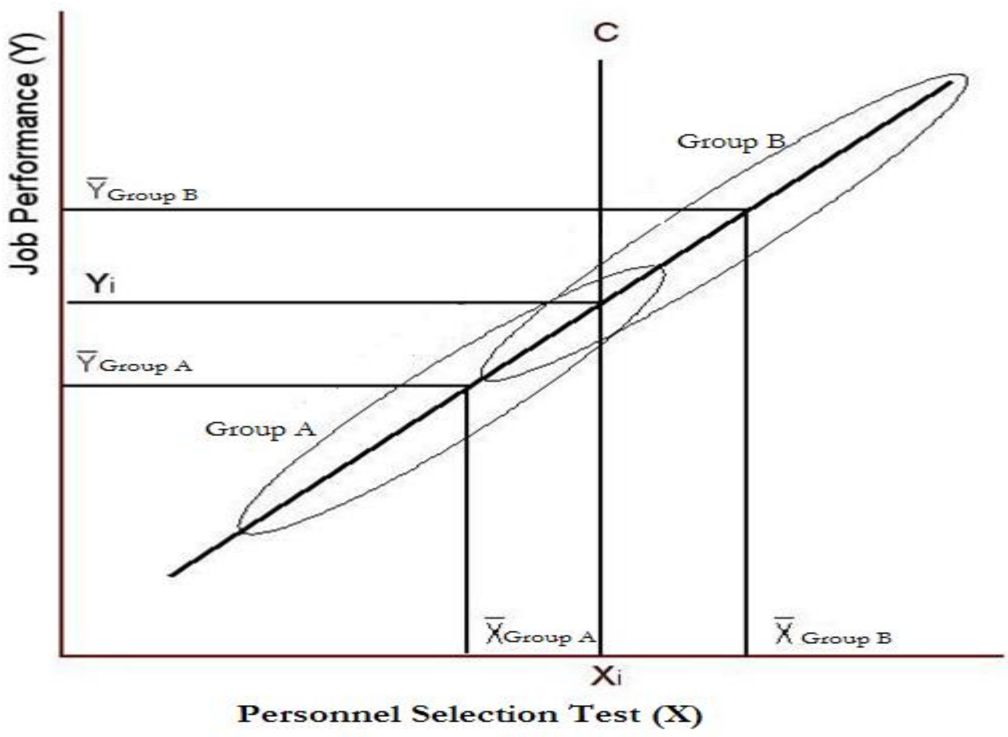

Figure 1.2. Predictive bias scenario 2. Adapted from "The Cleary model: Test bias as defined by the EEOC Uniform Guidelines on employment selection procedures," by J. Russell (2000). Retrieved from http://www.ou.edu/russell/whitepapers/Cleary_model.pdf

The last scenario describes a situation in which all the other factors, such as educational background are uniform. In this case (1) group A and B's mean job performance and mean selection test performance are equal; (2) no adverse impact will occur[6] - no matter where a cut-off score is drawn, the proportion of members of group B hired relative to the number of group B applying is expected to be equal to the proportion of members of group A hired relative to the number of group A that have applied and (3) the predicted job performance for a group A applicant and group B applicant who earned the same selection test score X will be the same (Bobko & Bartlett, 1978; Cascio &Aguinis, 2011; Russell, 2000). This is depicted in Figure 1.3.

In essence selection procedures/strategies are designed to discriminate fairly between the accepted and rejected candidates (Cascio & Aguinis, 2011). The achievement of fairness in the selection of a diverse population poses a formidable challenge. Valid criterion estimates derived without prediction bias will result in equal representation under strict top down selection only if the criterion distributions of groups coincide. If, however, the criterion distributions do not coincide, the use of valid criterion estimates derived without prediction bias will result in differential selection ratios (Theron, 2009). The group with the lower criterion mean will have the smaller selection ratio. If the difference in selection ratios is big enough, adverse impact will result (scenario 2). Adverse impact occurs in situations where a specific selection strategy affords members of a specific group a lower likelihood of selection compared to another group. It is normally operationalised in terms of the "80%" (or "4/5ths") rule. The rule states that adverse impact occurs if the selection ratio (that is, the number of people hired, divided by the number of people who apply) for any group of applicants is less than 80% of the selection ratio for another group (Muchinsky, 2000). In calculating the adverse impact ratio it is, however, critically

[6] Provided selection decisions are based on $E[Y|X_i]$ and not on $P[Y>Y_k|X_i]$.

important to base the calculation on the group-specific expected criterion performance distributions and not on the group-specific predictor distributions.

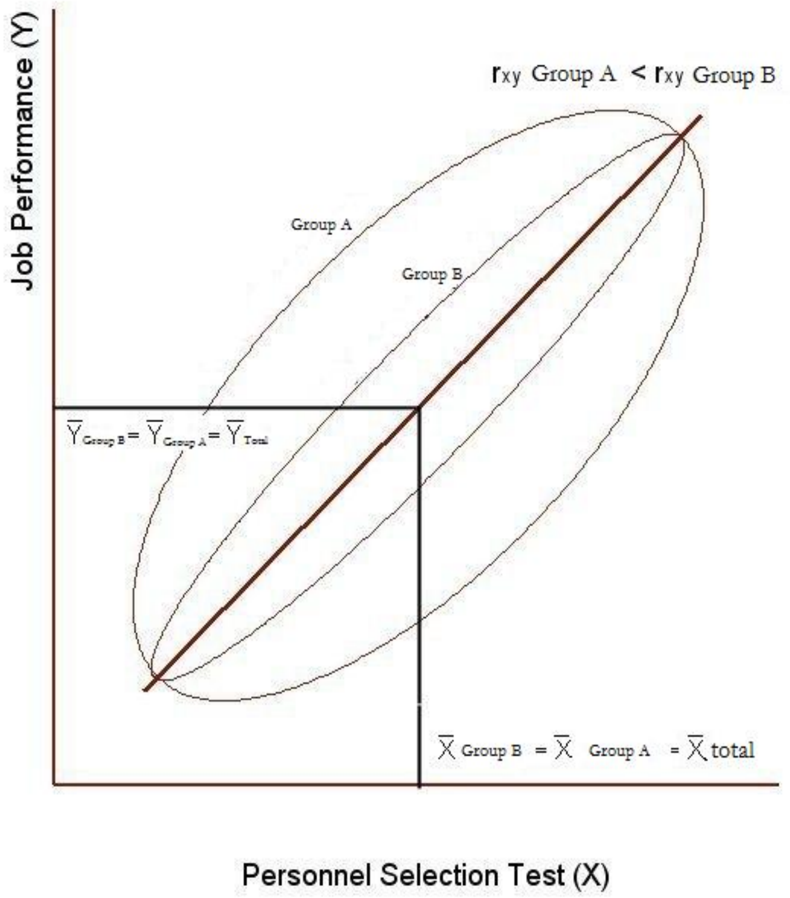

Figure 1.3. Predictive bias scenario 3. Adapted from "The Cleary model: Test bias as defined by the EEOC Uniform Guidelines on employment selection procedures," by J. Russell (2000). Retrieved from http://www.ou.edu/russell/whitepapers/Cleary_model.pdf

Adverse impact is unavoidable as long as sub group differences in the criterion exist and strict top-down selection occurs on valid and (in the Cleary sense of the term) fair criterion predictions. Subgroup differences in the predictor distributions will not result in adverse impact as long as the criterion distributions coincide and the predictor data is combined without prediction bias when deriving the criterion estimated on which the selection decision will be based (Aguinis & Smith, 2007).

In South Africa, it seems reasonable to argue that protected group members perform systematically lower on the criterion due to systematic, group-related differences in job competency potential latent variables required to succeed on the job (De Goede, 2007; Theron, 2009). The differences in the criterion distribution means are, in terms of this argument, attributable to the unequal development and distribution of the intellectual capital across races due to a historical system that fostered differential educational opportunities along racial lines. The legacy of Apartheid fostered certain stereotypical attitudes and culturally insensitive and inappropriate interventions as well as a lack of opportunities for certain groups (particularly Blacks and women) to engage in training. This has had a significant impact on the skill attainment, subsequent employability and the livelihoods of the previously disadvantaged groups. According to De Goede and Theron (2010), placing the blame for the under representation of the previously disadvantaged groups on the failure of psychological tests to offer equal chances of being selected for a job is therefore unwarranted. The solution to the adverse impact problem requires a multi-pronged approach from various stakeholders to address the criterion differences through the implementation of aggressive affirmative development aimed at developing the job competency potential latent variables required to succeed on the job.

There is an urgent need for the human resource (HR) function of the various private and public sector stakeholders to make concerted efforts to address the adverse impact problem and the historical imbalances with regards to educational opportunities. According to De Goede and Theron (2010, p. 32), "apologising and expressing regret for the wrongs committed under Apartheid would carry little value if it were not affirmed by concrete action that attempts to honestly and sincerely remedy the harm done by the Apartheid policies and practices." Why are we concerned with adverse impact? Failure to address the differences in criterion performance is likely to lead to social unrest as people become frustrated with their fruitless attempts to improve their conditions of living. Exposure to the affirmative developmental opportunities will most probably empower and enhance the exposed individuals' performance in conventional assessment situations, training and educational programs. The prevailing adverse impact problem affecting selection, indeed, requires urgent attention as various social trends seem to indicate some undesirable tendencies in societal functioning such as (1) the perpetual failure to meet the employment equity targets, (2) the widening gap between the rich and poor, and (3) the rising poverty levels among the previously disadvantaged group members.

Meeting the employment equity targets has long been a bone of contention between the government and the private sector. According to the annual report of the Commission for Employment Equity for 2011-2012 (Commission for Employment Equity, 2012), very little progress has been made in transforming the upper echelons of organisations in the private sector. White men still occupy the majority of the top management positions in the private sector (65.4%), enjoy 39.7% of all recruitment, and make up 46.5% of all employees promoted to this level. In contrast, Black men occupy only 18.5% of managerial positions, enjoy only 20.4% of all recruitment, and make up only 13.8% of all employees promoted to this level (Commission for Employment Equity, 2012). Generally, in the private sector the White male population had the highest representation with an average of 64.9%, followed by the Black male population with 9.99%, Indian male population with 4.5%, Coloured male population with 3% and foreigner male population accounting for about 2.1%. Figure 1.4 schematically depicts the demographic distribution in occupational levels of South African labour force

In 2009, the skewed distribution of employment equity targets stirred some angry and biting remarks from the then Labour Minister Membathisi Mdladlana and chair of the Commission for Employment Equity Jimmy Manyi who generally indicated that sterner measures should be taken against the organisations failing to address the employment equity targets (Williams, 2009).

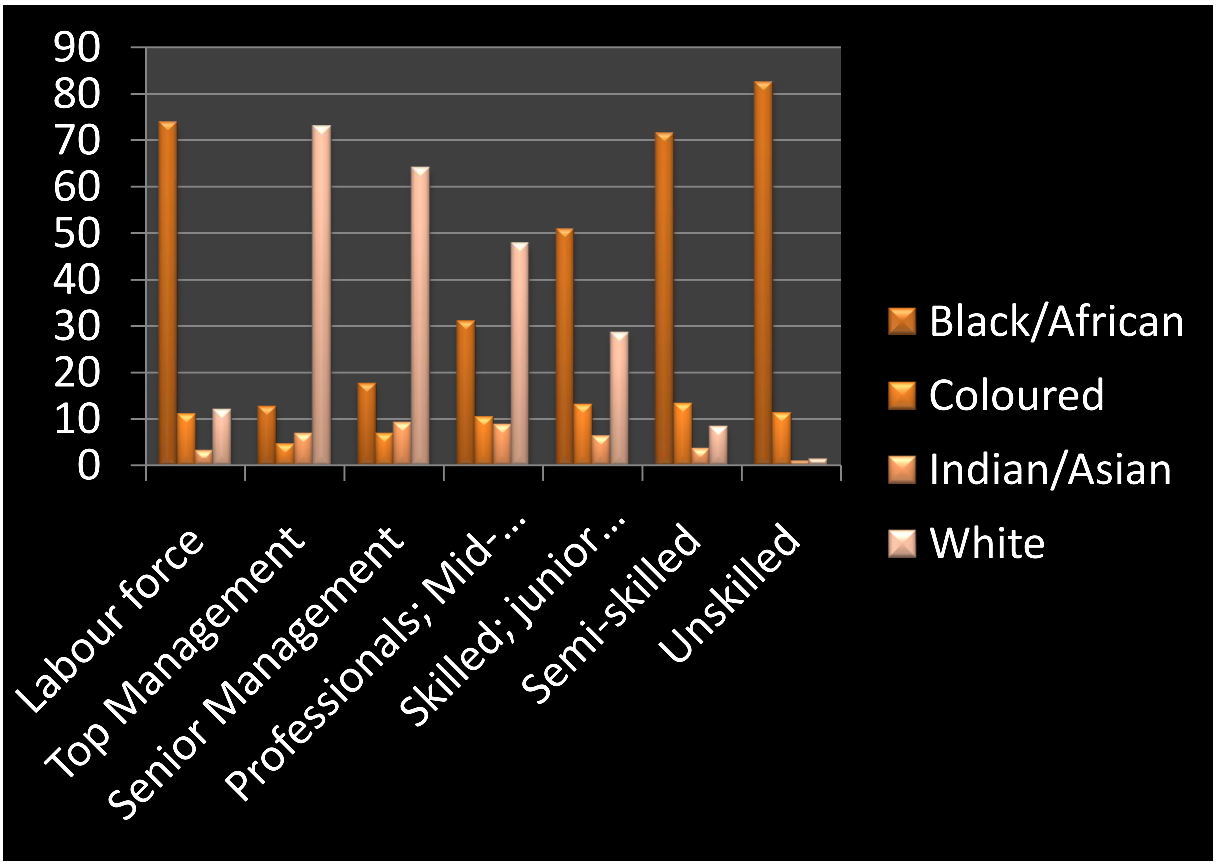

Figure 1.4. Demographic distribution in occupational levels of South African labour force. Adapted from "Commission of Employment Equity," by Stats SA, 2011. Copyright 2011 by Republic of South Africa.

Organisations' failure to meet the employment equity targets is most probably not attributable to a refusal to employ competent and efficient Black applicants but rather the dearth of suitably qualified Black applicants. A very real risk is that private enterprise will succumb to pressure from government and embrace traditional affirmative action as a solution to the problem. Affirmative action as it is traditionally interpreted in terms of gender-racial-ethnic based quotas and preferential hiring will ultimately result in a gradual systemic implosion of organisations due to a lack of motivated and competent personnel and a loss of institutional memory (Esterhuyse, 2008) and hurt the very people it is meant to help in the process. Moreover, affirmative action as it is traditionally interpreted is a cheap, shallow, insincere solution (De Goede & Theron, 2010) to the problem of the under-representation of previously disadvantaged groups in the formal economy because it chooses to ignore the fundamental cause of the problem and simply treats the symptoms.

In addition to the failure to meet the employment equity targets, other undesirable social trends also exist. Although South Africa has experienced positive economic growth since the election of a democratic government in 1994, it is important to note that South Africa has been ranked as one of the most unequal societies in the world with a Gini coefficient[7] of .666 (Office of the Presidency, 2009). Income inequality between race groups rather than inequality within race groups has been reported to be the leading cause of the rising income inequality (Bhorat, Westhuizen, & Jacobs, 2009). However, it appears that there is a rising inequality within racial groups as well, especially within the African group where a small minority is amassing great wealth through the Black Economic Empowerment programme (BEE) while the majority is reeling in poverty. The Growth Incidence Curve (GIC) for South Africa shows that economic growth did not benefit the rich and poor equally. Although growth did benefit the poor in the absolute sense, economic growth benefited the top end of the distribution more than the bottom end of the income distribution. The rising levels of inequality eroded most of the potential gains of economic growth. Since economic growth is not pro-poor any more, higher economic growth rates are needed to offset the rising inequality (Bhorat, Westhuizen, & Jacobs, 2009). Economic growth will, however, not be sustainable without access to a sufficient supply of high level knowledge and skills. The rising social and income inequality has some significant repercussions for societal functioning and poverty levels.

The foregoing discussion shows that uncontrolled adverse impact in selection has far reaching societal consequences, making it part of a vicious downward spiral of

[7] The Gini coefficient is a measure of statistical dispersion developed by the Italian Statistician and Sociologist Corrado Gini in 1912. It is usually defined mathematically based on the Lorenzo curve, which plots the proportion of the total income of the population (on the y-axis) that is cumulatively earned by the bottom x% of the population.

poverty. The effect of differences in criterion performance also impinge on the previously disadvantaged groups' psychological states and readiness for development. This is likely to lead to a backward-cum-inverse spiral of motivation characterised by psychological states such a low self-esteem, weak attribution and social identity processes which culminate in a state of learned helplessness or learned hopelessness. Learned helplessness (LH) refers to the behavioural consequences of exposure to stressful events over which the organism has no control (Maier & Seligman, 1976; Weiss, Goodman, Losito, Corrigan, Charry & Bailey, 1981). This state-of-affairs is likely to affect the previously disadvantaged groups' survival skills especially the self-motivation required in the attainment of skills that can help economically empower them and contribute towards the global fight against poverty.

Poverty alleviation has featured prominently in most humanitarian efforts aimed at promoting sustainable livelihoods and equitable, broadly shared economic growth world-over, particularly in the developing countries. Most humanitarian agencies have been extensively engaged in consultations at the national level to determine the causes and ways of addressing poverty. Progress towards poverty alleviation is generally measured against the achievements of the United Nations Millennium Development Goals (MDGs). Economically empowering the larger segment of the population which has been previously disadvantaged also helps realise the Millennium Development Goal of eradicating the hardships caused by poverty. To economically empower those currently excluded from the formal economy requires the development of the skills, knowledge and abilities needed to succeed in the world of work. In South Africa the government attempts to develop members of the previously disadvantaged society in the critical and highly sought after skills as outlined in the Accelerated and Shared Growth Initiative for South Africa (ASGISA) and the Joint Initiative on Priority Skills Acquisition (JIPSA).

In 2006, the government launched the Accelerated and Shared Growth Initiative for South Africa to address key constraints that hinder accelerated and broadly shared economic growth. The Accelerated and Shared Growth Initiative for South Africa (ASGISA) holds that improvements in living standards are to be shared by all segments of society, in particular the poor. Implicit in the ASGISA's argument is that the development of critical skills is key to achieving accelerated and broadly shared economic growth through improved educational access, which would equip a sufficient portion of the population with skills. Benefit only accrues from economic growth to those that formally participate in the economy. That is essentially where the current poverty problem has its origin. As long as a segment of the labour market has very little or no human capital to trade, that particular segment will remain locked out of the formal economy and its associated benefits.

The Joint Initiative on Priority Skills Acquisition (JIPSA) is a collaborative programme of government, business and labour stakeholders. The JIPSA objectives were derived from the underlying ASGISA objectives of (1) halving unemployment and poverty by 2014 and (2) increasing GDP growth to 4.5% (2005-2009) and to 6% (2010-2014). The shortage of suitably skilled people was identified as a binding constraint. JIPSA was then established to identify short to medium term solutions to address the skills shortage with the aim of:

- ✓ Facilitating, strengthening and coordinating activities to address skills shortages
- ✓ Accelerating the provision of priority skills to meet the ASGISA's objectives
- ✓ Mobilising senior leadership in business, government, organised labour, institutions concerned with education and training and science and technology to address national priorities in a more coordinated and targeted way
- ✓ Identifying blockages and obstacles within the system of education and training that stand in the way

- ✓ Promoting greater relevance and responsiveness in the education and training system and strengthening the employability of graduates (Lehlokoe, 2007)

The JIPSA has translated the skills shortage in South Africa into a short-term operational plan, focusing on a defined set of skills priorities such as:

- ✓ High-level, world class engineering and planning skills for the "network industries" such as transport, communications, water and energy
- ✓ City, urban and regional planning and engineering skills
- ✓ Artisan and technical skills, with priority attention to infrastructure development, housing and energy, and in other areas identified as being in strong demand in the labour market
- ✓ Management and planning skills in education and health
- ✓ Mathematics, science and language competence in public schooling

JIPSA's focus on the limited number of priority skills is viewed as key to the objectives of ASGISA and wider economic growth. Its mandate is not to deal with weaknesses in the whole skills development system but to engage with systemic issues to unblock obstacles in respect of the priority skills identified.

To augment the efforts made by the government, tertiary institutions such as Stellenbosch University have pledged their support by tailor-making their strategic plans to dovetail with the broader governmental objectives. Stellenbosch University's 2010 overarching strategic plan (OSP) was anchored on the "pedagogy of hope" notion to foster the development of useful skills vital for economic development. Previously the role of universities in economic development has been down played. However, according to Botman, Van Zyl, Fakie and Pauw (2009), the impact of knowledge societies has been so marked that the World Bank had to change its policies pertaining to higher education in developing countries. Hence, since the beginning of the new millennium, the World Bank has seen tertiary education as vital to development. Universities therefore play a crucial role in addressing the shortage of critical skills needed for economic development which ultimately helps alleviate poverty through the skill development vital for skill holders to participate in rewarding economic activities.

Despite the efforts initiated by the government and some tertiary institutions, every HR department has a role to play in skill development and the implementation of affirmative development programmes. For effective nation building, the government needs to "walk together" with the stakeholders from various spheres of influence as portrayed in the Dinokeng third scenario: (Dinokeng Scenarios)

> This is a scenario of active engagement with a government that is effective and that listens. It requires the engagement of citizens who demand better service delivery and governmental accountability. It is dependent on the will and ability of citizens to organise themselves and to engage the authorities, and on the quality of political leadership and its willingness to engage citizens. It entails a common national vision that cuts across economic self-interest in the short term." Hence working together helps overcome the social tribulations being experienced by the previously marginalised segments of the society through the adoption of a one-goal approach in the provision of economically viable skills.

Industry needs to complement the efforts of government to address the skills shortage that lies at the heart of adverse impact and that stunts sustainable economic growth by (amongst others) developing and implementing affirmative development programmes[8]. The successful implementation of the affirmative development programmes to minimise the adverse impact in selection decision-making and at the same time realise the objectives of eradicating poverty, as well as the priority skill

[8] The government and the private sector organisations can for example introduce 'night school' classes [conducted after work] for their employees who do not have some basic education regardless of their age. These basic education classes can be incorporated into the employee wellness programmes and the participants should be encouraged to sit for the final national examinations and be rewarded somehow for passing to encourage others. Numerous other examples can, however, be cited (e.g., in-house management development programmes, in-house technical training programmes. An important requirement is that the affirmative development programme should be substantial enough to equip an individual for entry into a specific job.

shortages, is hinged on the collaborative, leading effort of HR departments. Affirmative development programmes should facilitate the creation of an ideal selection scenario by HR departments that approximate the proportional representation of the various gender-racial-ethnic segments of the labour market.

To achieve this end, it is imperative for HR departments to filter out the previously disadvantaged members who cannot benefit from the affirmative development programmes since it is costly to involve everyone especially after the aftermath of the 2008-2009 economic recession. It is important that conscious effort is made to ensure a positive return on the investment made in the affirmative development intervention programmes. Not all disadvantaged individuals would have progressed equally far if development opportunities had not been denied them. Variance in learning performance exists. Selection into affirmative development programmes is therefore important.

The aim of selection into affirmative development programmes is to optimise the rate at which those that were admitted to the programme successfully complete the programme and preferably within the minimum allotted time. Indications, however, exist that current learnership programmes have a dismal output rate. Affirmative action candidates who enter skills development programmes, but fail to acquire the currently deficit skills, knowledge and abilities are still likely to be unable to contribute towards economic growth and the subsequent alleviation of social challenges discussed in a section above. Although there may be several mitigating factors that could be mobilised to account for the poor performance of learners, the poor performance of learners is frequently attributed to poor recruitment and selection of learners into the skills development programmes (Letsoalo, 2007).

The variance in learning performance is not a random event. The ability to learn differs across individuals. The level of performance achieved in learning is determined by a complex nomological network of latent variables characterising the learner and his/her learning environment. In order to successfully differentiate those that will succeed in an affirmative development intervention from those that will not, the latent variables that affect learning performance will have to be identified. To identify the latent variables that affect learning performance the identification and comprehensive understanding of the learning competencies and learning outcomes that constitute learning performance is in turn required. The foregoing argument points to the need to develop a comprehensive performance@learning structural model.

Ensuring that the appropriate people are selected into affirmative development interventions is not enough, it is also important to ensure that those admitted to these interventions successfully develop the job competency potential and job competencies required to succeed on the job. Selection ideally should target the non-malleable person-centred latent variables that affect learning performance. Learning performance is, however, not only affected by non-malleable person-centred latent variables but also by (malleable) latent variables characterising the environment/context, as well as malleable variables characterising the individual. In addition to selection, appropriate additional steps should therefore be taken to create the conditions conducive to successful learning. That, however, begs the question regarding what these conditions are and how they combine with non-malleable person-centred latent variables to determine the level of learning performance that is achieved. This again points to the need to develop a comprehensive performance@learning structural model.

Earlier it was argued that the identification of the learning competencies and learning outcomes that constitute successful learning performance is a precondition to the identification of the person and environmental characteristics that determine the level of learning performance that is achieved. It is only once it is clear what a learner needs to achieve in terms of outcomes and what a learner needs to do to achieve this, that it becomes possible to develop a comprehensive hypothesis in the form of a structural model on the determinants of learning performance.The pivotal question therefore is which learning competencies allow one individual to be more successful than another in acquiring novel, intellectually demanding skills. What are the learning competencies and learning outcomes that constitute learning performance?

De Goede (2007) and Taylor (1989, 1992, 1994, 1997) interpreted learning performance rather narrowly in terms of two learning competencies. Taylor (1989, 1992, 1994, 1997) conceptualised learning performance as comprising two learning competencies, namely the capacity to *Transfer* knowledge or skill and the rate of *Automisation*. The learning outcome that results from these two learning competencies is an elaborated crystalised ability. The elaborated crystalised ability forms the basis of future transfer (or action learning) attempts. When the learner is now faced with new novel task he/she can now apply the elaborated crystalised ability to master the new task which possibly might not have been possible without the addition of what has been learnt.

Learning potential was consequently interpreted equally narrowly by De Goede (2007) and Taylor (1989, 1992, 1994, 1997) who defined it only in terms of cognitive learning competency potential variables. Taylor (1992, 1994a, 1994b) proposed a two factor model of intelligence in which the capacity to form abstract concepts and information processing efficiency (speed, accuracy, flexibility) constitute the two learning competency potential latent variables that determine learning performance. The two factors are expressed in learning as the capacity to transfer knowledge or skill and the rate of automisation respectively. De Goede (2007) elaborated on Taylor's work on the APIL-B by investigating the internal structure of learning potential as measured by the APIL-B test battery. The test comprises cognitive abilities including both crystallised and fluid intelligence components that are crucial for learning potential. De Goede reported reasonable model fit to the data.

The second major weakness of both Taylor's thinking on learning potential and De Goede's model is that they fail to formally distinguish between *Learning performance in the classroom* and *Learning performance during evaluation*. In one sense no sharp division exists between classroom learning and practical application. Both essentially involve the adaptation and transfer of existing crystalised knowledge onto novel problems in an attempt to make sense of the initially meaningless problem data by creating/imposing meaningful structure on the data. Practical application can be described as action learning. Affirmative development programmes aspire to empower affirmees with the job competency potential and job competencies they initially lacked, but which are required to deliver the outputs for which the job they apply for exists. To develop the job competency potential and job competencies they initially lack, involves classroom learning. Once they leave the classroom the newly developed crystalised knowledge should allow them to successfully cope with job demands they initially were unable to meet. This should, however, involve more than simply retrieving previously transferred and automated responses to now familiar stimuli. Rather the ideal would be that the affirmee would be able to creatively apply the newly derived crystalised knowledge to novel problems not explicitly covered in the affirmative action development programme or action learning. It is this ability to transfer the crystalised knowledge developed through *Learning performance in the classroom* that should be evaluated when assessing *Learning performance during evaluation.* Both *Learning performance in the classroom* and *Learning performance during evaluation* should be therefore be formally modelled as conceptually similar but nonetheless procedurally distinct latent variables that are both required to obtain a valid description of the psychological process underlying learning performance.

De Goede (2007) and De Goede and Theron (2010) should in addition be critisised for the manner in which they operationalised the *Transfer* latent variable. The APIL-B test battery was used to measure *Transfer* as a dimension of *Learning performance in the classroom.* The APIL-B measures transfer in a simulated learning task comprised of geometric symbols for which no prior learning is required[9]. *Transfer* as a dimension of *Learning performance in the classroom* in contrast involves transfer of specific crystalised knowledge developed through prior learning in an actual learning task comprised of job-related learning content.

While the efforts of Taylor (1989, 1992, 1994, 1997) and De Goede (2007) represent significant and valuable progress in the development of learning potential models, the resultant models should be regarded as preliminary, and like most initial models should be seen as laying the foundation for further elaboration and expansion. Burger (2012) initially attempted to elaborate the De Goede (2007) model but in the end the empirical part of her research focused exclusively on non-cognitive learning competency potential latent variables and the manner in which they combine to affect learning performance. The learning performance structural model that she subjected to empirical test excluded the initial Taylor (1989, 1992, 1994, 1997) and De Goede (2007) cognitive emphasis on learning potential. Burger (2012), like De Goede (2007) and Taylor (1989, 1992, 1994, 1997), also failed to formally distinguish between *Learning performance in the classroom* and *Learning performance during evaluation* (or then subsequent action learning performance).

Classroom learning performance as well as *learning performance during evaluation* is determined by a complex nomological network of latent variables characterising the learner and his/her learning environment. Affirmative development interventions stand a greater chance of succeeding to the extent that this complexity is validly understood. To validly understand the complex nomological network underpinning learning performance it, however, first needs to be understood in what sense the nomological network can be considered to be complex. Three characteristics seem to be relevant. The nomological network underpinning learning performance is firstly complex in that a large number of latent variables combine to determine learners'

[9] The learning material in the APIL-B was purposefully chosen so that no prior learning was required to understand the basic principles involved in the initial solutions that subsequently had to be transferred onto ensuing problems.

classroom learning performance and *learning performance during evaluation*. The nomological network underpinning learning performance is complex, secondly, in as far as the latent variables are richly interconnected. The nomological network underpinning learning performance is complex, thirdly, in that the understanding of learning performance is not located in any given point in the nomological network but rather spread over the whole of the network (Cilliers , 1998). The latter characteristic is particularly important. It implies that any reduction of the full nomological network will invariably result in a loss of meaning. In as far as a simultaneous understanding of all the latent variables that play a role in *classroom learning performance* and *learning performance during evaluation* and of the manner in which they structurally combine will forever elude man are concerned a bounded explanation of affirmative development learning performance is inevitable. The fact that complete certainty and "truth" is beyond reach[10] (Babbie & Mouton, 2001) does, however, not mean that research aimed at obtaining valid[11] explanations of affirmative development learning performance should not attempt to approximate the full nomological network.

It is highly unlikely that one or two isolated explanatory studies will result in an valid understanding of the comprehensive nomological net underpinning learning performance. Progress towards a valid understanding of learning performance will therefore only be achieved if explicit attempts are made to formally model the nomological net underpinning learning performance and if cumulative research studies attempt to build on earlier learning potential structural models.

[10] In addition to the current argument, complete certainty and "truth" will always elude man because hypotheses on the nature of the nomological network are constructed in terms of intellectual constructs created by man and because support for empirically testable implications deductively derived from these hypotheses cannot be inductively interpreted as proof that the hypothesis must be true.

[11] Valid explanations should be understood to refer to explanations that fit observable data acceptably and in that sense can be regarded as permissible or plausible explanations.

The objective of the present study is consequently to elaborate and integrate the De Goede (2007) and the Burger (2012) learning potential models in a manner that circumvents the problems and shortcomings of these models. The second-generation research initiating question (Theron, 2011) underpinning this research is therefore the question why affirmative development learners vary in the degree of success they achieve in *learning performance during evaluation* conditional on the insights provided by De Goede (2007) and the Burger (2012). The purpose of the research is to derive appropriate HR interventions that will increase the probability that over time temporary affirmative development interventions will successfullly reduce adverse impact in strict top-down meritorious job selection in South Africa.

1.2 OBJECTIVES OF STUDY

The specific objectives of this study consequently are:

- To elaborate and integrate the De Goede (2007) and the Burger (2012) learning potential models in a manner that circumvents the problems and shortcomings of these models by developing an extended explanatory learning performance structural model that explicates additional cognitive and non-cognitive learning competency potential latent variables that affect learning performance and that describes the manner in which these latent variables combine to affect learning performance.
- To test the model's absolute fit;
- To evaluate the significance of the hypothesised paths in the model; and
- To derive practical human resource management interventions aimed at enhancing the learning performance of learners on affirmative development programmes.

1.3 STRUCTURE OF THE DISSERTATION

The dissertation comprises five chapters.

Chapter One

In this chapter, a funnel-like argument has been unfolded that described and motivated the research and that culminated in the research initiating question and the objectives of the study. The appropriate research problem will emerge from the literature study[12].

Chapter Two

Chapter two provides an in-depth presentation of the theoretical argument through which the structural model that is proposed, as a response to the research initiating question is derived. This literature study chapter is problem solving and contains an analytical search for an answer to the research initiating question and through that problem solving process the research objective is reached. The De Goede (2007) and Burger (2012) learning potential models are presented and the empirical findings on their models summarised. The learning competency latent variables that comprise *Learning performance in the classroom* and those that compromise *Learning performance during evaluation* are discussed. The cognitive and non cognitive learning competency potential latent variables that affect the learning competencies comprising *Learning performance in the classroom* and those that compromise *Learning performance during evaluation* are discussed. The proposed learning potential model is schematically presented as a structural model and mathematically as a matrix equation.

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[12] Traditionally many researchers view the positivistically orientated explanatory research process to be initiated by a research problem. The research problem refers to a question on the nature of the relationship existing between two or more latent variables. In terms of this view the research problem then dictates the focus of the literature study. This approach, however, marginalises theorising and thereby reduces the probability that a valid approximation of the cunning logic (Ehrenreich, 1991) underpinning learning performance will be uncovered. If it assumed that learning performance is complexly determined by a vast and richly interconnected nomological network of latent variables characterising the learner and his/her learning environment, the probability of validly modeling this nomological network increases as theorising is afforded a more pivotal role in the research process. To put theorising at the centre-stage, the explanatory research process should rather be set in motion by an open-ended research initiating question that naturally enforces theorising. Rather than the research problem dictating the literature study the research problem emerges from the literature study as the question whether the structural model that was borne out of the literature study's attempt to provide a convincing answer to the research initiating question is valid.

Chapter Three

Chapter three presents the methodology that was used to test the learning potential model derived in chapter two. The methodology incorporates the research hypotheses, research design, sampling strategy, data collection procedures, measuring instruments, imputation of missing values and the statistical analyses.

Chapter Four.

The results of the data analyses are presented in chapter four. The decisions on the statistical hypotheses are presented in this chapter.

Chapter Five

In this chapter a discussion of the findings presented in chapter four is presented. The chapter is devoted to the discussion of the implications of the results/findings for affirmative development practice, theory and future research.

1.4 SUMMARY

In this chapter the need for affirmative development programmes to redress differences in job competency potential in South Africa has been argued. The need for an explanatory affirmative development learning performance structural model to inform the management of the affirmative development programmes has been discussed. The De Goede (2007) and the Burger (2012) models have been introduced as pioneer attempts to develop such an explanatory structural model. The shortcomings from which these models suffer were pointed out. The need for the current study aimed at expanding the models with a view of explaining further variance in learning performance was subsequently argued in terms of these shortcomings.

CHAPTER TWO
LITERATURE REVIEW

2.1 INTRODUCTION

The only solution to the gender-racial-ethnic adverse impact problem currently characterising selection in South Africa that will not negatively impact on selection utility[13] lies in the establishment of uniform criterion performance levels across the

[13] In this argument selection utility is interpreted narrowly in the Brogden-Cronbach-Gleser (Boudreau, 1996) sense of the term. This narrow stance can, however, be criticised as unnecessarily narrow (Cascio & Aguinis, 2005). Those that are critical of the transitional interpretation of selection utility argue that the value of the outcomes of selection decision-making should not be judged solely in terms of the financial value of the performance of the selected group. Workforce diversity should be valued as a desirable outcome as well. Workforce diversity is valued as a selection outcome because it fosters growth, innovation and progress and thereby also, the performance of organisational units. Workforce diversity is, however, in the final analysis valued simply for its own sake. The diversity that fosters growth, innovation and progress and that has intrinsic value however, refers to much more than the superficial gender-racial-ethnic differences employment equity legislation focuses on. The danger exists that the critics can argue that by adapting the traditional Brogden-Cronbach-Gleser utility equation (Boudreau, 1996) it can be shown that a deviation from strict top-down selection that increases workforce diversity results in a recalculated utility on par with the traditional, more narrowly interpreted utility of strict top-down selection. This argument is problematic for two reasons. Firstly, workforce diversity should refer to much more than superficial gender-racial-ethnic differences. Differences in values, beliefs, ideals and numerous other attributes that are relevant to work performance are far more important than gender-racial-ethnic differences. Diversity in these fundamental variables, are however, largely unrelated to gender-racial-ethnic differences. It therefore seems questionable to argue that a reduction in adverse impact will bring about an increase in diversity in the attributes that will promote growth, innovation and progress. The critics plea for a broading of the traditional interpretation is secondly problematic in South Africa because it essentially treats the symptoms of the problem rather than the fundamental underlying causes. It, in addition, implies a pessimistic prognosis on the success of affirmative development interventions. It basically suggests that unless organisations value gender-racial-ethic diversity explicitly over and above performance, the ideal of a diverese workforce will never be realised. In

different gender-racial-ethnic segments of the population. Since selection decisions are based on clinically or mechanically derived criterion estimates ($E[Y|X_i]$), the only scenario in which fair selection decision-making (interpreted in the Cleary sense of the term) can avoid adverse impact against any specific gender-racial-ethnic groups is when the criterion distributions of the various gender-racial-ethnic groups coincide. Achieving this in practice will no doubt present an extremely daunting challenge. In principle though this is regarded as an attainable ideal. A fundamental meta-theoretical assumption underpinning this study is that the fundamental ability to learn is unrelated to gender-racial-ethnic status. In the absense of this assumption any attempt at reducing adverse impact without negatively impacting on selection utility would be futile. Criterion distributions currently do not coincide across gender-racial-ethnic groups because systematic differences exist in job competency potential across these groups. Job competency potential refers to the person characteristics that systematically, directly or indirectly influence the level that employees achieve on the competencies that constitute performance. These job competency potential differences are the result of differences in developmental opportunities. In terms of this argument the achievement of the ideal of ameliorating adverse impact is anchored on the successful identification of disadvantaged individuals with learning potential and the development of the job competency potential required to succeed in specific target jobs. Not all disadvantaged individuals would have progressed equally far if development opportunities had not been denied them. There always will be variance in learning performance in all gender-racial-ethnic groups. To ensure affirmative development with maximum utilily individuals with learning potential that would have progressed much further

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contrast this study optimistically believes that performance and diversity are not inherently incompatible. A drop in utility (narrowly interpreted in monetary scaled performance) is not a necessary, unavoidable sacrifice to achieve workforce diversity. In fact, this study is convinced that affirmative development can eventually result in strict top-down selection that makes financial business sense in terms of a narrow Brogden-Cronbach-Gleser interpretation of utility and that results in a truly diverse workforce without preferential hiring.

if it had not been for the lack of opportunity need to be selected into affirmative development opportunities. Moreover, appropriate steps should be taken to create the conditions conducive to successful learning. To achieve successful affirmative development through these flow and stock (Milkovich & Boudreau, 1997) interventions, an indepth understanding is required of the learning competencies that constitute *Classroom learning performance* and *Learning performance during evaluation,* the learning competency potential latent variables that determine learning performance and the manner in which these variables combine to affect *Classroom learning performance* and eventually *Learning performance during evaluation.* The present chapter provides some insight into the De Goede (2007) and Burger (2012) learning potential structural models as well as highlight their shortcomings and how the models can be elaborated to more closely approximate the psychological process determining *Classroom learning performance* and *Learning performance during evaluation.*

Although the learning potential construct has been extensively studied, most of the work has concentrated on formulating the most plausible dynamic assessment theories that explain learning potential and the subsequent transfer of the knowledge attained (Budoff, 1968; Campione & Brown, 1987; Carlson & Weidl, 1978; Feuerstein, Rand, Hoffman & Miller, 1980; Guthke, 1992, 1993; Guthke & Stein, 1996). Most of these dynamic assessment theories were more inclined towards thinking skills training (Taylor, 1992). Contemporary work on learning potential has focused on the learning competencies that distinguish between successful and unsuccessful learners. Recent contributions have been made by Taylor (1989; 1992; 1994; 1997), De Goede (2007) and Burger (2012). The present chapter discusses the preliminary learning potential contributions made by Taylor (1989; 1992; 1994; 1997), De Goede (2007) and Burger (2012) with a view of elaborating the models proposed by De Goede (2007) and Burger (2012).

2.2 DE GOEDE'S (2007) WORK ON LEARNING POTENTIAL

De Goede (2007) developed a learning potential structural model based on the work of Taylor (1989; 1992; 1994). Taylor developed the APIL-B (Ability, Processing of Information and Learning Battery) based on extensive research and theorising on the learning potential construct. The APIL-B provides an indication of an individual's intellectual adaptability rather than his/her previously acquired skills or abilities. The De Goede (2007) learning potential structural model was the product of an investigation into the internal structure of the learning potential construct as measured by the APIL-B Test Battery developed by Taylor (1989; 1992; 1994; 1997). The APIL-B, a test of learning potential measures the two cognitive abilities that Taylor (1989; 1992; 1994; 1997) considers important constituents of individuals' potential to learn as well the two learning competencies that according to Taylor (1989; 1992; 1994; 1997) comprises learning. The two learning competency potential variables that Taylor (1989; 1992; 1994; 1997) regard as essential for successful learning are fluid intelligence and information processing capacity To gain a thorough understanding of the De Goede (2007) model, it is vital to have some insight into the theory on which it is built. This requires reviewing Taylor's work on learning potential.

2.3 TAYLOR'S CONTRIBUTION TO LEARNING POTENTIAL

Taylor (1992) defined learning potential as the underlying fundamental aptitude or capacity to acquire and master novel intellectually or cognitively demanding skills demonstrated through the improvements in performance after a cognitive intervention such as teaching, feedback or repeated exposure to the stimulus material. Taylor (1992) identified two types of learning potential, type A and type B. Learning potential type A concerns the potential to benefit from thinking skills training and mediation while type B, which is more superficial, deals with the potential to learn novel material in controlled conditions. Learning potential type B is the one that human resource practitioners and educationalists should identify. Learning potential type A is assessed using clinical methods such as those used by Feuerstein (Taylor, 1992; 1994). Taylor (1992; 1994) proposed a two factor model of intelligence in which the capacity to form abstract concepts and information processing efficiency (speed, accuracy, flexibility) constitute the two factors. The two factors are expressed in learning as the capacity to transfer knowledge or skill and the rate of automisation respectively.

2.3.1 Transfer of knowledge or skill

The term transfer of learning is often used synonymously with transfer of training although transfer of training is often regarded as a subset of transfer of learning (Leberman, McDonald & Doyle, 2004; Subedi, 2004). According to Ferguson (1956), the concept of transfer occupies a crucial position in any theory that attempts to relate learning to human ability. Transfer is the adaptation of knowledge and skills to address problems somewhat different from those already encountered. It is the process through which the structure of abilities and skills becomes more elaborated with time, making it a fundamental aspect of learning and cognitive development (Taylor, 1994b). Transfer is the central and enduring goal of education (Lobato, 2006) which encompasses both maintenance of behaviour and its generalisation to new applications (Broad & Newstrom, 1992). The construct of transfer refers to more than mechanically applying that which has previously been learnt to the same or similar situation. Real transfer occurs when an individual carries over something that has been learnt in one context to a significantly different context to create meaningful structure in the latter context that initially presented an unfamiliar problem (Fogarty, Perkins & Barrell, 1992; Gagne, Yekovich & Yekovich, 1993; Perkins & Salomon, 1996).

Grigorenko and Sternberg (2002) distinguished between near and far transfer. Near transfer occurs when students apply their knowledge and skills in situations and contexts that are very similar to those in which the learning occurred while far transfer occurs when previously aquired knowledge is used to solve a novel problem in a context that is very different from the context in which the knowledge was originally learnt. Perkins and Salomon (1988) proposed two forms of transfer in the form of low road and high road transfer. The authors contend that transfer occurs partly because of the way the knowledge and skills were learnt. Low road transfer occurs when the surface features of the initial learning and the application context are similar. In contrast, the high road transfer requires some conscious attempts to recognise similar features across situations that are very different. A good example of the application of the high road transfer is when a military advisor realises that the rules of 'surround and capture' in chess can be applied in tactical planning.

According to Taylor (1994), the concept of fluid intelligence which is seen by many cognitive psychologists as the fundamental or core ability, is related to the concept of transfer, which is regarded by many learning theorists as the fundamental activity of learning. Hence transfer may be regarded as an expression of fluid intelligence in the process of learning. Taylor described transfer as:

> ..... a phenomenon which is expressed when an individual comes to terms with novel or partially novel problems. Each subsequent set of problems in a transfer test differs from those that have come before, and is usually more complex than those that have come before. Therefore, the subject is continuously challenged, and the attainment of full understanding and correct answers is the pursuit of a shifting target. The stimulus material is "open-ended" in that new material is continuously being added. The educational process, as well as the process of acquiring new job skills, tends to be like this: new competencies are built on older ones and have to be integrated into conceptual frameworks that become ever more general and elaborate. Transfer lies at the heart of this process of elaboration (p.6).

Transfer of knowledge refers to the intellectual adaptation and transformation of previously derived intellectual insights to make sense of a novel problem. Transfer involves the use of previously gained insight to find meaningful structure in a novel, initially meaningless, stimulus set. Transfer in essence is creative cognitive problem-solving.

The importance of transfer in the learning process cannot be underestimated and hence its inclusion in any model that purports to identify the learning competencies of the previously disadvantaged populations is difficult to challenge. Whether an individual has been subjected to some disadvantagement or not, transfer still plays a central role in the attainment of knowledge which need to be applied to other situations and contexts. In the recognition of the importance of transfer of learning (Desse, 1958, p. 213) wrote:

> There is no more important topic in the whole of psychology of learning than transfer of learning... Practically all educational and training programs are built upon the fundamental premise that human beings have the ability to transfer what they have learned from one situation to another. The basic psychological problem in the transfer of learning pervades the whole psychology of human ability. There is no point to education apart from transfer.

Transfer of knowledge plays a dominant role when learning involves material that continuously changes (novel in nature). Fundamentally the purpose of learning is to elaborate on prior learning that will allow the subsequent solving of insolvable novel problems that will be further elaborated in an ever rising spiral of learning. There is therefore no sharp boundary between classroom learning and the subsequent application of the newly derived knowledge to solve novel practical problems in action learning. However, once insight in initially novel learning material has been achieved the learner is faced with the challenge of writing the derived insight to memory where it will be accesable for future problem-solving. The newly derived knowledge has to be automated (Taylor, 1992). Unless the newly derived knowledge becomes part of the learner's readily available body of accessible crystallised knowledge the original novel learning problem will have to be solved through transfer every time it is encountered. Without automisation, learning will also lose its progressive, upward spiralling character. In situations where stimuli do not change dramatically over time, the learner is faced with the challenge of becoming more effective and efficient in performing the task (Taylor, 1992). The only way in which the individual can be more effective in the performance of the task is through automating all the operations involved in performing the task.

2.3.2 Automatisation

Automatisation is one of the cognitive learning competencies through which the capacity to form abstract concepts and information processing efficiency are manifested in Taylor's two factor model. *Automatisation* is an important capacity in the functioning of the individual. The faster the individual becomes adept at performing a specific task, the faster he or she can free the mental capacity to tackle a new task (Taylor, 1992).

Automatisation is one of the two concepts identified in Sternberg's (1984) triarchic theory which indicates the range and complexity of concepts which have been mastered at different points in the learning process. Sternberg suggested that controlled information processing is under the conscious direction of the individual and that it is hierarchical in nature. In contrast, Sternberg (1984) proposed that automatic information processing is pre-conscious and is not under the conscious direction of the individual and not hierarchical in nature. When an individual is processing some information from old domains or domains that are entrenched by nature, the individual primarily relies on automatic, local processing. Sternberg (1985, p. 96) writes:

> ...the present view essentially combines hierarchical and nonhierarchical viewpoints by suggesting that information processing is hierarchical and controlled in a global processing mode, and non-hierarchical and automatic in local processing modes. Expertise develops largely from the successively greater assumption of information processing by local resources. When these local resources are engaged, parallel processing of multiple kinds of tasks

> becomes possible. Global resources, however, are serial and of very limited capacity in their problem-solving capabilities.

It is vital for the individual to pack what has been learned from global processing of the new experience into a given local processing system, so that the next time such a situation arises, there will be no need to exit from the local processing system. Therefore, the extent to which one develops expertise in a given domain largely depends on the ability of the individual to pack new information, in a useable way, into a given local processing system and on the ability to gain access to this information (Sternberg, 1984). The process of packing what has been learnt from global processing into a specific local processing is *Automatisatio*n. According to Taylor (1994, p. 7), "the steepness of the learning curve is likely to be substantially influenced by the transfer-fluid intelligence factor of ability in the early stages of learning a closed-ended task, but throughout, information processing variables are likely to play a dominant role. Hence automatisation and information processing capacity may be analogues, just as transfer and fluid intelligence are analogues, one from the learning lexicon, and the other from the cognitive lexicon."

2.3.3 Abstract thinking capacity

Cattell (as cited in De Goede and Theron, 2010, p. 36) proposes that Spearman's (1904; 1927) general intelligence factor (g) is in fact not a unitary factor, but that it is made up of two distinct factors namely fluid (Gf) and crystallised intelligence (Gc) (Jensen, 1998; Eysenck, 1986). According to Eysenck (1986), Cattell's fluid intelligence is probably very similar to Spearman's (1904; 1927), g while crystallised intelligence is the same as the "group factors" or "primary abilities." Cattell's conceptualisation of intelligence in terms of fluid and crystallised intelligence probably explains why differences in individual abilities exist when viewed in conjunction with the *Transfer of knowledge learning* competency (De Goede & Theron, 2010).

Fluid intelligence or *Abstract thinking capacity* is a basic inherited capacity developed by an interaction with environmental characteristics which are found in any society, whereas crystallised intelligence are specialised skills and knowledge promoted by and required in a given culture. Fluid intelligence (Gf) refers to the ability to reason and to solve new problems independently of previously acquired knowledge (Jaeggi, Buschkuehl, Jonides & Perrig, 2008). It is the ability to think flexibly and to understand abstract relations (Preusse, Van der Meer, Deshpande, Krueger & Wartenburger, 2011). It is the fundamental abstract reasoning and concept formation capacity that an individual applies to novel problems (Cattell, 1971; Jensen, 1998) which reflects higher mental abilities such as reasoning (Carroll, 1993). Gf is also applied in the development of new abilities and in the acquisition of new knowledge (Cattell, 1971) via transfer of existing knowledge. Fluid intelligence comprises the set of abilities involved in coping with novel environments and especially in abstract reasoning (Sternberg, 2008). More importantly, Gf is relatively formless and appears independent of experience and education (Preusse, Van der Meer, Deshpande, Krueger & Wartenburger, 2011). Therefore, it is Gf that is demonstrated in mental tests (e.g. Ravens Progressive Matrices) in which prior learned knowledge, skills, algorithms, or strategies offer little or no advantage (Jensen, 1998). The study of Mathematics is an example of an area which relies heavily on the existence of fluid intelligence (Preusse *et al.,* 2011). Mathematics comprises various areas such as arithmetic, algebra, analysis, set theory, geometry, and probability, just to name a few. Although the content and demands of these areas differ, they all require the understanding of relations and the ability to mentally manipulate symbols or structure relations. These abilities are also referred to as fluid intelligence (Cattell, 1963, 1987; Horn & Cattell, 1966). Inter-individual differences in maths performance are associated with inter-individual differences in fluid intelligence (Spinath, Freudenthaler & Neubauer, 2010). Gf is, undoubtedly, critical for a wide variety of cognitive tasks and it is considered one of the most important factors in learning. Moreover, Gf is closely related to professional and educational success, especially in complex and demanding environments. People with high fluid intelligence perform better in analogical reasoning tasks than people with average fluid intelligence (Jaeggi *et al.*, 2008). This finding is corroborated by associations between fluid intelligence and shorter reaction times, as well as increased task performance for a number of memory tasks as reported by Vernon (1983) and Grabner *et al.*, (2004) as well as for elementary cognitive tasks (i.e., the Hick, Sternberg, and Posner paradigms; Neubauer *et al.*, 1997).

While fluid intelligence comprises the set of abilities involved in coping with novel environments and especially in abstract reasoning; crystallised intelligence (Gc) is the product of the application of these processes (Sternberg, 2008). Gc reflects knowledge acquired, through Gf in action, from culture, education, and other learning experiences (Carroll, 1993). Acquired abilities such as verbal and numerical comprehension can be categorised under crystallised intelligence. Hence crystallised intelligence appears to have a scholastic and cultural foundation (Jensen, 1998). The learning competency of *Transfer of knowledge* links Gf with Gc in as far as *Transfer of knowledge* in essence is Gf in action in the solution of novel problems. Existing Gc is elaborated via transfer by Gf using existing Gc (De Goede & Theron, 2010).

An individual's *Abstract thinking capacity* plays an important role in dealing both with novel kinds of problems and learning. Fluid intelligence is a prerequisite for solving novel problems and for coping with unfamiliar situations, situations that thereby allow an individual to acquire new knowledge and obtain new insights. Therefore *Abstract thinking capacity*, which is synonymous with fluid intelligence, influences an individual's capacity to perform a given task.

2.3.4 Information processing capacity

Although there are information-processing theorists who claim that *Information processing capacity* and speed form the core of intelligence and problem solving (e.g. Jensen, 1982; Vernon, 1986, 1987), Taylor (1994) argued that speed is one of the components of *Information-processing capacity* and that *Information-processing capacity* is not the complete foundation of intelligence but only constitutes one of the important core learning competency potential latent variables, in addition to *Transfer of knowledge, Automatisation* and *Abstract thinking capacity*. Jensen (1998, p. 205) describes information processes, as "hypothetical constructs used by cognitive theorists to describe how persons 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 (short-term or long-term), and later retrieved from storage to govern the person's decisions and behaviour in a particular situation." Taylor (1994) defined *Information processing capacity* in terms of three components namely:

- ✓ The speed with which information of a moderate difficulty level is processed (i.e. processing speed). According to Taylor (1997), *Information processing capacity* influences learning acquisition as individuals who are slow information processors may fall behind in learning situations because they may not have had enough time to investigate all the reasonable solutions to problems.
- ✓ The accuracy with which information of a moderate difficulty level is processed (i.e. processing accuracy). Inaccurate processing of information often leads to lapses in concentration accompanied by a failure to monitor and control quality (Taylor, 1997).
- ✓ The cognitive flexibility with which a problem-solving approach, which is appropriate to the problem, is selected (De Goede & Theron, 2010). The cognitive flexibility, with which an individual selects a problem-solving approach, appropriate to the problem from a personal 'toolkit' of cognitive strategies is a fundamental characteristic of intelligent behaviour (Hunt, 1980; Taylor, 1997). Individuals who keep on following an inappropriate strategy are regarded as having a lesser capacity to process information.

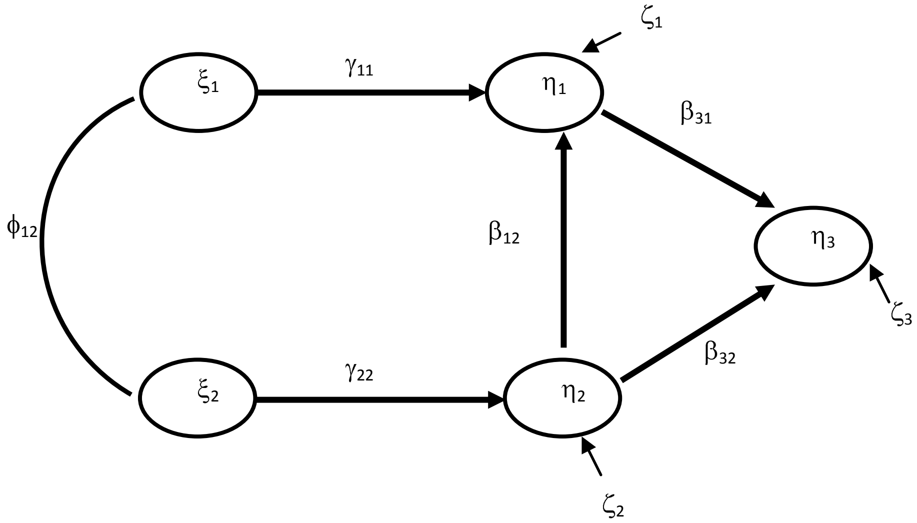
In a typical learning context the learner grapples with novel, intellectually challenging tasks which cause the individual to experience a lot of uncertainty; which he/she will naturally try to reduce. This is accomplished through the initial employment of executive processes (Sternberg, 1984) to process the bits of information or stimuli provided in the task leading to the mapping of a strategy to follow. The second step involves the use of non-executive processes (Sternberg, 1984) to execute the strategy. The processing of bits of information through cognitive processes (executive and non-executive), which are activated in an uncertain situation in order to reduce the amount of uncertainty, can be termed information processing. The strategy an individual selects to solve a given problem is one of the factors which either contributes to or counters the capacity to solve the problem (Hunt, 1980; Underwood, 1978). Strategy, however, seems not to be the only factor that limits an individual's capacity to process information (Taylor, 1992; Underwood, 1978). According to 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 maybe relevant to the problem, and of the speed and efficiency of any other system used in the total activity. This realisation could have influenced Taylor's definition of *Information processing capacity* in terms of processing speed, processing accuracy and cognitive flexibility.

Taylor (1997) believes that individuals who are low on *Information processing capacity* may fall behind in learning situations because they may not have enough time to investigate all the reasonable solutions to problems, and that they more often lose concentration and tend to select inappropriate cognitive processing strategies. In a learning context an individual with high *Information processing capacity* would be seen as if the individual who can more quickly, accurately and flexibly process information and who is able to acquire more, learn faster and perform better. This justified the inclusion of *Information processing capacity* as a dispositional learning competency potential construct in Taylor's (1994) theory.

2.3.5 Findings on the De Goede learning potential model

Taylor (1997; 1994; 1992; 1989) explained learning potential in terms of the four constructs, *Abstract reasoning capacity*, *Information processing capacity* (speed, accuracy, and flexibility), *Transfer of knowledge* and *Automatisation*. According to Taylor (1992), *Information processing capacity* and *Automatisation* should be causally linked, because it is the task or role specific information processes that have to be automated. The individual's ability to store what has been learned from global processing of a novel experience into a given local processing system (automatisation) depends on the speed, accuracy and flexibility with which information can be processed. Taylor (1992) also argues that there is a direct causal link between *Abstract thinking capacity* and *Transfer of knowledge* so that an individual's capacity to transfer knowledge is causally linked to the individual's abstract reasoning capacity. In addition, *Transfer of knowledge* and *Automatisation* are causally linked to Learning performance[14]. De Goede (2007) extended the derived structural model emerging from the foregoing discussion by making provision for a causal linkage between *Automatisation* and *Transfer of knowledge*. *Automatisation* of the operations required to perform complex tasks allows an individual to perform the tasks with minimal mental effort (Sternberg, 1984), thus freeing cognitive capacity, specifically Gf , for novel problem solving (i.e. transfer) (Taylor, 1994). This theoretical argument culminates in the learning potential structural model tested by De Goede (2007) (shown as Figure 2.1) that depicts the specific paths or hypothesised causal linkages between the constructs.

[14] Although never formally stated as such by Taylor (1992), De Goede (2007) or De Goede and Theron (2010) Learning performance here refers to Learning performance during evaluation. *Transfer of knowledge* and *Automatisation* constitutes Classroom learning performance.



Where:

ξ_1 = Abstract thinking capacity

ξ_2 = Information processing capacity

η_1 = Transfer of knowledge

η_2 = Automatisation

η_3 = Job competency potential

Figure 2.1. Graphical portrayal of the De Goede (2007) learning potential structural model. Adapted from " An investigation into the internal structure of the learning potential construct as measured by the APIL test battery, " by J. De Goede, 2007, *Unpublished Master's Thesis*, p. 59. Copyright 2007 by Stellenbosch University.

De Goede (2007) reported that both the measurement and structural models fitted the data reasonably well. The close fit null hypothesis was not rejected in both the measurement and structural models. Significant relationships were reported between *Information processing capacity* and *Automatisation* and *Information processing capacity* and *Learning performance*; *Automatisation* and *transfer of knowledge*. Support was also found for the mediating effect of *Automatisation* on the relationship between *Information processing capacity* and *Learning performance*.

Some of the original De Goede (2007) hypotheses are retained in the present study but are, however, expanded upon through the identification of other cognitive and non cognitive learning competencies.

While Taylor (1997; 1994; 1992; 1989) and De Goede's (2007) work represent significant and valuable progress in the identification of the learning competencies that constitute *Classroom learning performance* and *Learning performance during evaluation* and the learning competency potential latent variables that determine the learning performance of the previously marginalised groups, these efforts are clearly preliminary and deserve further substantiation and elaboration. *Classroom learning performance* and *Learning performance during evaluation* firstly comprise more dimensions of learning performance than is acknowledged by Taylor (1992) and by De Goede (2007). In addition *Classroom learning performance* and *Learning performance during evaluation* are determined by a far more complex nomological network of latent variables characterising the person and the learning environment than is acknowledged by Taylor (1992) and De Goede (2007). Human resource management interventions aimed at increasing the learning performance of learners on affirmative development programmes will only succeed if this complex nomological network of latent variables is accurately understood. The complex manner in which human behaviour is determined makes it highly unlikely that the human learning process can only be restricted to the cognitive competencies and cognitive learning competency potential latent variables identified by Taylor (1992, 1994) and by De Goede (2007). Human learning is governed by a complex system of structurally inter-related learning competency and learning competency potential latent variables. It is so multifarious that the interaction among constituents of the system, and the interaction between the system and its environment, is of such a nature that the system as a whole cannot be fully understood simply by analysing its components (Cilliers, 1998)[15]. Its dynamic and self-organising nature further complicates the situation. The dynamic and self-organising nature of human learning seems to point to the existence of structural feedback loops through which the level of competence that is reached in *Classroom learning performance* and *Learning performance during evaluation* are fed back to specific learning competency potential latent variables positioned upstream in the causal flow. Therefore according to Cilliers (1998), models attempting to explain complex systems will only become successful in

[15] In reality complex systems can never be fully understood. Complex systems are too extensive to be realistically captured in a single model. At the same time complex models cannot be reduced or simplified without losing some meaning. At best man can hope to obtain a valid approximation of the actual process at work.

scientific practice once there is an increased understanding of the nature of complexity. The complexity of human learning potential will therefore only be more realistically understood when more of the nomological network of cognitive and non cognitive variables that constitute learning potential can be formally modelled and when the resultant learning potential structural models formally acknowledge the key characteristics of complexity. The second generation research intiating question (Theron, 2011) that should be posed in response to the De Goede (2007) model is therefore the question what other cognitive and non-cognitive learning competencies and learning competency potential latent variables currently not contained in the De Goede (2007) model are required to explain variance in learning performance. Some additional cognitive and non-cognitive learning competencies and learning competency potential latent variables were proposed by Burger (2012).

2.4 THE BURGER (2012) LEARNING POTENTIAL MODEL

One of the initial attempts to elaborate on the De Goede (2007) model was made by Burger (2012) who identified other cognitive and non-cognitive learning competency potential and learning competencies that affect learning performance. Burger (2012) argued against the Taylor (1992) and De Goede (2007) view of *Transfer of Knowledge* and *Automatisation* as the only two learning competencies that constitute learning. Burger (2012) therefore regards it as extremely unlikely that cognitive ability would be the sole determinant of learning performance. Burger argues that learners probably have to invest numerous cognitive *but also* non-cognitive resources to succeed in learning. This led Burger (2012) to argue that if non-cognitive determinants are to affect learning performance, they most likely do so through other learning competencies in addition to *Transfer of Knowledge* and *Automatisation* (De Goede & Theron, 2010). The question for Burger therefore became which additional learning competencies other than *Transfer of Knowledge* and *Automatisation* constitute learning. Once the additional learning competencies through which the non-cognitive determinants are suspected to operate were identified the question then subsequently arose which learning competency potential latent variables, other than *Abstract Thinking Ability* and *Information Processing Capacity*, cause variance in the identified learning competencies and through which paths.

2.4.1 Additional learning competencies introduced in the Burger model

2.4.1.1 Time-cognitively-engaged

Although research has validated the fact that increased time-on-task is likely to increase over-all learning (Gest & Gest, 2005), it is not enough for students to only appear exhibiting some on-task behaviours such as 'looking busy'; they should also be engaged in the learning activity (Paris & Paris, 2001).

Student engagement is increasingly gaining momentum as a significant motivational facet of academic achievement and desirable school behaviour (Appleton, Christenson & Furlong, 2008; Klem & Connell, 2004; Rotgans & Schmidt, 2011). The student engagement concept has been used to provide a theoretical model for understanding school dropout (Finn, 1989) as well as a remedial tool for addressing the dropout problem (Reschly & Christenson, 2006). It reflects a person's active involvement in a task or activity (Reeve, Jang, Carrell, Jeon, & Barch, 2004). Students who are engaged show some sustained behavioural involvement in the task at hand and, in addition to task involvement, the engaged students exert intense effort and concentration as well as display some positive emotions such as enthusiasm, curiosity, optimism and interest (Skinner & Belmont, 1993). Student engagement is considered to be an important predictor of learning which is often positively related to college-reported grade point average, GPA scores, as well as personal development. This is due to the fact that the more students study or practice a subject; the more they tend to learn about it (Carini, Kuh & Klein, 2004). Engagement aspects include the number of words that were read or the amount of text that was comprehended with deeper processing of content (Appleton, Christenson & Furlong, 2008). Pintrich and colleagues (e.g., Pintrich & De Groot, 1990; Pintrich & Schrauben,

1992) associated engagement levels with students' use of cognitive, meta-cognitive and self-regulatory strategies to monitor and guide their learning processes.

Student engagement is a multi-dimensional construct made up of four dimensions: academic, behavioural, cognitive and psychological. Student academic engagement consists of variables such as time-on-task and homework completion while behavioural engagement includes attendance and voluntary class participation. Psychological engagement includes less observable indicators such as feelings of identification or belonging, and relationships with teachers and peers while cognitive engagement involves internal indicators, such as self-regulation, relevance of schoolwork to future endeavours, value of learning, and personal goals and autonomy (Appleton, Christenson, Kim & Reschly, 2006). Researchers recognise another type of student engagement labelled affective engagement. Affective engagement relates to the level of students' investment in, and their emotional reactions to, the learning tasks (Skinner & Belmont, 1993). Although only a few studies have focused on cognitive and psychological engagement in favour of the observable academic and behavioural engagement, there is some evidence of significant positive relationships between cognitive engagement and both personal goal orientation and investment in learning (Greene & Miller, 1996; Greene, Miller, Crowson, Duke & Akey, 2004) as well as academic achievement (Miller, Greene, Montalvo, Ravindran, & Nichols, 1996).

In recent years, cognitive engagement has gained considerable popularity as evidenced by the number of articles on the subject (e.g. Appleton, Christenson, Kim, & Reschly, 2006; Fredricks, Blumenfeld, & Paris, 2004; Richardson & Newby, 2006; Rotgans & Schmidt, 2011; Walker & Greene, 2009). Corno and Mandinach (1983) first coined the term "Cognitive Engagement" in research that examined classroom learning. Since then cognitive engagement has gained prominence and utility in various attempts to improve students' learning. Cognitive engagement has traditionally been operationalised by measuring the extent of students' homework completion, class attendance, extra-curricular participation in activities, or their general interactions with the teachers, and how motivated they seem while engaging in classroom discussions (Appleton *et al.*, 2006).

Cognitive engagement has commonly been conceptualised as linked to the use of deep versus surface learning strategies (Fredricks, Blumenfeld, & Paris, 2004). These two learning information processing strategies provide a significant bearing on the quality of learning, understanding and level of cognitive engagement undertaken by the learner. Deep learning is characterised by such strategies as elaborating ideas, thinking critically, and linking as well as integrating one concept with another (Biggs, 1987). In comparison, surface learning is characterised by such strategies as memorisation and reproduction of the learning materials (Biggs, 1987). Draper (2009) expanded upon this idea by concluding that shallow learners understand the material correctly, but simply do not possess the connections between concepts that deep learners do. Deep learners can transfer the learned concepts to a variety of situations thereby creating a denser matrix of connections within their knowledge and understanding. Therefore, the student's motive is integral to whether he or she engages in deep or surface learning strategies. Floyd, Harrington and Santiago (2009) investigated the relationships among perceived course value, student engagement, deep learning strategies, and surface learning strategies and reported statistically significant relationships between perceived course value, student engagement, and deep learning strategy. Surface learning strategies occur when the student's perceived value of the course is low. These findings suggest that deep learning strategies occur when students are engaged in the learning process and their perceived value of the course content is high. Burger (2012) also argued for the inclusion of the time component to the cognitive engagement to tap the amount of time the learner spends cognitively engaged on the task. The time component measures the quantity aspect of engagement. It has its roots in the notion of student engagement particularly cognitive engagement. Burger termed the resultant construct, time-cognitively-engaged which is now being used in the current study henceforth. Time-cognitively-engaged is one of the non-cognitive learning competencies identified by Burger (2012) as an essential additional dimension of learning performance. Burger also argues that time-cognitively-engaged is a function of the individual's motivation to learn, conscientiousness and self-leadership processes encompassed in self-leadership tendencies.

2.4.1.2 Self-leadership

Manz (1983,1986) is generally credited with the introduction of the self-leadership concept and describes self-leadership as: "a comprehensive self-influence perspective that concerns leading oneself towards performance of naturally motivating tasks as well as managing oneself to do work that must be done but is not naturally motivating. It includes the self-management of immediate behaviours and in addition similar to the notion of 'double loop learning' (Argyris, 1982a, 1982b), it challenges the appropriateness of operating standards that govern the employee self-influence system as the reasons for the behaviour" (Manz 1986, p. 589). Self-leadership is mostly concerned with explaining ways to enhance organisational performance through individual-dependent thinking and acting. Self-leadership practices can determine whether an individual performs well or fails (Manz, 1986; Neck & Manz, 1992, 1996; Prussia, Anderson, & Manz, 1998; Stewart, Carson, & Cardy, 1996). Individuals differ in their skills and use of self-leadership strategies and these differences can influence how effectively they achieve their goals (Manz, 1986; 1996; Prussia, Anderson, & Manz, 1998).

The roots of the self-leadership concept are based on several psychological theories that include: social learning theory (Bandura, 1977), social cognitive theory (Bandura, 1986), self-regulation theory (Carver & Scheier, 1981; Kanfer, 1970), self-control theory (Cautela, 1969; Mahoney & Arnkoff, 1979; Thoresen & Mahoney, 1974), intrinsic motivation theory (e.g., Deci & Ryan, 1985), and the notion of self-management. Social learning theory (Bandura, 1997) explains how people can influence their own cognition, motivation, and behaviour (Yun, Cox & Sims, 2006). Social cognitive theory explains that people and their environment interact continuously (Satterfield & Davidson, 2000) and behavioural consequences serve as sources of information and motivation (Bandura, 1986; Schunk, 2001). The development of the self-leadership concept is closely linked to the self-management notion. Manz (1991, p. 17) distinguished between self-management and self-leadership by articulating that:

> "self-management is a self-influence process and set of strategies that primarily addresses *how* work is performed to help meet standards and objectives that are typically externally set . . . [it] tends to rely on extrinsic motivation and to focus on behaviour" while self-leadership is "a self-influence process and set of strategies that address *what* is to be done (e.g., standards and objectives) and *why* (e.g., strategic analysis) as well as *how* it is to be done . . . [it] incorporates intrinsic motivation and has an increased focus on cognitive processes. (p. 17) Among other things, this emphasises that self-management processes are dependent on extrinsic incentives (e.g., pay and other external rewards for an employee performing autonomous work) whereas self-leadership is less driven by external forces, though still allows for influences such as the empowering actions of a leader who creates intrinsic reward opportunities as well as external incentives."

2.4.1.2.1 Manz's theoretical framework of the self-leadership construct

A theoretical framework for self-leadership presented by Manz (1986) is shown in Figure 2.2 and is anchored on the concept of control theory (Carver & Scheier, 1982) which states that an entity (e.g., individual or team) self-regulates by first perceiving the situation and comparing its current state with identified standards. If a discrepancy exists between the current and desired states, the entity engages in discrepancy reducing behaviours, assesses the impact of new behaviour and incorporates the new behaviour as feedback into a perception of the situation, which begins the self-regulation cycle anew. In essence, self-leadership occurs when an entity perceives a situation, chooses to engage in behaviour to align the situation with standards, monitor activities and cognitions to encourage the desired behaviour, and then assesses how the behaviour influences the situation (Manz, 1986).

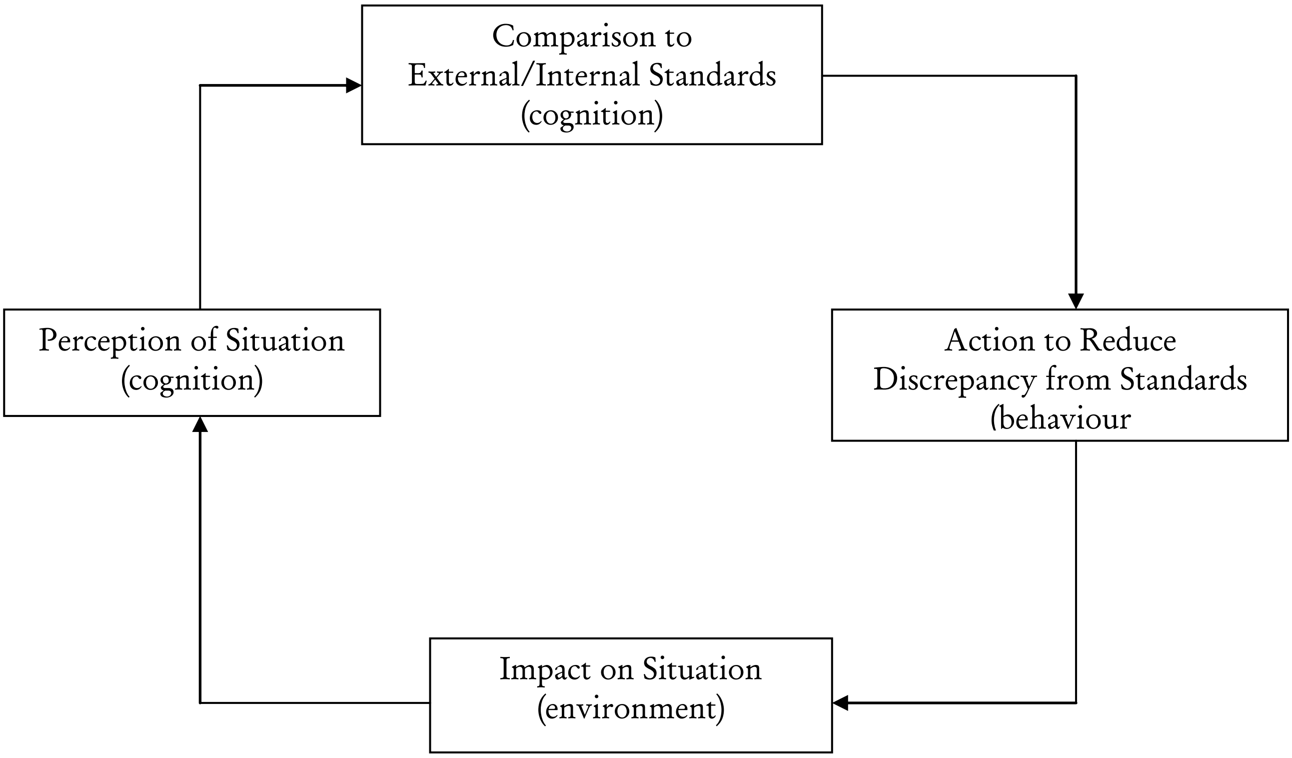


Figure 2.2. Graphical portrayal of the self-influence process of self-leadership. Adapted from "Toward an Expanded Theory of Self-Influence Processes in Organisations, " by C.C. Manz, 1986, *The Academy of Management Review*, *11*, p. 591. Copyright 1986 by the American Psychological Association.

The achievement of personal effectiveness in the self-influence process associated with self-leadership is a function of three primary self-leadership strategies comprising behaviour-focused, natural reward and constructive thought pattern strategies (Mans & Neck, 2004).

2.4.1.2.2 The behaviour-focused strategies

The behaviour-focused strategies strive to heighten an individual's self-awareness in order to facilitate behavioural management, especially the management of behaviours related to necessary but unpleasant tasks (Manz & Neck, 2004).

Behaviour-focused self-leadership strategies are designed to encourage positive, desirable behaviours that lead to successful outcomes, while suppressing negative, undesirable behaviours that lead to unsuccessful outcomes (Neck & Houghton, 2006). Behavioural-focused strategies include using self-goal setting (or the decision about what goals to pursue and how they should be pursued, self-observation (or increase of one's awareness about when and why to act), self-cueing (or external signalling), self-reward (or compensations to energize oneself) and self-punishment (or constructive self-feedback) to promote effective behaviour and discourage ineffective behaviour (Manz & Neck, 2004). Significant research has supported the role of setting and accepting specific, challenging, but achievable goals for facilitating motivation to increase individual performance (Locke & Latham, 1990), and writings on self-leadership recognise that individuals can set their own goals to promote performance (Manz & Sims, 1990). Self-observation fosters awareness of when certain behaviours occur and why they are chosen. This enhanced self-knowledge can provide information about behaviours that need to be strengthened, eliminated, or changed (Mahoney & Arnkoff, 1979). Self-awareness guides other self-leadership behaviours such as self-goal setting (Neck & Manz, 2010).

2.4.1.2.3 Natural reward strategies

Natural reward strategies are designed to enhance the intrinsic motivation vital for performance (Manz & Neck, 2004). They increase the feelings of competence and self-determination through the enhancement and focus on enjoyable task features (Alves, Lovelace, Matsypura, Toyasaki, & Ke, 2006). This entails building more pleasant and enjoyable features into a task or activity so that the task itself becomes more intrinsically rewarding, and shifting mental focus to inherently rewarding aspects of the task (Neck & Houghton, 2006; Neck & Manz, 2007) and shifting attention away from the unpleasant aspects of a task and refocusing it on the task's inherently rewarding aspects (Manz & Neck, 2004; Manz & Sims, 2001). In short, natural reward strategies are designed to help create and foster feelings of competence and self-determination, which in turn energise performance-enhancing task-related behaviours (D'Intino, Goldsby, Houghton & Neck, 2007).

2.4.1.2.4 Constructive thought strategies (thought self-leadership)

According to Alves, Lovelace, Matsypura, Toyasaki and Ke (2006), constructive thought strategies are geared towards the creation of positive thinking through the reduction of dysfunctional beliefs and assumptions, the reduction of negative self-talk and increase of positive self-image. In other words, constructive thought strategies facilitate the formation of constructive thought patterns and habitual ways of thinking that can positively influence performance (Manz & Neck, 2004). Constructive thought strategies incorporate visualising performance, engaging in positive self-talk, and examining individual beliefs and assumptions to align cognitions with desired behaviour (Neck & Manz, 2010).

Beyond the natural rewards focus, research has examined a variety of other specific strategies for "thought self-leadership" as a means for individuals to manage their own thinking tendencies (Neck & Manz, 2010; Stewart, Courtright & Manz, 2011). Specifically, mental imagery of performance, constructive self-talk, and identification of alternative beliefs to currently held dysfunctional beliefs can foster self-efficacy, the setting of challenging goals, and work persistence that can enhance effectiveness (Stajkovic & Luthans, 1998). Studies have examined how self-leadership links with individual cognitions. Much of this work centres on the self-influence of patterns of thinking and how they emerge and unfold via thought self-leadership strategies (Manz & Sims, 2001; Neck & Manz, 2010).

Other research supports the significant role of thought self-leadership. For example, a study found that incoming hotel room cleaners who saw performance as a result of effort as opposed to luck stayed in their jobs longer (Parsons, Herold, & Leatherwood, 1985). Employees who were able to avoid irrational thoughts felt more positively about their jobs (Judge & Locke, 1993; Wanberg & Kammeyer-Mueller, 2000). Finally, research studies that centred on interventions to enhance individual internal self-talk have strengthened or enhanced employee confidence for learning complex skills (Kanfer & Ackerman, 1996), reemployment of displaced managers (Millman & Latham, 2001), performance of student teams (Brown, 2003), and employee morale in a bankrupted firm (Neck & Manz, 1996). Individuals who focus on constructive thinking and natural rewards experience improved efficacy, which leads to higher performance. On the basis of the foregoing discussion, Burger (2012) deemed it fit to include academic self-leadership in the extended learning potential model as one of the essential learning competencies. Burger postulated that self-leadership will influence learning motivation, self-efficacy and time-cognitively engaged.

2.4.2 Additional learning competency potential latent variables introduced in the Burger model

2.4.2.1Motivation to learn

Motivation to learn is one of the non-cognitive competency potential variables that are suggested in literature as the driving force behind learning and trainability (Blume, Ford, Baldwin, & Huang, 2010; Chiaburu & Marinova, 2005; Pham, Segers, & Gijselaers, 2010; Weissbein, Huang, Ford, & Schmidt, 2011; Wexley & Latham; Noe, 1986). According to Nunes (2003), training practitioners have found that motivated trainees take a more active role in training and get more from the experience compared to individuals who are not motivated. Motivated individuals are more primed, or ready to learn. Motivation is considered as a complex concept, closely aligned with 'the will to learn', and complexly linked with self-esteem, self-efficacy, effort, self-regulation, locus of control and goal orientation (Harlen & Crick, 2003).

Considerable research has also confirmed that a trainee's motivation before training influences cognitive and skill-based learning outcomes as well as training transfer (Chiaburu & Marinova 2005; Tziner, Fisher, Senior, & Weisberg, 2007). Steers and Porter (1975) suggested that motivation is composed of energizing, directing, and maintenance components. In a training situation, motivation can be seen as a force that influences enthusiasm about the programme (energizer), a stimulus that directs participants to learn and attempt to master the content of the programme (director), and a force that influences the use of newly acquired knowledge and skills, even in the presence of criticism and lack of reinforcement for use of the training content (maintenance). Trainees who are more motivated to learn are more likely to exhibit better transfer (Blume *et al.,* 2010; Colquitt, LePine, & Noe, 2000; Pham, Segers, & Gijselaers, 2010). This is due to the fact that transfer is a function of the extent to which individuals are motivated to take advantage of the opportunities to apply the learning acquired in one setting to the transfer context (Ford, Quinones, Sego, & Sorra, 1992). Furthermore, individuals who are more motivated to learn in training are more likely to seek out practice opportunities once on the job (Ford *et al.,* 1992).

Deducing from the energiser, director and maintenance role that motivation plays one can infer that motivation constitutes one of the building blocks upon which both the cognitive and non-cognitive learning competencies anchor as they relate to influence learning performance. Maier (1973) asserted that even if individuals possess the prerequisite ability to learn the content of the course, low motivation is likely to lead to low performance. Warr and Bunce (1995) further predicted that an individual's motivation to learn is an important determinant of training outcomes although the individuals vary in their attitudes on the training as a whole. The attitudes are reflected in specific motivation tendencies about a particular set of training activities, with some activities being regarded as more attractive than others and consequently influencing the learning outcomes. Several other studies in the field of education and educational psychology have accentuated the need to foster student motivation in the classroom as one of the catalysts of learning (Ames, 1992;

Clark, 1990; Hicks & Klimoski, 1987; Pham, Segers & Gijselaers, 2010). Tubiana and Ben-Shakhar (1982) found a significant relationship between motivation to succeed in training and a composite criterion of training performance, a probability assessment of promotion potential, and a socio-metric measure of the trainee's popularity with peers. For transfer of learning to occur the learners must be firstly and foremostly be motivated to learn. In view of the role of motivation to learning performance, Burger postulated that it affects both time-cognitively engaged and transfer of knowledge.

2.4.3 Self-efficacy

Self-efficacy refers to "people's judgements of their capabilities to organise and execute courses of action required to attain designated types of performances. It is concerned not only with the skills one has but with judgements of what one can do with whatever skills one possesses" (Bandura, 1986, p. 391). Self-efficacy beliefs affect people's cognitions, motivations, affective processes, and ultimately their behaviour (Bandura, 1997). Several studies have shown that self-efficacy beliefs are formed by a cognitive weighting process using factors such as prior performance, self-perceptions of ability, effort expended, task difficulty, and the amount of assistance received (Bouffard-Bouchard, 1989; Schunk, 1982, 1983, 1984; Zimmerman, Bandura, & Martinez-Pons, 1992). Traditionally, the four main sources of self-efficacy development are enactive master experiences, vicarious experiences, verbal persuasion, and physiological and affective state (Bandura, 1997). According to Bandura (1986), self-efficacy develops gradually through repeated task-related experiences. Individuals monitor their experiences and base subsequent efficacy judgements, in part, on the extent to which they attribute their performance to their abilities and effort (Bandura, 1991). Personality needs such as achievement motivation exert some indirect influence on performance by impacting on efficacy perceptions (Bandura, 1989).

Self-efficacy relates to task choice, task effort and persistence in task achievement. Furthermore, it is also viewed as having a generative nature that influences behaviour over and above specific ability levels (Gist & Mitchell, 1992). Self-efficacy levels at the conclusion of training have been found to exhibit significant correlations with post-training transfer and job performance measures (Ford, Quinones, Sego & Sorra, 1992; Frayne & Latham, 1987; Latham & Frayne, 1989). This explains why self-efficacy is considered as one of the potential antecedents of training effectiveness. Trainees who enter training with the belief that they can succeed in mastering the training content (i.e. having high levels of pre-training self-efficacy) are likely to learn more during training (Gist, Schwoerer & Rosen, 1989). It has been found to be positively related to motivation to learn and to training outcomes such as skill acquisition, post training self-efficacy, transfer and performance (Colquitt, LePine & Noe, 2000; Gist, Stevens & Bavetta, 1991; Martocchio & Webster, 1992; Mathieu *et al.*, 1992, Quinones, 1995). Thus self-efficacy can be regarded as a predictor of training success, as a process variable during training, or as a desirable outcome of training (Tannenbaum & Yukl, 1992). The positive effects of learning self-efficacy are in part due to a person being able to predict his or her performance on the basis of previous attainments, through the intervening effect of an enduring ability and awareness of that level of ability (Warr & Bunce, 1995). Research has indicated a relationship between self-efficacy and transfer of knowledge (Bandura, Barbaranelli, Caprara & Pastorelli, 2001; Mathieu, Tannenbaum & Salaa, 1992). According to Kozlowski, Gully, Brown, Salas, Smith and Nason (2001), self-efficacy is related to the adaptability of knowledge and skills to meet the demands of the new situation as well as resilience in order to maintain motivation and concentration. Colquitt, LePine and Noe (2000) established that self-efficacy relates strongly with transfer of knowledge ($r = .47$) and moderates relationships with declarative knowledge ($r = .30$), skill acquisition ($r = .32$) and job performance ($r = .22$). On the basis of the foregoing discussion, Burger (2012) deemed it fit to include self-efficacy in the extended learning potential as one of the essential non cognitive determinants of learning, which is likely to influence self-leadership and learning motivation.

2.4.4 Conscientiousness

Highly conscientious individuals are characterised by a high degree of perseverance, and hardworking which is directed by a clear goal orientation. Barrick, Mount and Strauss (1993) found that conscientiousness was related to the tendency to set and be committed to goals, and that these constructs partially mediated the relationship between conscientiousness and performance. The conscientiousness personality type includes traits such as hardworking, careful, thorough, responsible, organised, and persevering (Barrick & Mount, 1991). High conscientiousness individuals are methodical, dependable, and risk aversive (Goldberg, 1990). These individuals are responsible, dependable, persistent, careful, hardworking and achievement oriented which are important attributes for performing work tasks (Barrick & Mount, 1993). Gellatly (1996) reported that conscientiousness was related to expectancy for success, which was, in turn, related to the goals set by participants and to performance. These characteristics are given some impetus by the high level of self-efficacy which is a notable attribute of conscientious individuals (Judge & Erez, 2007). The self-efficacy quality and the ensuing behaviours are consistent with those of individuals who believe in their ability to complete a task as well as more engaged in initiating and implementing strategies predicting higher levels of performance (Gerhardt, Rode, & Peterson, 2007).

Holton (1996) adds that 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 (Chen, Casper & Cortina, 2001) and generally have a stronger desire to learn (Colquitt & Simmering, 1998). Simmering, Colquitt, Noe and Porter (2003) found that conscientiousness was positively related to the pursuit of various developmental activities, including training. Similar findings have also been reported by Major, Turner and Fletcher (2006) in a study on employees of a financial services firm. Burger (2012) postulated that conscientiousness is likely to influence participants' motivation to learn, time-cognitively-engaged and self-leadership.

2.4.5 Findings on the Burger learning potential structural model

The initial learning potential structural model proposed by Burger (2012) and shown in Figure 2.3 failed to converge. The problem was diagnosed to be caused by the path leading from *Learning Motivation* to *Academic Self-leadership.* When the path was deleted the model converged and showed close fit (RMSEA=.0463). A detailed discussion of the model fit indices and significant paths is presented in paragraph 2.5. Burger's theorisation culminated in the structural model displayed in Figure 2.3.

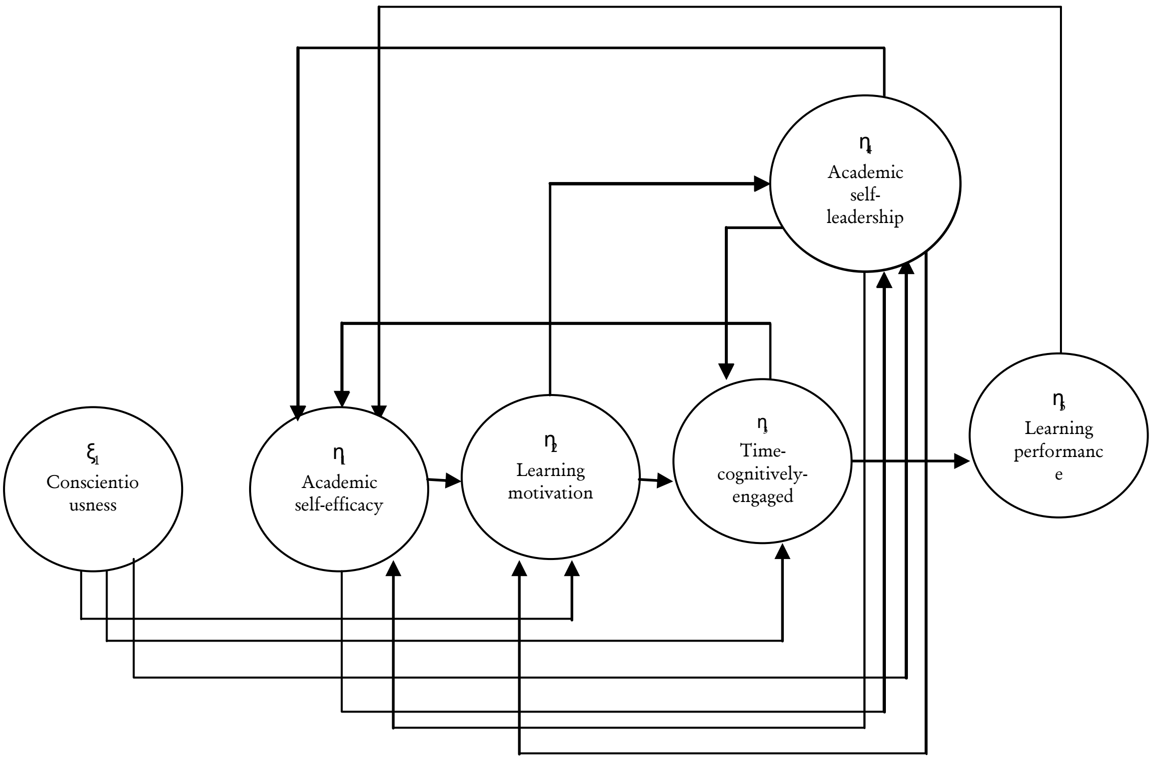


Figure 2.3. Graphical portrayal of the Burger's (2012) extended learning potential structural model . Adapted from "Elaboration and empirical evaluation of the De Goede learning potential structural model, " by R. Burger, 2012, *Unpublished Master's Thesis*, p. 85. Copyright 2012 by Stellenbosch University.

The Burger's (2012) study positively confirmed the following hypotheses: *Conscientiousness* positively affects *Time cognitively engaged; Conscientiousness* positively influences *Learning motivation*; *Conscientiousness* and *Academic self-leadership*; *Time cognitively engaged* and *Learning performance*; *Academic self-leadership* and *Time cognitively engaged*; *Academic self-leadership* and *Learning motivation*; *Learning motivation* and *Time cognitively engaged*; and *Academic self-efficacy* and *Learning motivation*, *Self-leadership* and *Academic self-efficacy; Learning performance* and *Learning motivation* and a negative relationship was found between *Academic self-efficacy* and *Self-leadership*.

2.5 DEVELOPING THE PROPOSED DE GOEDE – BURGER – MAHEMBE LEARNING POTENTIAL STRUCTURAL MODEL

Non-cognitive factors that can contribute to transfer of learning and learning performance include individual characteristics, work environment characteristics and training design characteristics (Baldwin & Ford, 1988; Keith & Frese, 2008; Lim & Johnson, 2002; Noe, 1986; Weissbein, Huang, Ford & Schmidt, 2011). These factors have for long been the traditional focus of several attempts to document the determinants of transfer. Trainees come into the learning situation equiped with various experiences, beliefs, assumptions about their ability as well as assumptions about the level of effort needed to acquire the skills to be learnt (Baldwin & Magjuka, 1997). These assumptions and beliefs need to be tapped and incorporated in models that attempt to explain learning. So, however, do latent variables characterising the training context. Human behaviour is not solely determined by characteristics of the person but also by variables characterising the situation (Mischel, 1973; 2004). The characteristics of the trainer and his/her action represent an important category of contextual variables that will highly likely affect the learning performance of affirmative development learners. The present study, however, chose only to focus on individual learner characteristics in the form of learning competency potential dispositions and attainments that influence learning and learning competencies that constitute learning for possible inclusion in the elaborated De Goede-Burger-Mahembe learning potential model.

An attempt was made to replicate the comprehensive, systematic and reasoned argument that Burger (2012) followed in the identification of additional learning competencies that constitute learning performance and additional learning competency potential latent variables that also influence learning performance. The review of the two learning potential models will form the theoretical foundation on which the elaborated De Goede-Burger-Mahembe model will be based.

2.5.1 Learning performance

The selection of the previously disadvantaged group members for affirmative developmental purposes is hinged on their expected learning performance. More specifically it depends on their expected *Learning performance during evaluation*. Both Taylor in his thinking on learning potential and De Goede in his attempt to model the internal structure of the learning potential construct failed to formally distinguish between *Learning performance in the classroom* and *Learning performance during evaluation*. In a very real sense classroom learning and subsequent practical application of that which has been learnt is essentially the same process. Both classroom learning and subsequent practical application of that which has been learnt to novel problems (and therefore *Learning performance during evaluation*) require the adaptation and transfer of existing crystallised knowledge onto novel problems in an attempt to make sense of the initially meaningless problem data by creating/imposing meaningful structure on the data. Practical application can also be termed action learning. Affirmative development programmes attempt to develop the job competency potential and job competencies affirmees initially lacked but which they need to succeed in the job they apply for. To develop the job competency potential and job competencies they initially lack involves classroom learning. Once they leave the classroom the newly developed crystallised knowledge should allow them to successfully cope with job demands they initially were unable to meet. This will however, involve more than simply retrieving previously transferred and automated responses to now familiar stimuli. Rather it will require that the affirmee creatively apply the newly derived crystalised knowledge to novel problems not explicitly covered in the affirmative action development programme. It is this ability to transfer the crystalised knowledge developed through *Learning performance in the classroom* that should be evaluated when assessing *Learning performance during evaluation.*

The level of competence a learner achieves on *Learning performance during evaluation* depends on the level of competence that the learner has achieved on *Learning performance in the classroom.* The level of competence a learner achieves on both these forms of learning performance is not a random event but is rather systematically determined by a complex nomological network of latent variables characterising the learner and his learning environment. These determining latent variables characterising the learner and his learning environment collectively constitute the learning potential of the learner. It is these latent variables characterising the learner and his learning environment that determine the level of *Classroom learning performance* the learner will achieve, and through that, the level of *Learning performance during evaluation* the learner will achieve when the learner is allowed to move into learning action. These learning potential latent variables can be described as learning competency potential latent variables. *Learning performance during evaluation* essentially requires the learner to display his/her *post-development* learning potential. A distinction therefore, has to be made between *Classroom learning performance*, *Learning performance during evaluation* and learning potential. Taylor (1994, p. 190) distinguished between learning performance and learning potential by saying:

> Learning performance is demonstrated when an individual acquires specialised skill through transfer from other fairly specialised skills or abilities. The more elaborated and developed a person's skill repertoire, the more effectively and swiftly he or she is likely to acquire the new skill. Learning potential is shown when a person comes to grips with a novel learning task involving unfamiliar stimulus material; in this case previously developed specific skills are of relatively

> little help to him or her, and the learner has to use very general transfer and skill acquisition strategies…

What Taylor (1994) seems to refer to here is *Classroom learning performance*. According to De Goede (2007) learning performance should be understood as crystallised learning potential (acquired job competency potential) in action. What De Goede (2007) seems to refer to is *Learning performance during evaluation*. When candidates are being selected for a specific educational or training programme decision-makers are faced with the dilemma of not having information at the time of the selection-decision, on the criterion variable they are trying to maximise, that is, on the *Learning performance during evaluation* that each candidate will achieve at the end of the programme. The decision whether to accept an applicant is, therefore, based on the mechanically or judgementally derived expected *Learning performance during evaluation* conditional on information on the applicant or, if a minimally acceptable *Learning performance during evaluation* level can be defined, the conditional probability of success (or failure) given information on the applicant (Ghiselli, Campbell & Zedeck, 1981; Schmitt, 1989). In terms of Taylor's theory, learning potential should be understood as the substitute predictor construct (ξ) of *Learning performance during evaluation*. Expected *Learning performance during evaluation* is therefore mechanically or clinically inferred from measures of learning potential.

Learning performance during evaluation can therefore be regarded as the extent to which an individual has acquired a specific skill, knowledge or ability (job competency potential) and the extent to which that specific skill, ability or knowledge can be used in *Transfer of knowledge* to solve novel problems in a situation corresponding to the job for which the affirmative development has been initiated. Learning potential refers to the individual's capacity to be modified and the capacity to acquire novel skills. Learning potential needs to be assessed in disadvantaged individuals to infer the level of *Learning performance* that such individuals will achieve if granted an affirmative development opportunity. It is learning potential that is crystallised through remedial affirmative development intervention, and which allows an individual to demonstrate successful *Learning performance during evaluation* (Taylor, 1989). The effect of learning potential on *Learning performance during evaluation* is, however, partially mediated by *Classroom learning performance*. The level of *Classroom learning performance* that is achieved depends on the level of learning potential. The level of *Learning performance during evaluation* that is in turn achieved reflects the level of *Classroom learning performance* that occurred. At least some of the learning competency potential latent variables that constitute learning potential can, however, be expected to also affect *Learning performance during evaluation* directly. *Abstract thinking capacity* and (post-development) crystallised ability (*Post-knowledge*) serve as two examples. It is, however, more than likely that more of the learning competency potential latent variables that directly affect *Classroom learning performance* also directly affect *Learning performance during evaluation*.

Classroom learning performance can be considered to be analogous to job performance hence a learning competency framework moulded along the same lines as the SHL performance@work model (SHL, 2001) should be possible. Successful job performance is a function of a myriad of factors that included a good match between the job and the person. Selection represents a potentially powerful instrument through which the human resource function can add value to the organisation through the selection of the appropriate job competencies and competency potential variables required for an employee to perform successfully on the job. SHL (2001) proposed a conceptual model of performance at work, which defines the relationships between job competency potential, job competency requirements, job competencies and job outcomes in a manner, which allows for the integration and alignment of the spectrum of human resource interventions. According to SHL (2001, p. 6), the performance@work model represents:

> … a model of performance at work that defines the relationship between competency potential, competency requirements and competencies themselves. "Competencies" are defined as desired behaviours that support the attainment of organisational objectives. "Competency potential" is seen to derive from individual dispositions and attainments, and "competency requirements" involve both facilitators of and barriers to effective performance in the workplace. The framework points to ways in which people and work settings interact, and has implications for how performance in the workplace can be managed.

The performance@learning competency model proposed by De Goede (2007) linked a structurally inter-related set of learning competency potential latent variables characterising the learner to a structurally inter-related set of (classroom) learning competencies and these are in turn structurally linked to a structurally inter-related set of learning outcome latent variables. The learning competencies refer to the common abstract theme in bundles of related behaviours that constitute learning. The learning competency potential latent variables refer to the learner attributes that affect the level of competence that is achieved on the learning competencies. The learning outcomes latent variables refer to learner characteristics (i.e., learning competency potential latent variables) that are affected by the level of competence that is achieved on the learning competencies. A system of feedback loops are thereby implied. Alternatively a longitudinal performance@learning competency model is implied. In this respect the performance@learning competency model differs from the performance@work competency model. In the latter case the job outcome latent variables refer to latent variables that are qualitatively distinct from the job competency potential latent variables. In addition to the learning competency potential latent variables, situational latent variables characterising the learning context also affect the level of competence that is achieved on the learning competencies as main effects and/or in interaction with the learning competency potential latent variables. These situational latent variables were not formally acknowledged in either the De Goede (2007) or the Burger (2012) structural models. Neither will they be formally acknowledged in the proposed De Goede-Burger-

Mahembe learning potential structural model. Future learning potential structural model will, however, have to formally start acknowleging the influence of situational latent variables.

De Goede (2007) argued that the performance@learning model should be sequentially linked to the performance@work competency model to provide a fertile conceptual model to explore the relationship between the characteristics of the learner required to exhibit the learning behaviours needed to develop the qualities necessary to exhibit the work behaviours that are instrumental in achieving the outcomes for which the job in question has been created. In the sequentially linked performance@learning and performance@work competency model the learning outcomes latent variables in the performance@learning part of the model at the same time also represent the malleable job competency potential latent variables in the performance@work part of the model that determine the level of competence that is achieved on the job competencies. The argument put forward earlier was that previously disadvantaged South Africans tend to display lower levels of competence on the job competencies because of lack of opportunity to develop the job competency potential required to succeed on the job. The objective of affirmative development is to develop the malleable job competency potential latent variables to a level that will allow successful learners to succeed on the job. In addition in as far as competence on the various job competencies require novel problem solving or action learning succeeding on the job should in part be understood to mean succeeding in the subsequent practical on-the-job action learning. In that sense the job competencies and the learning competencies also partly overlap. Moreover, again pointing to the conceptual overlap between the (classroom) learning competencies and the job competencies, ideally when evaluating the level of *Classroom learning performance* that was achieved by assessing the level of *Learning performance during evaluation,* problems and questions a job incumbent typically would be expected to solve through transfer of post-development knowledge will be presented to the learner in a simulation of the job. The basic sequentially linked performance@learning and performance@work competency model is shown in Figure 2.4

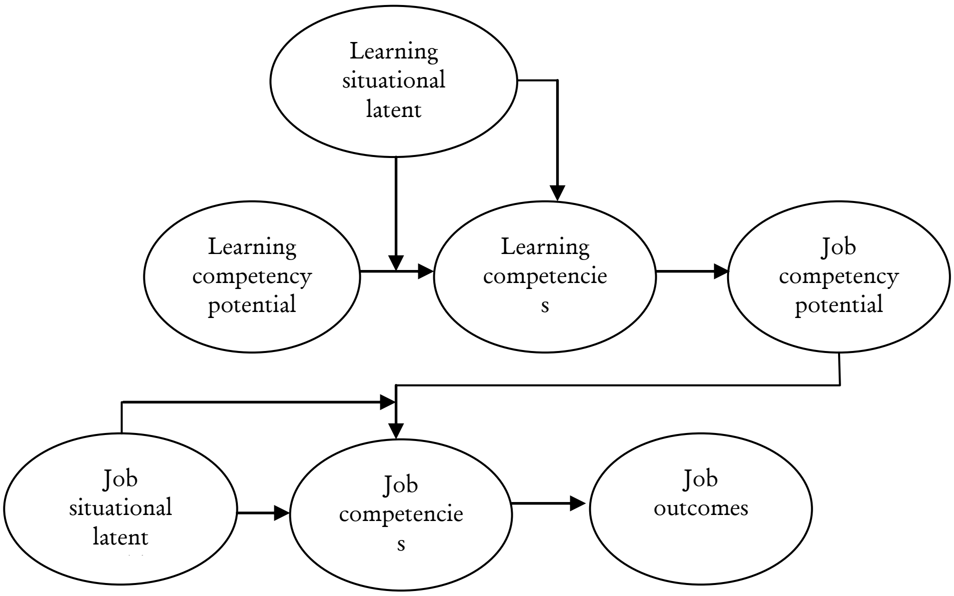


Figure 2.4. Sequentially linked performance@learning and performance@work competency model[16] (based on De Goede (2007)

The sequentially linked performance@learning and performance@work competency model initially suggested by De Goede (2007) will form the conceptual foundation of the proposed De Goede – Burger – Mahembe learning potential structural model. In developing the De Goede – Burger – Mahembe learning potential structural model as an elaboration and an integration of the De Goede (2007) and Burger (2012) models the following three questions need to be considered:

- The question whether any of the existing paths and/or latent variables need to be deleted from the existing models;
- The question whether any additional paths need to be added to the existing models;
- The question on how the De Goede (2007) and Burger (2012) models should be integrated and which additional learning competency potential and learning competency latent variables need to be added to the integrated De

[16] The learning outcome latent variables are the job competency potential latent variables (e.g., post-development knowledge, academic self-efficacy, and crystallised abilities) that are required to achieve competence on the job competencies. The job competencies in turn partially overlap with the learning competencies to the extent that the job requires action learning.

Goede – Burger learning potential structural model to form the De Goede – Burger – Mahembe learning potential structural model

2.5.2 Possible deletions from the De Goede (2007) and/or Burger (2012) learning potential structural models

The decision on whether any of the existing paths and/or latent variables needs to be deleted from the existing models should be based on the empirical research findings of De Goede (2007) and Burger (2012), the scientific rigour of the research methodology and the persuasiveness of the theoretical argument underpinning the hypothesised structural linkages. The De Goede (2007) model fitted reasonably well (RMSEA=.075 (p>.05). Nonetheless quite a few of the hypothesised structural relations were not supported. Specifically De Goede failed to find support for the hypotheses that *Abstract thinking capacity* affects *Transfer of knowledge*; that *Automatisation* affects *Learning performance* and that *Transfer of knowledge* affects *Learning performance*. The question arises whether this warrants the deletion of those paths from the model. Such a step seems premature despite the lack of empirical support. The argument offered in support of the hypotheses that failed to be empirically supported is theoretically persuasive. In addition De Goede (2007) and De Goede and Theron (2010) should be questioned for the manner in which they operationalised the *Transfer of knowledge* and *Automatisation* latent variables. The APIL-B test battery was used to measure *Transfer of knowledge* and *Automatisation* as a dimension of *Learning performance in the classroom*. The APIL-B measures transfer in a simulated learning task comprised of geometric symbols with which all learners are equally unfamiliar. *Transfer of knowledge* as a dimension of *Learning performance in the classroom* involves transfer in an actual learning task comprised of job-related learning content. *Automatisation* likewise involves the writing of intellectual insights in an actual learning task gained via *Transfer of knowledge* from prior learning. Lack of support for the paths hypothesised between *Transfer of knowledge* and *Learning* *performance* and between *Automatisation* and *Learning performance* could therefore be explained in terms of the inappropriate manner in which these two learning competency latent variables were operationalised. It was therefore decided to retain all the structural relations hypothesised by De Goede (2007).

The initial model that Burger (2012) fitted failed to converge. The preliminary LISREL output suggested that the problem may lie with the *Learning Motivation* latent variable. Burger (2012) subsequently deleted the path running from *Learning Motivation* to *Academic Self-leadership* which she considered the least convincingly argued path in the model and refitted the model. The revised model converged and showed good fit (RMSEA=.0463; p>.05). The path hypothesised from *Time Cognitively Engaged* to *Academic Self-efficacy* was not supported (p>.05). In addition the sign associated with the β_{41} estimate disagreed with the direction of the effect *Academic self-efficacy* was hypothesised to have on *Academic-Self-leadership*. The substantive path hypothesis was therefore not supported. Burger (2012) originally hypothesised that an increase in *Academic Self-efficacy*, will lead to an increased use of academic self-leadership strategies. In retrospect Burger (2012) however, then argued that a negative relationship between *Academic Self-efficacy* and *Academic Self-leadership* does, to some degree make theoretical sense. She argued that if an individual believes that he or she is capable of succeeding in a learning task, that individual probably will see less need to implement academic self-leadership strategies as the individual probably feels that he/she is capable of learning successfully with less reliance on these strategies. The modification indices calculated for **β** (Beta) in addition indicated that adding a path from *Learning Performance* to *Learning Motivation* would statistically significantly (p<.01) improve the fit of the model.

The model was subsequently again revised by deleting the path from *Time Cognitively Engaged* to *Academic Self-efficacy* and by adding the path from *Learning Performance* to *Learning Motivation.* The final revised model converged and showed excellent fit (RMSEA= .046; p>.05). All the remaining path coefficients were statistically significant. It was therefore decided to retain all the structural relations hypothesised in the final revised Burger (2012) learning potential structural model. It was also decided to accept Burger's (2012) amended argument that *Academic Self-efficacy* should have a negative impact on *Academic Self-leadership.*

2.5.3 Possible additions to the De Goede (2007) and/or Burger (2012) learning potential structural models

The following paths were retained from the De Goede (2007) and the revised Burger (2012) learning potential structural models. These paths represent the following structural hypotheses: *Conscientiousness* positively affects *Learning motivation; Conscientiousness* positively affects *Self-leadership; Self-efficacy* positively affects *Time-cognitively engaged; Self-efficacy* positively affects *Learning motivation; Information processing capacity* positively affects *Automatisation; Automatisation* positively affects *Transfer of knowledge* and *Abstract thinking capacity* positively affects *Transfer of knowledge.*

The following latent variables were added to the De Goede-Burger-Mahembe learning potential structural model that did not form part of the original De Goede (2007) and Burger (2012) models: *Knowledge about cognition; Regulation of cognition; Openness to experience; Learning goal orientation; Prior learning* and *Post learning.* The addition of these latent variables allowed the formulation of a number of further structural hypotheses. It was hypothesised that: *Prior learning* moderates the effect of *Abstract thinking capacity* on *Transfer of knowledge; Post learning* moderates the effect of *Abstract thinking capacity* on *Learning performance; Knowledge about cognition* positively affects *Regulation of cognition; Regulation of cognition* positively affects *Time-cognitively engaged; Openness to experience* positively affects *Learning goal orientation; and Learning goal orientation* positively affects *Learning motivation.*

The theorisation underpinning the addition of the abovementioned new learning competencies, learning competency potential variables and the newly hypothesised structural linkages are discussed in paragraphs 2.5.4 and 2.6 below.

2.5.4 Additional learning competency variables

Although the complex nomological network of the learning competencies and learning competency potential variables may be infinite, the competencies identified thus far are regarded as sufficient to develop a comprehensive extended model of learning potential that goes beyond the scope covered in both the De Goede (2007) and Burger (2012) models.

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

2.6.1 Learning competency variables

The broad criterion (η) in the proposed De Goede – Burger – Mahembe learning potential structural model is learning performance. A distinction has been made between *Classroom learning performance* and *Learning performance during evaluation*. In order to obtain the optimum return on the investment made into affirmative development, opportunities should be restricted to those individuals who would achieve the highest possible level of competence in the behaviours that constitute *Classroom learning performance* and eventually also *Learning performance during evaluation*; thus those individuals whose relevant job competency potential could be lifted to the highest possible level. *Learning performance during evaluation* is the final outcome in the proposed extended model. *Learning performance during evaluation* depends on the level of *Classroom learning performance* that is achieved. Both forms of learning performance are defined in terms of a number of core learning competencies. Taylor (1989; 1992; 1994; 1997) and De Goede (2007) identified *Transfer* *of knowledge* and *Automatisation* as two key learning competencies. Burger (2012) identified *Time cognitively engaged* and *Academic self-leadership* as two additional learning competencies that, along with *Transfer of knowledge* and *Automatisation*, constitute classroom learning[17]. This study will combine these four learning competencies identified by De Goede (2007) and Burger (2012) in the proposed De Goede – Burger – Mahembe learning potential structural model and will add a fifth learning competency, *Regulation of cognition*.

2.6.1.1 Transfer of knowledge

Transfer of knowledge in the classroom or during training is an important learning competency that has a significant bearing on the final *Learning performance during evaluation* latent variable (Leberman, McDonald & Doyle, 2004; Subedi, 2004). The classroom is the first context in which transfer of knowledge takes place. It is classroom learning that is transferred to the job in the form of attained knowledge and skills. *Transfer of knowledge* is the adaptation of knowledge and skills to address problems somewhat different from those already encountered. It is the process through which the structure of abilities and skills becomes more elaborated with time, making it a fundamental aspect of learning and cognitive development (Taylor, 1994b). *Transfer of knowledge* is the influence of prior learning on performance in a new situation such as the job performance context or assessment situation. The failure to transfer some of the skills and knowledge from prior learning could mean that learning in each new situation would start from scratch implying that in each new situation the human mind is like a *tabula rasa*, a blank slate, waiting to be written upon by experience and of which the learning experience will soon vanish due to failure to transfer the learnt information and knowledge. Hence transfer of

[17] Although Burger (2012) did not formally distinguish between *Classroom learning performance* and *Learning performance* during evaluation, the nature of the arguments she presented to justify the inclusion of these two learning competencies in her model had a stronger bearing on the former than the latter. In as far as evaluation of learning involves solving novel problems based on the insights gained via the training programme, it can be argued that these learning competencies (along with *Transfer of knowledge* and *Automatisation*) also constitute action learning during evaluation.

knowledge in essence is the process through which crystallised abilities attained from some prior learning experiences develop from the confrontation between fluid intelligence (Cattell, 1971) and novel stimuli (Taylor, 1994). The learners' ability to perform proficiently on a given novel task depends to a considerable extent on the amount of prior practice on a series of related tasks. Therefore encouraging transfer of knowledge in the classroom is likely to provide the skills and knowledge for its successful implementation in other contexts. *Learning performance* is demonstrated when an individual acquires specialised skills through transfer from other fairly specialised skills or abilities. *Transfer of knowledge* may encompass both maintenance of behaviour, and its generalisation to new applications (Broad & Newstrom, 1992). According to Taylor (1997), a good student is one who is able to apply the knowledge gained from prior learning to a different but related context. In the light of the foregoing discussion, it seems reasonable to include *Transfer of knowledge* in the proposed De Goede-Burger-Mahembe (DBM) model as it is one of the critical learning competencies.

2.6.1.2 Automatisation

Transfer of knowledge is a complex process which also depends upon the learners' ability to automatise the knowledge and skills learnt. In order for learners to diligently and proficiently resolve novel problems outside the training context, prior learning and automatisation play a crucial role. As the learner attempts to resolve the novel problems, they do not solely rely on the *Transfer of knowledge* but also the ability to access what has been stored in memory in the form of prior learning. In such circumstances the challenge for the learner is to become more effective and efficient at what he or she is doing (Taylor, 1992). The learner tries to be more adept at resolving the novel task in the shortest time possible especially when the task is recurring in nature. The learner can only be effective and efficient if he or she is able to internalise and automate the operations required for successful task performance. It is the *Automatisation* of a substantial proportion of the operations required to perform complex tasks that allows an individual to perform the task with minimal effort (Sternberg, 1984). *Automatisation* is defined in the present study as: the extent to which the learner develops the ability to pack new information, in a useable way, into a given local processing system and on the ability to gain access to this information whenever it is needed (Sternberg, 1984). According to Sternberg (1997), people that are adept at managing a novel situation can take the task and find new ways of solving it in a manner that the majority of people would not notice. Operations that have been automated are likely to have been performed several times with little or no extra effort and it can be performed with the same or other processes. A good example is that of a driver who has managed to master all the procedural skills required to drive a car. With more driving experience the driver can drive from home to work without noticing all the procedural operations performed along the way. Furthermore, although it is not advisable, the driver can even speak on the phone or engage in other behaviours without any interruption on the driving. However, when dealing with novel problems and automatisation, the problem is that being skilled in one component does not ensure that you are skilled in the other (Sternberg, 1997). This is understandable given the complex nature of most novel problems. In the present study *Automatisation* is expected to positively affect *Transfer of knowledge*. The following hypothesis is therefore postulated:

Hypothesis 1:

Automatisation positively affects *Transfer of knowledge*

2.6.1.3 Time-cognitively-engaged

The cognitive dimension of engagement concerns students' psychological involvement in learning, for example, engaging in effortful learning and task-oriented goals. According to Rotgans and Schmidt (2011), cognitive engagement relates to a psychological state in which students put in a lot of effort to truly understand a topic and in which students continue studying over a long period of time. Students' cognitive engagement represents a motivated behaviour associated with students' persistence on difficult tasks and the usage of cognitive strategies (Pintrich & Schrauben, 1992). It defines the extent to which students' are willing and able to tackle the learning task at hand. This includes the amount of effort students are willing to invest in working on the task (Corno & Mandinach, 1983; Darabi, Nelson, & Paas, 2007), and how long they persist (Richardson & Newby 2006; Walker, Greene, & Mansell, 2006). This continuous engagement with the learning material is likely to facilitate the process of automating and retrieval of information that has been stored in memory. Cognitive engagement also refers to the extent to which students perceive the relevance of school to future aspirations and is expressed as interest in learning, goal setting, and the self-regulation of performance (Furlong & Christenson, 2008). Engaged sudents are likely to set aside some time to master their learning material in such a way that the recurring material is automated and eventually applied in resolving novel problems. Hence it is expected that *Time-cognitively-engaged* positively relates to *Transfer of knowledge* and *Automatisation*.

Hypothesis 2

Time-cognitively-engaged positively affects *Transfer of knowledge*

Hypothesis 3

Time-cognitively-engaged positively affects *Automatisation*

2.6.1.4 Regulation of cognition

Metacognition is regarded in literature as one of the most powerful predictors of learning (Wang, Haertel, & Walberg,1990). Flavell (1976; 1979) is credited with the coining of the metacognition concept in the 1970s. Metacognition is generally defined as thinking about thinking or cognition about cognition. It is a person's knowledge about the cognitive processes necessary for understanding and learning (Flavell, 1976). It involves the active monitoring, regulation and orchestration of these processes in relation to the cognitive objects or data on which they bear, usually in service of some concrete goal or objective (Flavell, 1979). Hacker (1998) refined Flavell's (1976) definition by incorporating knowledge of one's own cognitive, affective processes and states as well as the ability to consciously and deliberately monitor and regulate those processes and states. Metacognitive ability develops very early in life when children first become conscious of their own and others' mind (Kuhn & David, 2004; Piaget, 1964; Vygotsky, 1962). By late childhood, children show competence in evaluating their attempts to solve problems with strategies (Dembo, 1994).

According to Krätzig and Arbuthnott (2009), metacognition taps on a person's ability to think about their own thinking, to think about their own cognitive ability in relation to their knowledge and then to take the appropriate regulatory steps when a problem is detected. Other cognitive psychologists defined metacognition as the "executive control" system of the human mind and as a higher-order cognitive process that supervises a person's thoughts, knowledge and actions (Weinert, 1987). The supervision is achieved through perception of what is known or unknown, knowledge of oneself as a thinker and regulation of how one goes about thinking and dealing with a problem. A typical metacognitive individual is able to verify for understanding and regulates his/her understanding by using a metacognitive strategy (Wilson & Bai, 2010).

Metacognition is generally conceptualised in terms of two distinct aspects namely: knowledge about cognition and the regulation of cognition. Regulation of cognition is interpreted as a learning competency and therefore discussed here whereas knowledge of cognition is interpreted as a learning competency potential latent variable and therefore discussed in paragraph 2.6.2.8.

The *Regulation of cognition* learning competency refers to a person's procedural competence at regulating one's problem solving and learning activities (Veenman, 2005). The widely cited cognitive regulatory skills are planning, monitoring and evaluation (Veenman *et al.* 2006; Winne 1996). Planning involves the selection of appropriate strategies and the allocation of resources that affect performance. Monitoring refers to one's on-line awareness and comprehension of task performance. Evaluation refers to appraising the products and efficiency of one's learning, such as re-evaluating one's goals and conclusions. The knowledge and the regulation components of metacognition supplement each other and are both essential for optimal performance (Livingston 1997; Schraw 1998) as they both influence decisions on which strategy to use (Luwel, Torbey & Verschaffel, 2003; Sperling, Howard, Staley & DuBois, 2004).

For successful *Regulation of cognition* and in that sense successful classroom learning performance to occur, self-regulatory behaviour plays a fundamental role. Self-regulated learners rely on different types of metacognitive strategies in the achievement of success. In fact, according to Veenman, Van Hout-Wolters and Afflerbach (2006), some researchers consider self-regulation to be a subordinate component of metacognition (e.g., Brown & DeLoache, 1978; Kluwe, 1987), whereas others regard self-regulation as a concept superordinate to metacognition (e.g., Winne, 1996; Zimmerman, 1995).

Students who engage in metacognitive *Regulation of cognition*, can actively scan their memory for relevant prior knowledge before commencing a task and this prior knowledge includes content and metacognitive knowledge about the task and strategies (Alexander, Schallert & Hare, 1991; Pintrich, 2000). Pintrich (2000) proposed a general framework for explaining how the metacognitive self regulation/*regulation of cognition* works.

2.6.1.4.1 Pintrich's (2000) general framework for self-regulated learning

Pintrich (2000) proposed a general framework for self-regulated learning comprising four phases namely: forethought, planning and activation; monitoring; control and the reaction and reflection phases.

2.6.1.4.2 Cognitive planning and activation

The first phase (forethought, planning and activation) entails planning, target goal-setting and the ensuing activation of perceptions and knowledge of the task, context and the self in relation to the task. Target goal setting entails setting task-specific goals that can guide general cognition and cognitive monitoring. The goal is the criterion used to assess, monitor and guide cognition and can occur or be modified at any point during task performance in response to the monitoring, control and reflection processes. This phase also involves the activation of relevant prior knowledge which can occur automatically without conscious thought. According to Pintrich (2000), the automatic activation of knowledge should not be regarded as self-regulatory as it involves general cognitive processing. This is consistent with Sternberg's (1984) assertion that automatic information processing is pre-conscious and is not under the conscious direction of the individual and not hierarchical in nature. When an individual is processing some information from old domains or domains that are entrenched by nature, the individual primarily relies on automatic, local processing. It is vital for the individual to pack what has been learned from global processing of the new experience into a given local processing system, so that the next time such a situation arises, there will be no need to exit from the local processing system. Therefore, the extent to which one develops expertise in a given domain largely depends on the ability of the individual to pack new information, in a useable way, into a given local processing system and on the ability to gain access to this information (Sternberg, 1984). It is also important to note that students who are more self-regulating or metacognitive, can actively scan their memory for relevant prior knowledge before commencing a task and this prior knowledge includes content and metacognitive knowledge about the task and strategies (Alexander, Schallert & Hare, 1991; Flavell, 1979; Pintrich, 2000).

The activation of metacognitive knowledge involves the activation of knowledge about cognitive tasks and cognitive strategies (Pintrich, 2000; Schneider & Pressley, 1997) which can be automatic, stimulated by individual tasks or contextual features or it can be under the conscious control of the individual. The individual has to engage with the task at hand using different metacognitive strategies. Metacognitive knowledge can be further subdivided into declarative, procedural and conditional metacognitive knowledge (Alexander, Schallert & Hare, 1991; Paris, Lipson & Wixson, 1983; Schraw & Moshman, 1995). According to Pintrich (2000), declarative knowledge of cognition is the knowledge of the what of cognition and includes knowledge of the different cognitive strategies such as rehearsal or elaboration. Procedural knowledge pertains to knowing how to perform and use the various cognitive strategies for instance how to use the summarising and paraphrasing strategies. Conditional knowledge includes knowing when and why to use the various cognitive strategies, for instance elaboration can be used when learning from a text and rehearsal when memorising a telephone number.

2.6.1.4.3 Cognitive Monitoring

In the second phase (monitoring), various monitoring processes that represent metacognitive awareness of different aspects of the self or task and context takes place. Pintrich (2000) distinguishes between two types of metacognitive judgements or monitoring namely: judgements of learning (JOL) and feeling of knowing (FOK).

Judgements of learning (JOL) manifest themselves in various forms such as individuals becoming aware of the fact that they do not understand something they have just read or heard or becoming aware that they are reading too quickly or slowly given the text and their goals as well as when students are conscious of their inadequate preparation for an examination (Pintrich, 2000). On the other hand, the feeling of knowing judgement occurs when a person fails to recall something when called upon to do so, but has a strong feeling that he or she knows it (Pintrich, 2000).

2.6.1.4.4 Cognitive control and regulation

Phase three (control) involves efforts to control and regulate different aspects of the self or task and context. In most models of metacognition and self-regulated learning, control and regulation activities are perceived as strongly related to metacognitive monitoring. This is so because cognitive monitoring activities provide information about the relative discrepancy between a goal and current progress towards attaining that goal. According to Pintrich (2000), one of the central aspects of the control and regulation of cognition is the actual selection and use of various cognitive strategies for memory, learning, reasoning, problem-solving and thinking. Previous studies indicate that the use of imagery helps in the encoding of information on a memory task as well as visualising the correct implementation of a strategy. Other strategies such as the use of mnemonics, paraphrasing, summarising, outlining, networking, constructing tree diagrams and note-taking are important.

2.6.1.4.5 Cognitive reaction and reflection

Phase four, the final phase, represents various kinds of reactions and reflections on the self, task or context. Although the phases represent a time-ordered sequence that learners go through as they perform a task, there is no strong assumption that the phases are hierarchically or linearly structured such that earlier phases must precede the later phases (Pintrich, 2000). According to Zimmerman (1998b), good self-regulators are more likely to make adaptive attributions for their performance and these adaptive attributions have been associated with deeper cognitive processing and better learning achievement (Pintrich & Schrauben, 1992).

2.6.1.4.6 Metacognitive self-regulated learning strategies

Zimmerman and Martinez-Pons (1986) identified 14 types of self-regulated learning strategies used in and out of class using interviews on a sample of 80 high school students. The strategies that most of the students used included: organising and transforming information, sub-goal setting and planning, seeking information, keeping records and self-monitoring, environmental structuring, creating consequences, rehearsing and memorising, seeking peer, teacher, or adult assistance, reviewing notes, tests or textbooks. The students' use of these strategies was highly correlated with their academic placement and, in fact, student placement in advanced achievement tracks was predicted with 93% accuracy. Furthermore, the students in an advanced achievement group used 13 of the 14 self-regulated learning strategies significantly more often than youngsters in the other tracks.

2.6.1.4.7 Environmental structuring

One of the self-regulatory strategies used by successful students is environmental structuring (Zimmerman, 1990). Self-regulated students are not only aware of the potential benefits or adverse impact of the immediate environment on their learning but they actively try to improve it as well as select, organise and even create environments they believe will optimise their learning. This involves arranging one's study room to eliminate distracting stimuli and to provide ready access to needed resources such as lighting, writing materials and books (Zimmerman & Martinez-Pons, 1986, 1988).

2.6.1.4.8 Self-monitoring

Self-monitoring is an extremely important *Regulation of cognition*/self-regulated learning strategy that students use in order to engage in self-regulated learning and regulation of cognition. Academic self-monitoring refers to students' efforts to observe themselves as they evaluate information about specific personal processes or actions that affect their learning and achievement in school (Zimmerman & Paulsen, 1995). Self-monitoring enhances self-improvement by enabling students to direct their attention, to set and adjust their goals, and to guide their course of learning more effectively (Bandura, 1986; Corno, 1989). The resultant information garnered through self-monitoring can be used as a yardstick to measure personal progress, discern patterns of causality, to initiate some remedial strategies or interventions aimed at modifying or redirecting the action, and to eventually set realistic performance standards (Bandura, 1986). The successful employment of the *Regulation of cognition* strategies requires the learners to set aside some time to grapple with the task and discover the discrepancies in their way of studying or task resolution. In other words, students should cognitively engage with the task via the use of self-monitoring and other Regulation of cognition strategies. The employment of self-monitoring strategies is beneficial because it, firstly, focuses students' attention on a limited number of responses thereby enhancing selective focus on the task which facilitates an analysis of the student's role in any ongoing activity (Bandura, 1986). Secondly, it helps students discriminate between effective and ineffective performance (Thoresen & Mahoney, 1974). Thirdly, self-monitoring brings to the fore the inadequacy of a learning strategy and prompts the student to find a viable alternative strategy (Pressley & Ghatala, 1990). Finally, it enhances the management and use of study time (Zimmerman, Greenberg & Weinstein, 1994) and fosters reflective thinking (Bandura, 1986). Self-monitoring can affect motivation. If poorly motivated students are taught to self-monitor their performance, unexpected progress is achieved which in turn increases perceptions of self-efficacy, outcome expectations, and goal setting and, ultimately, their overt motivation (Bandura, 1986). Students who employ self-monitoring strategies display greater self-efficacy, motivation and achievement (Schunk, 1983). Self-monitoring is vital and beneficial to the extent that it leads to more effective goal setting, greater awareness of the power of using the learning strategies, or to better planning and use of an individual's time (Zimmerman & Paulsen, 1995).

The main psychological components of self-monitoring are rooted in information processing, cognitive-behavioural, metacognitive and social-cognitive theories. Information processing theorists, view self-monitoring within a cybernetic system consisting of four stages namely: sensory environmental input (perception), comparison with a standard, corrective behaviour and behavioural outcome. According to Zimmerman and Paulsen (1995), information about the effectiveness of an individual's current activity enters the system as a perception and is compared with a standard or goal. If the standard is met, no further action is necessary but if a discrepancy is detected, effort must be directed towards reducing the discrepancy. Cognitive behavioural theorists highlight the need to engage in overt forms of self-monitoring such as self-recording as tools for adapting both covert cognitions and overt behaviour to environmental conditions. Two forms of overt adaptations are used, namely stimulus control and response control. Stimulus control entails the expenditure of effort towards avoiding or managing problem situations while response control involves rewarding oneself for daily achievements. The metacognitive theorists conceive of self-monitoring in terms of meta-awareness and meta-control of knowledge and of cognitive experiences and strategies. An awareness of personal ineffectiveness on the part of a student is likely to increase the student's focus on self-monitoring of the task and behaviour sources. Finally, social-cognitive theorists stress the importance and interdependence of all three forms of self-monitoring: cognitive, behavioural and environmental. Cognitive factors and external sources of information should be monitored and used to self-regulate learning and performance. Social cognitive researchers have incorporated the overt self-recording methods of the cognitive behaviourists and the decisional feedback loop used by information-processing theorists, which they describe in terms of self-observation, self-judgement and self-reaction which correspond to the sensor, comparator and corrective behaviour components of an information-processing feedback model. The self-judgement and self-reaction sub-processes correspond also to meta-awareness and meta-control processes identified by metacognitive theorists (Zimmerman & Paulsen, 1995). Self-monitoring is likely to be a very important learning competency which deserves to be included in future proposed learning potential models.

In the process of trying to resolve a novel problem, learners are likely to monitor and evaluate their understanding through checking whether the steps followed have been stored in memory and whether it has become part of the crystallised knowledge. When the learner detects through *Regulation of cognition* via strategies such as self-monitoring that a skill has not been adequately learnt and rehearsed, a good learner is likely to allocate some more time on the skills. *Regulation of cognition* via self-monitoring or other meta-cognitive regulatory strategies brings to the fore the inadequacy of a learning strategy and prompts the student to find a viable alternative strategy (Pressley & Ghatala, 1990). Finally, it enhances the management and use of study time (Zimmerman, Greenberg & Weinstein, 1994) and fosters reflective thinking (Bandura, 1986). In short, to achieve success through the use of the *Regulation of cognition* strategies focus is needed to discover discrepancies between the current levels of understanding of a concept and the ideal. This focus requires students to be cognitively engaged. Hence it is expected that *Regulation of cognition* will positively affect *Time-cognitively engaged*.

Hypothesis 4

Regulation of cognition positively affects *Time-cognitively engaged*

From the foregoing discussion, it can be deduced that regulation of cognition is an essential learning competency while knowledge of cognition is a competency potential. It is argued that metacognition ought to play a crucial role in an eleaborated learning potential structural model that aspires to identify additional learning competencies and learning competency potential variables that have a significant bearing on the learning potential of the previously disadvantaged group members.

2.6.1.5 Self-leadership

The self-leadership construct was discussed in detail in paragraph 2.4.1.3. The intrinsically derived self-influence characteristic of self-leadership is likely to be an extremely important learning competency of a successful learner. Through its behavioural, cognitive and natural reward strategies, self-leadership theory is expected to influence the initiation, direction, intensity and persistence of learning behaviour (Manz, 1992; Prussia, Anderson & Manz, 1998). In addition, self-leadership has been documented to lead to positive outcomes such as improved work performance (Stewart, Courtright & Manz, 2011); enhanced individual innovation and creativity potential (Curral & Marques-Quinteiro, 2009; DiLiello & Houghton, 2006). Self-leading individuals are better adjusted, more confident (Stajkovic & Luthans, 1998). Recently, Burger (2012) found support for the role of self-leadership in influencing learning motivation in a study involving grade 11 learners, who had completed their first semester (term 1 and 2) at selected schools in the Western Cape province. It is also hypothesised that self-leadership will positively affect learning motivation in the present study.

Hypothesis 5

Academic self-leadership positively affects *Learning motivation*

2.6.2 Learning competency potential variables

2.6.2.1 Abstract thinking capacity

Abstract thinking capacity is an extremely important learning competency potential variable relevant for the continued production of new information from the encounter between novel problems, prior learning and its subsequent transfer to settings outside the classroom. *Abstract thinking capacity* is synonymous with the ability to think flexibly and to understand abstract relations (Preusse, Van der Meer, Deshpande, Krueger & Wartenburger, 2011) and is vital for solving novel problems as well as the acquisition of new knowledge (Cattell, 1971). *Abstract thinking capacity* is closely related to professional and educational success, especially in analogical reasoning tasks (Jaeggi *et al.*, 2008). While fluid intelligence comprises the set of abilities involved in coping with novel environments and especially in abstract reasoning; crystallised intelligence is the product of the application of these processes (Sternberg, 2008). Therefore *Abstract thinking capacity*, which is synonymous with fluid intelligence, influences an individual's capacity to perform a given task. The learning competency of transfer links fluid intelligence with crystallised intelligence in as far as *Transfer of knowledge* in essence is fluid intelligence in action in the solution of novel problems (De Goede & Theron, 2010; Taylor, 1994). The following hypothesis is postulated:

Hypothesis 6

Abstract thinking capacity positively affects *Transfer of knowledge*

2.6.2.2 Prior learning

Fluid intelligence cannot affect transfer in a vacuum. Transfer refers to the adaptation and modification of existing insight and knowledge derived from previous transfer. Taylor argued that fluid intelligence constitutes the cognitive engine driving transfer. In the APIL-B the learning material was purposefully designed so that no prior learning was required to solve novel problems in the learning material. In the case of the APIL-B it therefore makes sense to argue that transfer depends only on fluid intelligence. The argument does, however, not generalise to real-life training material. There prior learning does matter. Without sufficient crystalised ability learners will fail at transfer despite strong fluid intelligence. That is precisely the reason why disadvantaged individuals fail when appointed in a position for which they do not possess the requisite job competency potential. This line of reasoning suggests that the effect of fluid intelligence on transfer is moderated by the level of prior learning with which learners enter the affirmative development opportunity. It is therefore hypothesised that:

Hypothesis 7:

The level of *Prior learning* moderates the effect of *Abstract thinking capacity* on *Transfer of knowledge*

2.6.2.3 Post learning

A similar argument to the one developed with regards to *Transfer of knowledge* as a dimension of *Classroom learning performance* applies to learning performance during evaluation. As was argued earlier C*lassroom learning performance* and *Learning performance during evaluation* essentially comprises the same learning competencies. *Transfer of knowledge* again seems to be the pivotal learning competency in *Learning performance during evaluation*. The assessment taken at the end of the development programme attempts to determine whether successful classroom learning took place. Given the rationale behind affirmative development programmes this suggests that successful classroom learning should be understood to mean that meaningful structure was created in the classroom learning material, that insight was successfully automated and that automated insight can be successfully used by the fluid intelligence of the learner to solve the novel (cognitively challenging and job related) problems encountered in the end-of-program assessment. Again a learner with strong fluid intelligence will only successfully cope with the problems posed in the post-development assessment if the initially deficient job competency potential has been successfully elaborated. Fluid intelligence will therefore successfully find meaningful structure in the novel problems encountered in the post-development assessment if the level of post-development learning is sufficiently high. It is therefore hypothesised that:

Hypothesis 8:

Abstract thinking capacity affects *Learning performance during evaluation*

Hypothesis 9:

The level of Post-development *learning* moderates the effect of *Abstract thinking capacity* on *Learning performance during evaluation*

2.6.2.4 Information processing capacity

Information processing capacity is one of the genetically determined learning competency potential variables that are likely to affect learning. The processing of bits of information through cognitive processes (executive and non-executive), which are activated in an uncertain situation in order to reduce the amount of uncertainty, can be termed information processing. *Information processing capacity* has been defined by Taylor (1994) in terms of three basic components namely the speed, accuracy and cognitive flexibility with which the information is processed. Information processing capacity facilitates the choice of the strategy to use which in turn is affected by 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, 1992; Underwood, 1978). In the extended learning potential model, *Information processing capacity* is likely to affect learners' *Automatisation* as it directly deals with the processing of information. For instance during transfer of knowledge in the classroom, when the learner is confronted with some novel problems, the ability to process some information retrieved from prior learning is likely to facilitate both *Abstract reasoning capacity* and *Transfer of knowledge*. According to Taylor (1997), *Information processing capacity* influences learning acquisition as individuals who are slow information processors may fall behind in learning situations because they may not have had enough time to investigate all the reasonable solutions to problems (De Goede & Theron, 2010). Furthermore, the inaccurate processing of information often leads to lapses in concentration accompanied by a failure to monitor and control quality. The cognitive flexibility, with which an individual selects a problem-solving approach, appropriate to the problem from a personal 'toolkit' of cognitive strategies is a fundamental characteristic of intelligent behaviour (Hunt, 1980; Taylor, 1997). This justified the inclusion of *Information processing capacity* as a dispositional learning competency construct in the present study.

Hypothesis 10

Information processing capacity positively affects *Automatisation*

2.6.2.5 Personality

In addition to the cognitive competencies identified in the foregoing section, personality is also indirectly expected to play a role in influencing both *Classroom learning performance* and T*ransfer of knowledge*. Personality refers to the relatively stable characteristics of individuals (other than ability) that influence their cognition and behaviour (Colquitt, Le Pine & Noe, 2000). Personality is one of the variables that relates with motivation to engage in the behaviours that lead to training success. The theoretical arguments for a linkage between personality and motivation are based on cognitive/information processing conceptualisations of motivation such as Campbell's (1990) definition of motivation as the combined effects of three choices or decisions: (a) the decision to exert effort (direction); (b) the decision made as to the level of effort (level); and (c) the decision to persist at a given level of effort (persistence). Dispositions influence these decisions by creating differences in self-set goals, assessments of situations, interpretations of situations, and reactions to these interpretations. These differences create between-person differences in observed behaviour (Kanfer, 1991). According to Herold, Davis, Fedor and Parsons (2002, p. 853), 'if dispositions (or any other individual characteristic) affect motivation, then such effects should also be dynamic, interacting with situational factors (e.g. events at each stage of training), and across the stages of training.'

A growing body of evidence suggests that job performance also depend to a significant extent on attributes other than malleable abilities, knowledge and skills, that is, on individual dispositions (Barrick & Mount, 2005; Forero, Gallardo-Pujol, Maydeu-Olivares & Andrés-Pueyo, 2009; Mansur, Ahmed, Ishaq, Ahmad & Ali, 2011). The effect of personality on job performance has changed over the years. In their review of research published in the *Journal of Applied Psychology and Personnel Psychology* from 1952 to 1963 on the role of personality in job performance, Guion and Gottier (1965) concluded that very little evidence exists to support the stance that personality affects job performance. This position was not really questioned until Barrick and Mount (1991) and Tett, Jackson and Rothstein (as cited in Morgeson, Campion, Dipoye, Hollenbeck, Murphy & Schmitt, 2007) published their meta-analytic studies in 1991. Personality is now again generally viewed as an important deteminant of job performance (Borman & Motowidlo, 1997) and especially contextual performance (Borman & Motowidlo, 1993; Van Scotter & Motowidlo, 1996). A considerable number of studies have examined the relationship of personality traits to job performance and reported significant relationships between personality traits and performance dimensions (e.g., Barrick, Mount & Judge, 2001; Barrick, Parks &Mount, 2005; Hurtz & Donovan, 2000; Salgado, 1999). Personality has been found to have an influence on the types of environments that people seek (Barrick, Mount, & Gupta, 2003; Mansur, Ahmed, Ishaq, Ahmad & Ali, 2011; Milfont & Sibley, 2012); the type of people and activities that one prefer (Barrick & Mount, 2005) and organisational citizenship behaviour (Elanain, 2007) among several others.

Mount and Barrick (1998) investigated the relation of the "Big Five" personality dimensions (extraversion, emotional stability, agreeableness, conscientiousness and openness to experience to job proficiency, training proficiency and personnel data obtained from five occupational groups comprising professionals, police force members, managers, sales and skilled as well as semi-skilled employees. The results indicated that conscientiousness showed consistent relations with all job performance criteria for all occupational groups. Extraversion was a valid predictor for occupations involving social interaction such as that of managers and sales. Openness to experience and extraversion predicted training proficiency across occupations. Martocchio and Judge (1997) reported that conscientious individuals had more confidence in their ability to learn the training materials. In the same vein, Colquitt and Simmering (1998) stated that conscientious learners had higher self-efficacy and a stronger desire to learn the training content. On the contrary, introversion was reported to be negatively associated with training proficiency (Barrick & Mount, 1991). However, from a theoretical perspective, training design was found to moderate the relationship between introversion and training motivation (Mount & Barrick, 1995). Introverts prefer learning on their own through self-study or reading books while extraverts prefer learning in groups such as training groups. In view of the literature on the role of personality in learning, conscientiousness seems to be a consistent predictor of job performance and learning motivation.

2.6.2.5.1 Conscientiousness

Conscientiousness was shown to influence the time a student spends cognitively engaged on to a task (Burger, 2012). In a learning situation conscientious students are not only organised, motivated, and hard-working, but they also approach learning with deep and achieving motives and strategies, rather than surface strategies. Conscientious students are achievement oriented and ambitious and no doubt discover that deep as well as achievement strategies work best in securing good grades (Chamorro-Premuzic & Furnham, 2002; Chamorro-Premuzic, Furnham & Lewis, 2007). The choice of strategy also gives a clue on the amount of time expended. It is anticipated that students who take the deep learning approach spend more time on the task compared to those who take the surface approach. In the present study *Conscientiousness* is also expected to positively influence the *Time-cognitively-engaged*. The argument often presented to explain how *Conscientiousness* affects *Time-cognitively-engaged* and *Learning performance during evaluation* is based on the role of motivation (Biderman, Nguyen, & Sebren, 2008; Burger, 2012; Judge & Ilies, 2002). Motivation enables individuals to determine the amount of effort and level of persistence required for successful performance. Highly conscientious individuals are characterised by a high degree of perseverance, and as being hardworking which is directed by a clear goal orientation. The *Conscientiousness* personality type includes traits such as hardworking, careful, thorough, responsible, organised, persevering (Barrick & Mount, 1991). High *Conscientiousness* individuals are methodical, dependable, and risk aversive (Goldberg, 1990). These individuals are responsible, dependable, persistent, careful, hardworking and achievement oriented which are important attributes for performing work tasks (Barrick & Mount, 1991, 1993). These characteristics are given some impetus by the high level of self-efficacy which is a notable attribute of conscientious individuals (Judge & Erez, 2007). The self-efficacy quality and the ensuing behaviours are consistent with those of individuals who believe in their ability to complete a task as well as are more engaged in initiating and implementing strategies predicting higher levels of performance (Gerhardt, Rode & Peterson, 2007). Individuals with high conscientiousness tend to have a high achievement-striving motivation (Kim, Shin & Swanger, 2009). It is hypothesised that *Conscientiousness* positively affects *Time cognitively engaged.*

Hypothesis 11

Conscientiousness positively affects *Time cognitively engaged*

2.6.2.5.2 *Openness to experience*

Although openness to experience has not been found to be a significant predictor of job performance (Barrick *et al.,* 2001; Barrick & Mount, 1991; Salgado, 1997), it could be demonstrated that a sub-dimension labelled epistemic curiosity and, especially, the facet openness to ideas, which includes aspects like curiosity, flexibility, willingness to learn, and creativity, are highly relevant for work-related criteria and so far understudied in organisational research (Mussel, Winter, Gelle´ ri & Schuler, 2011).

Openness to experience has been found to significantly correlate with fluid intelligence or abstract reasoning capacity (Furnham, Chamorro-Premuzic, & Moutafi, 2005; Moutafi, Furnham & Crump, 2003). According to Moutafi, Furnham and Crump (2006), a possible explanation of the relationship between *Openness to experience* and fluid intelligence is that individuals with lower fluid intelligence may become less curious and have narrower interests, due to their lower ability to handle novel experiences, which in turn discourages openness to experience. In contrast, individuals with higher fluid intelligence may have sought to stimulate and challenge themselves, by exposing themselves to novel experiences, and thus becoming more curious and with wider interests, and therefore, in turn, more open (Moutafi, Furnham, & Paltiel, 2005). Furthermore, individuals who are high on *Openness to experience* are inquisitive when faced with novel situations (Judge, Thoresen, Pucik,&Welbourne, 1999), can easily adapt to change as well as creatively solve complex problems (LePine, Colquitt, & Erez, 2000) and it is expected that they would be better performers in a learning or training context.

Openness to experience is associated with attributes such as being creative, cultured, curious, and broad-minded. It is the disposition that involves paying attention to beauty, abstract ideas, and liberalism (Cárdenas & Stout**,** 2010). Personality theory suggests that individuals who are open to experience value training as an opportunity to learn new skills (Goldstein & Ford, 2002; Kanfer, 1990). *Openness to experience* is related to measures of training proficiency (Barrick & Mount, 1991; Salgado, 1997). It correlates with intellectual abilities at different stages of life (Ackerman & Heggestad, 1997; Baker & Bichsel, 2006; Furnham, Dissou, Sloan & Chamorro-Premuzic, 2007). People who are high on *Openness to experience* are also described as being imaginative, sensitive to aesthetics, independent thinkers, tolerant of ambiguity, and amenable to new ideas, experiences and perspectives (Costa & McCrae, 1992; McCrae & Costa, 1997). Lievens, Harris, Van Keer, and Bisqueret (2003) reported a significant relationship between *Openness to experience* and training performance. It has also been reported to be significantly related to aspects of training-related motivation such as learning goal orientation (Naquin &Holton, 2002). Learning goal oriented individuals react to challenges with positive affect, pride, and intrinsic motivation and have a high openness to experience (Dweck & Leggett, 1988). In view of the role of *Openness to experience* in the learning or training contexts, the following hypothesis is derived:

Hypothesis 12:

Openness to experience is likely to affect the learner's *Learning goal orientation*

2.6.2.6 Motivation to learn

In addition to the expected role that *Conscientiousness* plays in influencing *Time-cognitively engaged*, *Motivation to learn* is also anticipated to influence *Time-cognitively-engaged*. *Motivation to learn* determines the extent to which an individual directs his or her energy towards the learning task in an attempt to form structure and ultimately transfer existing knowledge to the current task (Tannenbaum et al., 1991). It is the desire on the part of the trainee to learn the content of a training program (Noe, 1986). It can be inferred that since *Motivation to learn* gives directions to student on how to expend their effort, it also, to a considerable extent, influences the amount of time that the students spends engaged on the task. According to Ryman and Biersner

(1975), learning motivation can influence the amount of effort exerted during a training session and serves as the force that brings an individual's intention to learn into action. It is one of the chief determinants of the choices individuals make to engage in, attend to, and persist in learning activities (Klein, Noe & Wang, 2006). Burger (2012) recently confirmed the role that *Motivation to learn* plays in influencing *Time-cognitively-engaged*. As the time learners engage with the learning material is under their volitional control *Motivation to learn* is expected to positively influence *Time-cognitively-engaged*.

Hypothesis 13:

Motivation to learn is expected to positively influence *Time-cognitively-engaged*

2.6.2.7 Academic Self-efficacy

Perceived *Self-efficacy* is the belief that people have in their capabilities to perform a specific task (Bandura, 1986, 1997). The *Self-efficacy* belief is a key factor in regulating behaviour leading to human competence (Pintrich, 1999; Pintrich & De Groot, 1990). *Academic Self-efficacy* regulates the way in which an individual perceives his or her academic competence. This perception influences an individual's ability to complete a task and a set, attainable goal (Pajares & Schunk, 2001).

People with high generalised self-efficacy across many diverse domains have been found to have higher levels of success in general, excelling in outcomes related to academic achievement (Multon, Brown, & Lent, 1991) and job performance (Burns & Christiansen, 2011; Paunonen &Hong, 2010; Stajkovic & Luthans, 1998). Generally, in a training situation, individuals with a high degree of *Academic self-efficacy* are likely to exert considerable effort to master the programme content. These individuals are more likely to persevere in the face of difficulties, demonstrate intrinsic motivation when engaged in task performance, and are less likely to feel disappointed in the face of failure. They frequently perceive a difficult situation as challenging as opposed to perceiving it as difficult and unassailable. Moreover, setbacks and failure affect individuals with low levels of self-efficacy more strongly, even in the cases of mild failure (Prat-Sala & Redford, 2010). According to Prat-Sala and Redford (2010), students classified as high in self-efficacy (reading and writing) were more likely to adopt a deep or strategic approach to studying, while students classified as low in self-efficacy (reading and writing) were more likely to adopt a surface approach. More importantly, changes in students' approaches to studying over time were related to their self-efficacy beliefs, where students with low levels of self-efficacy decreased in their deep approach and increased their surface approach across time. Students with high levels of self efficacy (both reading and writing) demonstrated no such change in approaches to studying. In terms of thinking, a strong sense of efficacy facilitates cognitive processes and performance in a variety of settings, including quality of decision-making and academic achievement (Zulkosky, 2009). *Academic self-efficacy* is positively related to academic performance (Bong, 2001; Burger, 2012; Bouffard, Boileau & Vezeau, 2001; Lane, Lane & Kyprianou, 2004; Ofori & Charlton, 2002; Richardson, 2007), academic motivation (Bong & Clark, 1999), self-regulated learning (Pintrich & De Groot, 1990; Schunk & Zimmerman, 1997), and reading/writing performance (McCarthy, Meier, & Rinderer, 1985; Meier, McCarthy, & Schmeck, 1984). It is expected that *Academic self-efficacy* will positively influence the *Academic self-leadership* which encompasses both the self-regulated learning and self-management that is required by learners to engage in the necessary behaviours vital for the final classroom. Therefore it is expected that *Academic self-efficacy* positively affects *Academic Self-leadership.*

Hypothesis 14:

Academic self-efficacy positively affects *Academic Self-leadership*

2.6.2.8 Knowledge of cognition

Knowledge about cognition alludes to a person's declarative knowledge about the interactions between the person, task, and strategy characteristics (Flavell, 1979). *Knowledge about cognition* sheds some light on the individuals' awareness of their own knowledge, learning preferences, styles, strengths, and limitations, as well as their awareness of how to use this knowledge and this can determine how well they can perform different tasks (Magno, 2010). Cross and Paris (1988) discerned three kinds of metacognitive knowledge: declarative knowledge (knowing what factors influence human cognition), procedural knowledge (knowing how certain skills work and how they should be applied), and conditional knowledge (knowing when strategies are needed).

2.6.2.8.1 Cognition and metacognition

The distinction between cognition and metacognition centres on how the information is used and that metacognitive ability usually precedes and follows cognitive activity (Flavell, 1979). Ku and Ho (2010, p. 253) distinguished between cognitive and metacognitive ability as follows:

> The border between what is metacognitive and what is cognitive has been unclear, and many have acknowledged the two may be mutually dependant on each other and thus cannot be entirely separated (Flavell 1979; Livingston 1997; Veenman, 2006). In fact, the same activity may be invoked for either purpose depending on its goal (Ward & Traweek, 1993). The principle difference lies in the goal of the activity: Cognitive activities help to acquire, retain and transfer knowledge for task execution, whereas metacognitive activities allow one to regulate and govern task execution (i.e. how a task is carried out to ensure satisfactory level of performance).

Meta-cognition thus regulates cognitive activity by enabling individuals to be aware of how they think and by guiding them in the strategies they are to employ in order to solve a problem during learning (Shamir, Mevarech & Gida, 2009). Veenman, Van Hout-Wolters and Afflerbach (2006, p. 5) reinforced the afore-mentioned understanding of the difference between cognition and metacognition by arguing that:

> metacognition draws on cognition. It is very hard to have adequate metacognitive knowledge of one's competencies in a domain without substantial (cognitive) domain-specific knowledge, such as knowledge about relevant concepts and theories in a domain, about intrinsic difficulties of a domain, and about what is irrelevant (cf. Pressley, this issue). In terms of metacognitive skills, one cannot engage in planning without carrying out cognitive activities, such as generating problem-solving steps and sequencing those steps. Similarly, one cannot check one's outcome of a calculation without comparing the outcome with an estimation of it, or recalculating the outcome in another way.

Nelson (1996) as well as Nelson and Narens (1990) explained the distinction between cognition and metacognition in terms of the "object" level of cognition and metacognition. The object level of cognition refers to the level on which cognitive activity takes place. The "meta" level governs the object level. The relationship between the two levels of cognition is understood to be in the form of a reciprocal flow between monitoring and control. During learning, the monitoring function provides the information used by the control function to guide and regulate cognition. Meta-cognition thus regulates cognitive activity by enabling students to be aware of how they think and by guiding them in the strategies they are to employ in order to solve a problem during learning. In short, cognitive and metacognitive abilities play some complementary functions that serve to enhance learning and transfer.

Metacognition has been documented to be positively related to mastery goals (Schraw *et al.*, 1995; critical thinking (Ku & Ho, 2009); learning orientation (Ford *et al.*, 1998) and success in school (Sternberg, 1998). Metacognition has also been frequently linked to reading comprehension - various studies have consistently found that skilled readers pay more attention to important information in texts, and engage in comprehension monitoring and revision more often (Griffith & Ruan, 2005; Palincsar & Brown 1984; Paris & Jacobs, 1984). According to Veenman et al., (2006, p. 6), "there is ample evidence that metacognitive skills, although moderately correlated to intelligence, contribute to learning performance on top of intellectual ability. On the average intellectual ability uniquely accounts for 10 percent of variance in learning, metacognitive skills uniquely account for 17 percent of variance in learning, whereas both predictors share another 20 percent of variance in learning for students of different ages and background, for different types of tasks, and for different domains (Veenman, Wilhelm & Beishuizen, 2004; Veenman & Spaans, 2005; Veenman, Van Hout-Wolters & Afflerbach, 2006).

2.6.2.8.2 Metacognition and other constructs

Borkowski, Carr, Rellinger and Pressley (1990) focused on the key role strategy attributions play in linking metacognitive functioning to academic outcomes. The development of these attributional beliefs is assumed to be closely related to perceptions of self-efficacy, intrinsic motivation and other self-system constructs. Students who believe in themselves and their ability are more likely to apply their strategic knowledge in appropriate situations.

Ku and Ho (2010) examined the role of metacognitive strategies in critical thinking using ten university students (five in the high-performing group and five in the low-performing group) with comparable cognitive ability, thinking disposition and academic achievement but with different levels of critical thinking performance. The students were tested on six thinking tasks using thinkaloud procedures. The results showed that good critical thinkers engaged in more metacognitive activities, especially high-level planning and high-level evaluating strategies. In another study, Choy and Cheah (2009) reported that critical thinking is encouraged inside the classroom among the students when the teacher provides guidelines on metacognitive strategies to learn materials effectively. These *Regulation of cognition* strategies instituted to apply one's *Knowledge of cognition* include techniques, prompts, topics, and keywords. In addition, they also found that structuring a more conducive environment can help facilitate critical thinking. These cognitive strategies and environmental structuring taught to students are specific metacognitive skills that are used to develop critical thinking. They concluded in their study that critical thinking requires higher levels of cognitive skills in processing information such as metacognition.

Vrugt and Oort (2008) developed and tested a model of effective self-regulated learning. The model comprised achievement goals (mastery, performance-approach and avoidance goals), metacognition (metacognitive knowledge, regulation and experience), study strategies (metacognitive, deep cognitive, surface cognitive and resource management strategies) and academic achievement. The relationships in the model were tested while controlling for intellectual ability, gender and age. The results showed that effective self-regulated learning involved two pathways: a metacognitive and a strategy pathway. The first pathway involved a positive relationship of mastery goals and a negative relationship of performance-avoidance goals with metacognition. Metacognition positively affected the use of the four study strategies. The strategy pathway involved positive effects of mastery and performance-approach goals on the use of metacognitive and deep cognitive strategies. Further, performance-approach goals positively affected the use of surface cognitive and resource management strategies. The use of metacognitive and resource management strategies had a positive and the use of surface cognitive strategies had a negative effect on exam scores.

Rozencwajg (2003) conducted a study to determine whether and to what extent students' metacognitive level is linked to their conceptualisation and performance in problem solving at school, especially science problems among 42 seventh graders (ages 12-13) using two indices namely: an index of metacognitive knowledge about classroom learning, and an index of metacognitive monitoring in relation to task difficulty on a non-academic problem. These two indexes were related to the students' intelligence test scores and solving strategies on electricity problems. The results showed that (1) the metacognitive knowledge level was more closely related to crystallised intelligence (Gc), and (2) metacognitive monitoring was more closely associated with fluid intelligence (Gf). Furthermore, both metacognitive indexes were strongly linked to scientific problem-solving strategies (correlations around .50). The knowledge of cognition and the regulation components of metacognition supplement each other and are both essential for optimal performance (Livingston 1997; Schraw 1998). Hence it is expected that *Knowledge of cognition* will positively influence the application of the factual knowledge through the use of *Regulation of cognition*.

Hypothesis 15:

Knowledge of cognition affects *Regulation of cognition*

2.6.2.9 Goal Orientation

Goal orientation refers to the general reasons for engaging in a task or a general orientation for approaching the task and evaluating performance on the task (Ames, 1992; Dweck & Leggett, 1988; Elliot, 1997; Pintrich, 2000). Dweck's motivational theory suggests that goal orientation is a relatively stable dispositional trait that co-varies with the individual's implicit theory of ability (Bempechat, London, & Dweck, 1991; Dweck, 1989).

2.6.2.9.1 Models of goal orientation

Dweck and Leggett (1988) proposed a two factor goal orientation model made up of learning and performance goals. Ames (1992) termed these orientations mastery and performance goals.

2.6.2.9.2 Learning/Mastery goal orientation

Mastery goals orient learners to developing new skills, trying to understand their work, improving their level of competence, or achieving a sense of mastery based on self-referenced standards. Learning goals reflect an individual's pre-occupation with increasing competence. Individuals with a high *Learning goal orientation* hold the general belief that intelligence is a malleable quality that can only be changed through competence development. Individuals with a high *Learning goal orientation* pursue an adaptive response pattern in which they persist, escalate effort, and report enjoying the challenge. Learning goal-oriented individuals construe ability as an incremental skill that can be incessantly improved by acquiring knowledge and perfecting competencies (Wood & Bandura, 1989). These individuals promote a challenge-seeking and mastery oriented response in the face of failure regardless of their perceived ability (Elliot & Dweck, 1988). This is due to their optimism, maintenance of task interest and persistence in task performance (Dweck, 1999). Learning oriented individuals react to challenges with positive affect, pride, and intrinsic motivation (Dweck and Leggett, 1988). Individuals with a mastery or learning approach are more motivated to learn and learn more than individuals with a performance approach (Chiaburu & Marinova, 2005; Colquitt & Simmering, 1998).
These individuals believe in the power of effort and hard work in the enhancement of ability and are likely to display higher levels of *learning motivation* and accept mistakes or setbacks as learning opportunities that is likely to result in further motivation (Button, Mathieu & Zajac, 1996; VandeWalle, Ganesan, Challagalla, & Brown, 2000). It is also clear that individuals with a mastery or learning approach are

more motivated to learn and learn more than individuals with a performance approach (Chiaburu & Marinova, 2005; Colquitt & Simmering, 1998). It is expected that *Learning goal orientation* positively affects *learning motivation.*

Hypothesis 16

Learning goal orientation positively affects *learning motivation*

2.6.2.9.3 Performance goal orientation

Individuals with a performance orientation, on the contrary, are concerned with gaining favourable judgments of their competence or avoiding negative judgments (Elliot & Dweck, 1988). These students are more concerned with demonstrating their abilities relative to other students. These students perceive intelligence as a fixed trait which cannot be changed (Dweck, 1986) and prefer tasks that minimise errors at the expense of acquiring new skills. Individuals with a performance goal orientation pursue a maladaptive response pattern in which they withdraw from the task, make negative ability attributions, and report decreased interest in the task (Dweck & Leggett, 1988).

Individuals with a *Performance goal orientation* would look for cues in the environment to determine whether to engage in skill transfer or not even if they have a high learning motivation (Ford & Weissbein, 1997). This decision to transfer can be complicated by the absence of such cues in the learning environment especially for the novel skills that the trainees acquired during instruction. When faced with situations that require reliance on more complex and integrated concepts and principles, performance-oriented individuals are likely to display lower training outcomes (Schmidt & Bjork, 1992). Hence in the face of complex novel situations that require the use of abstract thinking capacity, the performance oriented individuals are likely to shun the challenging tasks due to fear of the resulting negative evaluations of their task competence. According to Chiaburu and Tekleab (2005), in a work training setting, reported that when the trainees maintained a high level of performance goal orientation, their high levels of training motivation resulted in diminished training transfer. On the other hand, high training motivation resulted in a higher level of transfer when the participants maintained lower levels of performance goal orientation. In view of the basic behavioural tendencies of the performance oriented individuals, the perfomance goal orientation may work best as a competency potential construct. Although perfomance goal orientation is an important competency potential variable. It was not formally acknowledged in either the De Goede (2007) or the Burger (2012) structural models. Neither will it be formally acknowledged in the proposed De Goede-Burger-Mahembe learning potential structural model. Future learning potential structural model will, however, have to study the influence of performance goal orientation.

2.6.2.9.4 Other goal orientation models

The terms task goals and performance goals have also been used to refer to mastery and performance goals identified by Dweck and Ames (Anderman & Midgley, 1997; Kaplan & Midgely, 1997; Maehr & Midgely, 1991, 1996; Middleton & Midgely, 1997). Task focused goals denotes an orientation towards the attainment of mastery goals, that is, the strive for increasing one's competence as in Dweck and Ames's conceptualisation of learning and mastery goals (Pintrich, 2000). Performance goals involve concerns with out-performing others and demonstrating ability to the teachers and peers.

A somewhat different conceptualisation of goal orientation perceived from the stand-point when individuals feel most successful resulted in the operationalisation of goal orientation as task-involved and ego-involved goals or task orientation and ego-orientation (Nicholls, 1984, 1989; Thorkildsen & Nicholls, 1998). Task-involved goals refer to experiencing success when individuals learn something new, gain new skills or knowledge or do their best. Ego-involved goals involve individuals feeling successful when outperforming or surpassing their peers or avoiding looking incompetent.

Two general goal orientations, mastery and performance orientations have been postulated (Harackiewicz, Barron, Carter, Lehto & Elliot, 1997; Elliot & Church, 1997; Elliot & Harackiewicz, 1996;). In this model, a mastery goal orientation reflects a focus on the development of knowledge, skill and competence in comparison to one's own previous performance making the mastery orientations self- referential (Pintrich, 2000). On the other hand, performance orientation involves the strive to demonstrate competence by outperforming peers on academic tasks. These two goal orientations function in much the same way as the Dweck and Ames conceptualisations except that a distinction was made between two different types of performance goals: a performance-approach goal and a performance-avoidance goal (Elliot, 1997; Elliot & Church, 1997). A performance-approach goal involves the motivation to outperform others to demonstrate competence while individuals can be negatively motivated to avoid failure as a way of shunning the incompetence label thereby engaging in an avoidance orientation to the performance goal.

Other researchers have also put forward a different operationalisation of the work by Elliot and colleagues on performance-approach and performance-avoidance goals resulting in the proposition of relative ability goals (Urdab, 1997; Wolters, Yu & Pintrich, 1996), self-enhancing ego orientation and self-defeating ego orientation (Skaalvik, 1997; Skaalvik, Valas & Sletta, 1994). The relative ability goal is similar to the approach performance goal construct put forward by Elliot and colleagues. The self-enhancing and self-defeating ego orientation goals were derived from the performance or ego goals. In the self-enhancing ego orientation goals, the emphasis is on outperforming peers and demonstrating superior performance, as in the approach-performance goal while the self-defeating ego orientation goals is about avoiding negative judgements as in the avoidance-performance.

Several other goal orientations have been identified in literature namely extrinsic orientation which is almost similar to extrinsic motivation; work avoidance and academic alienation. Extrinsic orientation focuses on getting good grades or seeking approval or avoiding punishment from teachers or other adults (Pintrich, 1989; Pintrich & De Groot, 1990; Pintrich & Garcia, 1991; Pintrich, Roeser & De Groot, 1994; Pintrich, Smith, Garcia & McKeachie, 1993; Wolters, Yu & Pintrich, 1996). The work avoidance goals relate to feeling successful when work or tasks are easy while academic alienation goals concern feeling successful when the students feel they can fool around and not do their school work and get away with it (Pintrich, 2000). Meece, Blumenfeld and Hoyle (1988) also defined work avoidant goals in terms of a desire to complete school work without expending much effort, a goal of reducing effort.

2.6.2.9.5 Goal orientation and other constructs

Individuals with a learning goal orientation demonstrate behaviours and hold beliefs that are consistent with those who are high in openness to experience (Zweig & Webster, 2004). Given that individuals with high conscientiousness tend to set high performance goals and believe they can achieve them with exerting effort (Barrick et al., 1993), it is likely that they will also set high learning goals and strive to attain them as well. Previous research has found that extraverts are more likely to use self-promotion tactics in job-related communications to serve impression management purposes (e.g., Kristof-Brown, Barrick, & Franke, 2002). Therefore, it is conceivable that extraverts may be more likely than introverts to adopt the proving goal orientation. A learning goal orientation is expected to relate positively with learning motivation.

Klein, Noe and Wang (2006) conducted a naturally occurring quasi-experiment that examined how *Learning goal orientation* (LGO), delivery mode (classroom versus blended learning), and the perception of barriers and enablers are related to motivation to learn and course outcomes using students in classroom or blended learning courses. The results indicated that the learners in the blended learning condition, high in (LGO), and who perceived environmental features as enablers rather than barriers had significantly higher motivation to learn. Motivation to learn, in turn, was significantly related to course outcomes (satisfaction, metacognition and grades).

The performance@learning framework depicted in Figure 1 proposes that for successful learning performance to occur there is a need to identify the learning competency and competency variables that interact to influence the learning outcomes. The proposed learning competencies have been identified. The identified learning competencies do not constitute an exhaustive list. More learning competencies can still be identified but, however, for model plausibility and manageability the identified learning competencies seem to suffice. The proposed competency potential variables that combine with the learning competencies identified above are discussed in the following section. The foregoing theoretical arguments drawn from an extensive review of literature aimed at deriving a convincing answer to the research initiating question have culminated in the development of a structural model depicted in the form of a path diagram in Figure 2.5. Figure 2.5, in essence represents the over-arching substantive research hypotheses postulated in the present study.

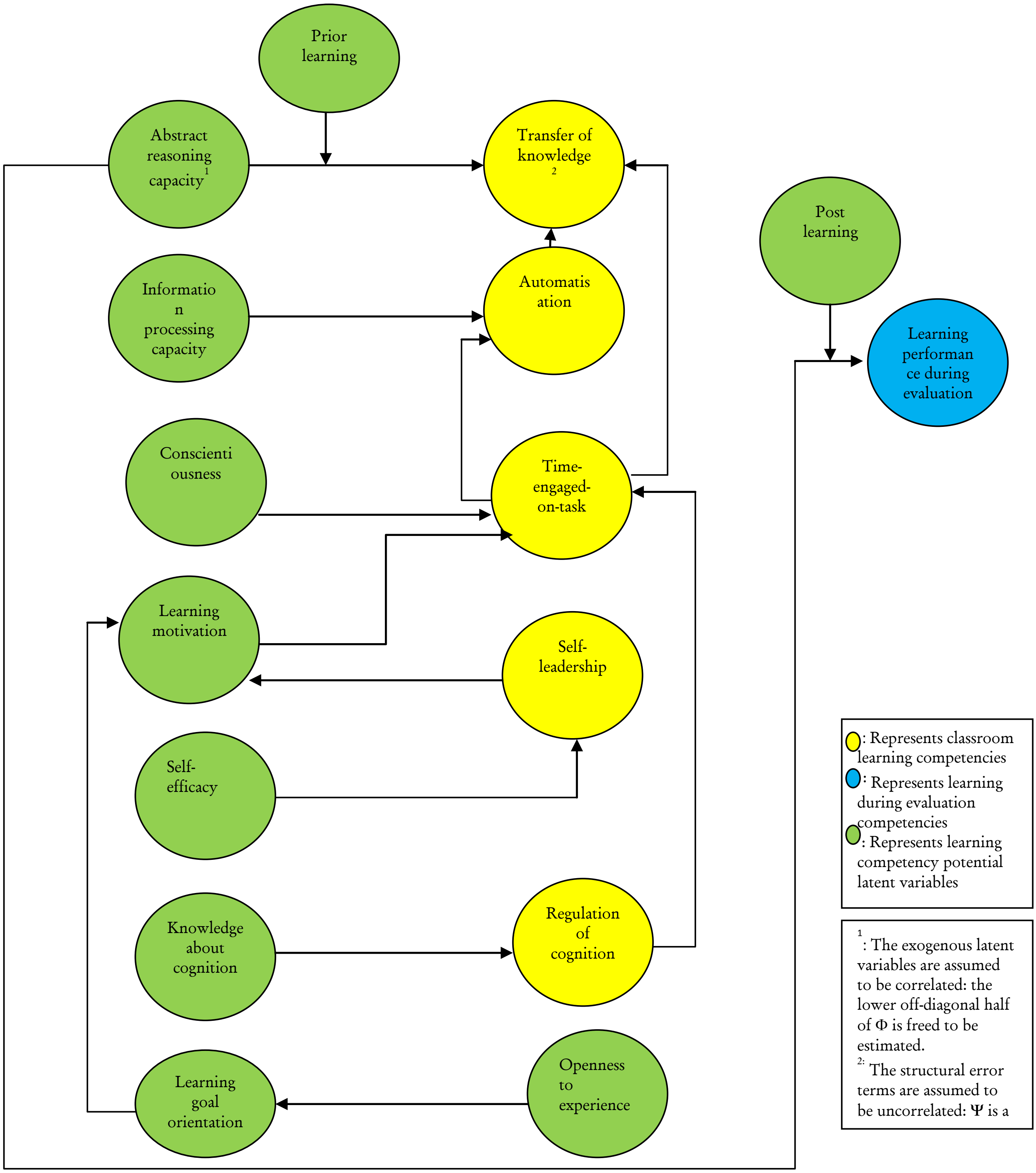


Figure 2.5. The proposed extended De Goede-Burger-Mahembe learning potential structural model

2.7 SUMMARY

The current chapter presented the literature study and the theoretical arguments aimed at deriving a convincing answer to the research initiating question. The theoretical argument developed through theorising culminated in the elaboration of both the De Goede (2007) and the Burger (2012) models. A distinction was made between *Learning performance in the classroom and Learning potential during evaluation. Transfer of knowledge* as a dimension of *Learning performance in the classroom* involves transfer in an actual learning task comprised of job-related learning content. *Automatisation* involves the writing of intellectual insights in an actual learning task gained via *Transfer of knowledge* from prior learning. *Learning performance during evaluation* refers to the extent to which an individual has acquired a specific skill, knowledge or ability that can be transferred to solve novel problems in a situation corresponding to the job for which the affirmative development has been initiated. Additional competencies and competency potential variables identified and included in the De Goede-Burger-Mahembe learning potential structural model that did not form part of the original De Goede (2007) and Burger (2012) models are: *Knowledge about cognition; Regulation of cognition; Openness to experience; Learning goal orientation; Prior learning* and *Post learning*. The addition of these latent variables led to the formulation of a number of further structural hypotheses. It was hypothesised that: *Prior learning* moderates the effect of *Abstract thinking capacity* on *Transfer of knowledge; Post learning* moderates the effect of *Abstract thinking capacity* on *Learning performance; Knowledge about cognition* positively affects *Regulation of cognition; Regulation of cognition* positively affects *Time-cognitively engaged; Openness to experience* positively affects *Learning goal orientation; and Learning goal orientation* positively affects *Learning motivation.* The theorising presented in this chapter culminated in the unbridged structural model presented in Figure 2.5.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 INTRODUCTION

The literature study led to the conclusion that *Classroom learning performance* and *Learning performance during evaluation* comprises a number of learning competencies. From the review of the literature in Chapter two, it was hypothesised that *Classroom learning performance* and *Learning performance during evaluation* directly and indirectly depend on an array of cognitive and non-cognitive learning competency potential latent variables. The present study intends to test an explanatory structural model that explicates the manner in which cognitive and non-cognitive learning competency potential latent variables discussed in the previous chapter structurally relate to the learning competencies comprising *Classroom learning performance* and *Learning performance during evaluation*.

3.1.1 The abridged learning potential structural model

In the model proposed in Figure 2.5, the measurement of *Transfer of knowledge* and *Automatisation* present conceptual and practical challenges. Earlier it was argued that the manner in which De Goede (2007) and De Goede and Theron (2010) operationalised the *Transfer of knowledge* and *Automatisation* latent variables should be questioned. The fundamental problem seems to be that De Goede (2007) and De Goede and Theron (2010) failed to formally make the distinction between *Classroom learning performance* and *Learning performance during evaluation*. The APIL-B test battery was used to measure *Transfer of knowledge* and *Automatisation* as dimensions of *Learning performance in the classroom.* It measures transfer in a simulated learning task comprised of geometric symbols with which all learners are equally unfamiliar. In contrast *Transfer of knowledge* as a dimension of *Learning performance in the classroom* involves transfer of specific prior knowledge onto the actual job-related learning material comprising the development programme content. *Automatisation* likewise involves the writing of intellectual insights in an actual learning task gained via *Transfer of knowledge* from prior learning.

To operationalise *Transfer of knowledge* as a dimension of *Learning performance in the classroom* in terms of geometric symbols with which all learners are equally unfamiliar, provides a measure with low content validity. To obtain a more content valid measure of *Transfer of knowledge* as a dimension of *Learning performance in the classroom* would require that the extent to which learners succeed in intellectually adapting and transforming previously derived intellectual insights so as to make sense of the novel learning material they are actually confronted with in the classroom and how successfully those insights can be adapted and transformed to gain intellectual insights in more advanced learning material covered later in the programme. This suggests that the presentation of the course and the *Transfer of knowledge* assessment will have to be integrated into a single intertwined process.

The same argument applies to the operationalisation of *Automatisation* as a dimension of *Learning performance in the classroom*. To obtain a content valid measure of the success with which learners write the insight gained in the learning material that they are actually confronted with in the classroom to knowledge stations, the speed at which previously gained insights into the learning material that they are actually confronted with in the classroom can be retrieved from memory needs to be evaluated. Again this suggests that the presentation of the course and the *Automatisation* assessment will have to be integrated into a single intertwined process.

The successful operationalisation of *Transfer of knowledge* and *Automatisation* created a formidable practical challenge that was be difficult to overcome. It was therefore decided to remove *Transfer of knowledge* and *Automatisation* from the learning potential structural model shown in Figure 2.5. Figure 3.1 presents an abridged learning potential structural model that represents the hypotheses that will actually be empirically tested and evaluated in the present study.

3.2 Substantive research hypotheses

The objective of this study is to integrate, modify and elaborate the De Goede (2007) and Burger (2012) learning potential structural models. The theoretical argument presented in the literature study resulted in the inclusion of additional learning competencies and learning competency potential latent variables in the original models and the integration of the two models. The resultant elaborated and modified structural model was depicted in Figure 2.5. Due to the difficulty of obtaining content valid measures of *Transfer of knowledge* and *Automatisation* as dimensions of *Classroom learning performance* these two learning competencies were removed from the learning potential structural model that will be empirically tested.

The overarching substantive research hypothesis (Hypothesis 2[18]) states that the abridged structural model depicted in Figure 3.1 provides a valid account of the manner in which the cognitive and non cognitive determinants of learning performance combine to affect *Classroom learning performance* and *Learning performance during evaluation*.

[18] Hypothesis 1 states that the indicator variables used to operationalise the latent variables provide valid and reliable measures of the latent variables in the learning potential structural model they were designated to reflect.

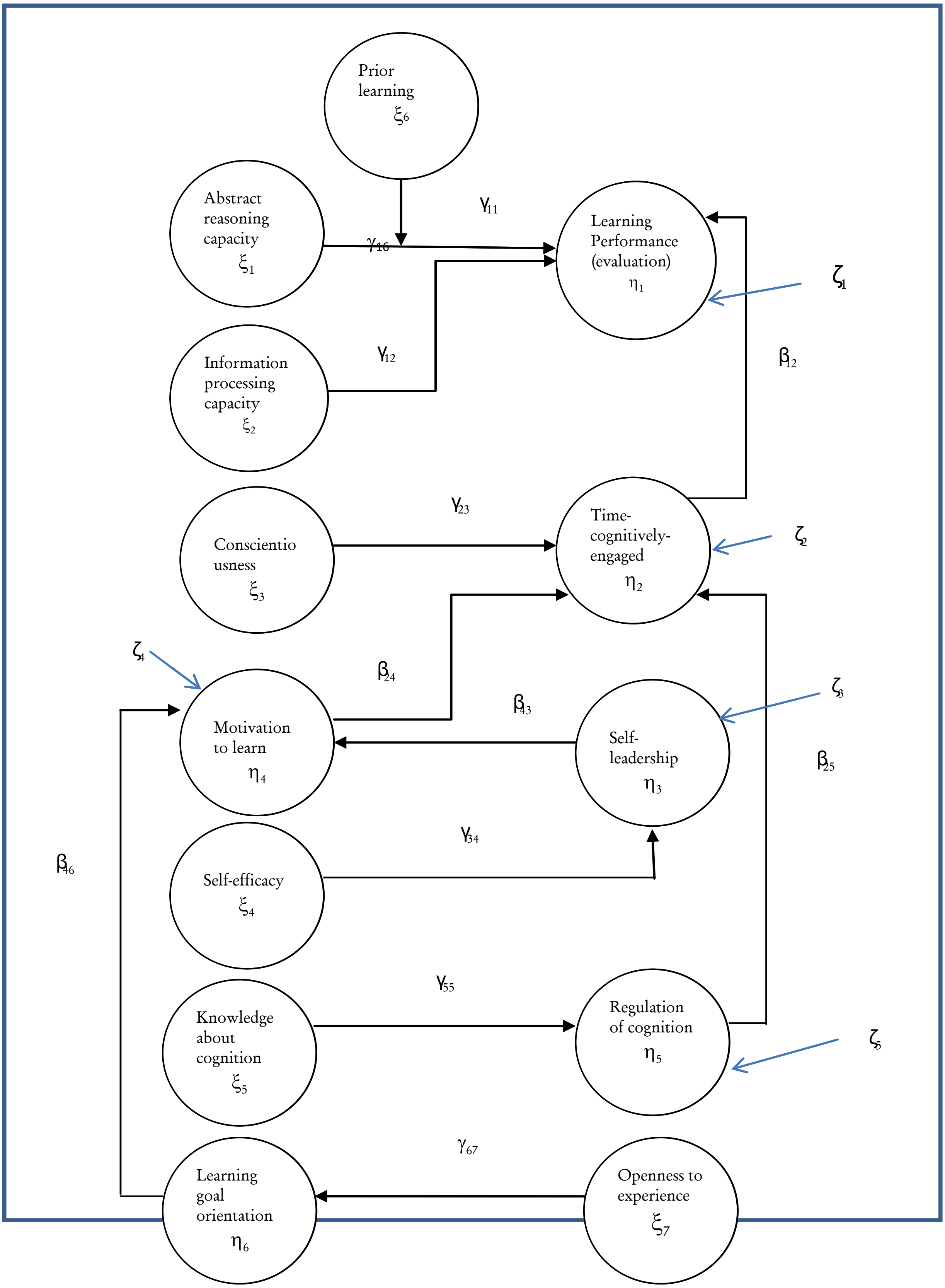


Figure 3.1. **The proposed abridged extended learning potential structural model**

The overarching substantive hypothesis was dissected into the following twelve more detailed, path-specific substantive hypotheses:

Hypothesis 3: *Abstract reasoning capacity* positively affects *Learning performance during evaluation*

Hypothesis 4: *Information processing capacity* positively influences *Learning Performance during evaluation*

Hypothesis 5: *Self-leadership* positively influences *Motivation to learn.*

Hypothesis 6: *Conscientiousness* positively influences *Time cognitively engaged*

Hypothesis 7: *Motivation to learn* positively influences *Time cognitively engaged*

Hypothesis 8: *Self efficacy* positively influences *Self-leadership*

Hypothesis 9: *Knowledge about cognition* positively affects *Regulation of cognition*

Hypothesis 10: *Regulation of cognition* positively affects *Time cognitively engaged*

Hypothesis 11: *Learning goal orientation* positively affects *Motivation to learn*

Hypothesis 12: *Time cognitively engaged* positively affects *Learning performance*

Hypothesis 13: *Openness to experience* positively affects *Learning goal orientation*

Hypothesis 14: *Prior learning* moderates the relationship between *abstract reasoning capacity* and *Learning Performance during evaluation*

3.3 RESEARCH DESIGN

The overarching substantive research hypothesis make specific claims with regards to the psychological dynamics underpinning *Classroom learning performance* and *Learning performance during evaluation*. The abridged learning potential structural model as depicted in Figure 3.1 explicates the hypothesised nature of this psychological process by hypothesising specific structural relations between the various latent variables contained in the model.

The overarching substantive research hypothesis comprises the following five structural equations expressed as Equation 3.1 – Equation 3.6.

$\eta_1 = \gamma_{11}\ \xi_1 + \gamma_{12}\ \xi_2 + \beta_{12}\eta_2 + \gamma_{16}\ \xi_6$[19] $+ \zeta_1$ ---------- [3.1]

$\eta_2 = \gamma_{23}\ \xi_3 + \beta_{24}\ \eta_4 + \beta_{25}\ \eta_5 + \zeta_2$ ---------- [3.2]

$\eta_3 = \gamma_{34}\ \xi_4 + \zeta_3$ ---------- [3.3]

$\eta_4 = \beta_{46}\ \eta_6 + \beta_{43}\ \eta_3 + \zeta_4$ ---------- [3.4]

$\eta_5 = \gamma_{55}\ \xi_5 + \zeta_5$ ---------- [3.5]

$\eta_6 = \gamma_{67}\ \xi_7 + \zeta_6$ ---------- [3.6]

The five structural equations comprising the structural model can be expressed in matrix form as Equation 3.7[20]:

$$\begin{pmatrix}\eta_1\\ \eta_2\\ \eta_3\\ \eta_4\\ \eta_5\\ \eta_6\end{pmatrix} = \begin{pmatrix}0 & \beta_{12} & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & \beta_{24} & \beta_{25} & 0\\ 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & \beta_{43} & 0 & 0 & \beta_{46}\\ 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0\end{pmatrix}\begin{pmatrix}\eta_1\\ \eta_2\\ \eta_3\\ \eta_4\\ \eta_5\\ \eta_6\end{pmatrix} + \begin{pmatrix}\gamma_{11} & \gamma_{12} & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & \gamma_{23} & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & \gamma_{34} & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & \gamma_{46} & 0\\ 0 & 0 & 0 & 0 & \gamma_{55} & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 0\end{pmatrix}\begin{pmatrix}\xi_1\\ \xi_2\\ \xi_3\\ \xi_4\\ \xi_5\\ \xi_6\end{pmatrix} + \begin{pmatrix}\zeta_1\\ \zeta_2\\ \zeta_3\\ \zeta_4\\ \zeta_5\\ \zeta_6\end{pmatrix} \text{ ----------[3.7]}$$

[19] ξ_6 represents the latent interaction effect ξ_1 x ξ_6. The structural model does not make provision for a Prior learning latent main effect. ξ_6 in Equation 3.7 does not refer to ξ_6 in Figure 3.2.

[20] $\xi 6$ in Equation 3.7 represents the *Prior learning* x *Abstract thinking capacity* interaction effect. ξ_6 in Equation 3.7 does not refer to ξ_6 in Figure 3.2.

The matrix equation depicted as Equation 3.7 can in turn be reduced to Equation 3.8:

$\eta = \mathbf{B}\eta + \mathbf{\Gamma}\xi + \zeta$ -- [3.8]

Where:

- η is a 6 x 1 column vector of endogenous latent variables;
- **B** is a square, non-symmetric 6 x 6 matrix of partial regression coefficients describing the slope of the regression of η_i on η_j;
- $\mathbf{\Gamma}$ is a 6 x 6 matrix of partial regression coefficients describing the slope of the regression of η_i on ξ_j;
- ξ is a 6 x 1 column vector of exogenous latent variables;
- ζ is a 6 x 1 column vector of structural error terms.[21]

[21] Equations 3.7 and 3.8 do not fully specify the structural model. The variance-covariance matrices $\mathbf{\Phi}$ and $\mathbf{\Psi}$ also need to be specified. Due to the inclusion of a latent interaction effect in the structural model, these matrices will only be specified once the procedure that will be used to operationalise the latent interaction effect in the model has been explained.

To empirically test the merit of the structural relations hypothesized by the abridged learning potential structural model requires a strategy that will guide the gathering of empirical evidence to test the overarching substantive research hypothesis and the more detailed path-specific substantive research hypotheses. The research design constitutes this strategy (Kerlinger & Lee, 2000). The primary purpose of the research design is to attempt to ensure empirical results that can be interpreted unambigiously for or against the overarching substantive research hypothesis and the more detailed path-specific substantive research hypotheses.

A correlational *ex post facto* research design was used to test the substantive research hypotheses. In this kind of study there is no control or manipulation of the independent variable (Terre Blanche & Durrheim, 1999), the aim being to discover what happens to one variable when the other variables change (Thomas, 2003). This study employed a quantitative research approach using multiple measures.

In terms of the logic of the *ex post facto* correlational design the validity of the measurement relation and structural relation hypotheses made by the comprehensive LISREL model can be tested by observing the indicator variables representing each of the latent variables in the abridged learning potential structural model (i.e., the items parcels used to operationalise each of the latent variables in the structural model) and calculating the observed inter-parcel variance-co-variance matrix. Estimates for the freed measurement model and structural model parameters are obtained in an iterative fashion with the purpose of reproducing the observed variance-co-variance matrix as accurately as possible (Diamantapoulos & Siguaw, 2000). The variance and covariance terms in the observed matrix are estimated via Equation 3.9 (Jöreskog & Sörbom, 2001):

$$\boldsymbol{\Sigma} = \begin{pmatrix} \boldsymbol{\Lambda}_y \mathbf{A}(\boldsymbol{\Gamma\Phi\Gamma}' + \boldsymbol{\Psi})\mathbf{A}'\boldsymbol{\Lambda}'_y + \boldsymbol{\Theta}_\varepsilon & \boldsymbol{\Lambda}_y \mathbf{A}\boldsymbol{\Gamma\Phi\Lambda}'_x \\ \boldsymbol{\Lambda}_x \boldsymbol{\Phi\Gamma}'\mathbf{A}'\boldsymbol{\Lambda}_y' & \boldsymbol{\Lambda}_x\boldsymbol{\Phi\Lambda}_x' + \boldsymbol{\Theta}_\delta \end{pmatrix} \text{-------------------------------[3.9]}$$

Where A = $(1 - \mathbf{B})^{-1}$.

If the fitted model fails to accurately reproduce the observed variance-co-variance matrix (Byrne, 1989; Kelloway, 1998) the conclusion would invariably follow that the comprehensive LISREL model does not provide an acceptable explanation for the observed variance-co-variance matrix. If it has been shown in an earlier analysis that the measurement model does fit the data at least closely such an outcome necessarily means that the structural model does not provide a valid account of the psychological process that determines *Classroom learning performance* and *Learning performance during evaluation*. The opposite, however, is not true. If the reproduced variance-co-variance matrix derived from the estimated comprehensive LISREL model parameters closely corresponds to the observed variance-co-variance matrix it does not necessarily mean that the processes postulated by the structural model must have produced the observed co-variance matrix (even if the measurement model fitted closely). Such an outcome would therefore not justify the conclusion that the psychological process described by the learning potential structural model necessarily accurately describes the psychological process that actually determines *Classroom learning performance* and *Learning performance during evaluation*. A high degree of fit between the observed and reproduced variance-co-variance matrices would only mean that the processes portrayed in the structural model provide one plausible account of the psychological process that determines *Classroom learning performance* and *Learning performance during evaluation* (given that the measurement model shows at least close fit).

3.3.1 Evaluation of the design

The *ex post facto* design employed in the present has its own limitations. The major limitations relate to: (1) The inability to manipulate independent variables; (2) The lack of power to randomise; and (3) the risk of improper interpretation. A comparison of an experimental and an ex post facto design indicates that the *ex post facto* lacks control and that the probability for incorrect interpretations may occur (Kerlinger & Lee, 2000). The results and interpretations of an *ex post facto* correlational design should therefore be treated with caution. Furthermore, to empirically test the merits of the measurement relation assumptions made by the measurement model, using the logic of the *ex post facto* correlational design, the researcher observes the observed variables (item parcels) and calculates the observed inter-item covariance matrix. Estimates of the freed measurement model parameters are obtained in an iterative fashion with the purpose of reproducing the observed covariance matrix as accurately as possible (Diamantopoulos & Siguaw, 2000). If the fitted model fails to accurately reproduce the observed covariance matrix (Byrne, 1989; Kelloway, 1998) the conclusion would unavoidably follow that the measurement model implied by the design intention does not provide an acceptable explanation for the observed covariance matrix. Such an outcome would invariably mean that the measurement model does not measure the *Learning performance during evaluation* construct as intended. The converse, however, is not true. If the covariance matrix derived from the estimated model parameters closely corresponds to the observed covariance matrix it does not necessarily mean that the processes postulated by the measurement model must have produced the observed covariance matrix. Such an outcome would therefore not warrant the conclusion that the measurement model definitely measures the *Learning performance during evaluation* construct as intended. A high degree of fit between the observed and estimated covariance matrices would only mean that the processes portrayed in the measurement model provide one plausible explanation for the observed covariance matrix.

The use of questionnaires and the collection of data at a single point in time can be identified as some of the inherent drawbacks of the research design used in the current study. It is still widely accepted that measures employed in social sciences research are subject to a number of sources of error (Burton-Jones & Gallivan 2007; Mackenzie & Podsakoff, 2012). One such source of errors pertains to the collection of research data at a single point in time (by making use of a single-point-in-time survey measurement) rather than long-term and continued measurement (e.g. longitudinally over a period of time), which may exacerbate same-source or common method bias (Arnolds & Boshoff, 2004; Rylander, 2003). However, MacKenzie, Podsakoff and Fetter (1991, 1993) examined the effects of specifically, Organisational Citizenship Behaviours on managerial evaluations, and found that such biases did not appear to be very strong. Despite this finding, Podsakoff and MacKenzie (1994) posit that a longitudinal design could reduce this potential influence. Podsakoff and MacKenzie (1994) stated three advantages that a longitudinal study would have over cross-sectional studies such as the one reported in this study. These include the following:

1. It would permit a better assessment of the causal priority of the variables understudy and how they influence learning performance;
2. It would permit the examination of the longer-term effects of the variables under study; and
3. It would reduce the potential effects of same-source or common method biases.

Campbell and Fiske (1959) drew attention to the existence of (a) systematic trait/construct variance arising from features intended to represent the trait/construct of interest; (b) systematic error variance emanating from the specific method being employed which may be common to measures of other traits/constructs and (c) random error variance. It is important to identify sources of measurement error as this can lead to regular or irregular changes in the means, variances and/or covariances of observations (Bagozzi, 1984; Mackenzie & Podsakoff, 2012). Systematic method variances should also be controlled since it creates bias in the estimates of construct validity and reliability leading to incorrect conclusions about the adequacy of a scale's reliability and convergent validity. Furthermore, systematic method variance can bias parameter estimates of the relationship between two different constructs (Mackenzie & Podsakoff, 2012).

3.4 STATISTICAL HYPOTHESES

Close measurement model fit is a logical prerequisite for unambigiously deriving inferences on the fit of the structural model from the fit statistics of the comprehensive LISREL model. The measurement model substantive research hypothesis states that the measurement model implied by the way in which the latent variables in the abridged learning potential structural model have been operationalised provides a valid account of the process that produced the observed variance-covariance matrix. If the measurement model substantive research hypothesis is interpreted to mean that the measurement model provides a perfectly accurate description of the process that produced the observed variance-covariance matrix the measurement model substantive research hypothesis translates to the following exact fit null hypothesis

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

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

If, however, the measurement model substantive research hypothesis is interpreted to mean that the measurement model provides only an approximate description of the process that produced the observed variance-covariance matrix the measurement model substantive research hypothesis translates to the following close fit null hypothesis

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

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

If the overarching structural model substantive research hypothesis is interpreted to mean that the structural model provides a perfect account of the psychological process that determines learning performance, the substantive research hypothesis translates into the following exact fit null hypothesis:

$$H_{02a}: RMSEA = 0$$

$$H_{a2a}: RMSEA > 0$$

If the overarching structural model substantive research hypothesis would be interpreted to mean that the structural model provides an approximate description of the psychological process that determines learning performance, the substantive research hypothesis translates into the following close fit null hypothesis:

$$H_{02b}: RMSEA \leq .05$$

$$H_{a2b}: RMSEA > .05$$

The overarching structural model substantive research hypotheses was dissected into 12 more detailed, path-specific substantive research hypotheses[22]. These 12 path-specific research hypotheses translate into the following path coefficient statistical hypotheses:

Hypothesis 3: *Abstract reasoning capacity* (ξ_1) positively affects *Learning performance during evaluation* (η_1)

H_{03}: $\gamma_{11} = 0$

[22] Indirect effect substantive hypotheses in which mediator variables mediate the effect of ξ_i on η_j or the effect of η_i on η_j were not formally stated. Neither are formal statistical hypotheses formulated for these effects here. The significance of the indirect effects will nonetheless be tested.

H_{a3}: $\gamma_{11} > 0$

Hypothesis 4: *Information processing capacity* positively influences *Learning Performance during evaluation*

H_{04}: $\gamma_{12} = 0$

H_{a4}: $\gamma_{12} > 0$

Hypothesis 5: *Self-leadership* positively affects *Motivation to learn*

H_{05}: $\beta_{43} = 0$

H_{a5}: $\beta_{43} > 0$

Hypothesis 6: *Conscientiousness* positively affects *Time cognitively engaged*

H_{06}: $\gamma_{23} = 0$

H_{a6}: $\gamma_{23} > 0$

Hypothesis 7: *Motivation to learn* positively influences *Time cognitively engaged*

H_{07}: $\beta_{24} = 0$

H_{a7}: $\beta_{24} > 0$

Hypothesis 8: *Self efficacy* positively influences *Self-leadership*

H_{08}: $\gamma_{34} = 0$

H_{a8}: $\gamma_{34} > 0$

Hypothesis 9: *Knowledge about cognition* positively influences *Regulation of cognition*

H_{09}: $\gamma_{55} = 0$

H_{a9}: $\gamma_{55} > 0$

Hypothesis 10: *Regulation of cognition* positively influences *Time cognitively engaged*

H_{010}: $\beta_{25} = 0$

H_{a10}: $\beta_{25} > 0$

Hypothesis 11: *Learning goal orientation* affects *Motivation to learn*

H_{011}: $\beta_{46} = 0$

H_{a11}: $\beta_{46} > 0$

Hypothesis 12: *Time cognitively engaged* affects *Learning performance*

H_{012}: $\beta_{12} = 0$

H_{a12}: $\beta_{12} > 0$

Hypothesis 13: *Openness to experience* positively affects *Learning goal orientation*

H_{013}: $\gamma_{67} = 0$

H_{a13}: $\gamma_{67} > 0$

Hypothesis 14: *Prior learning* moderates the relationship between *Abstract reasoning capacity* and *Learning performance during evaluation*[23]

H_{014}: $\gamma_{16} = 0$[24]

H_{a14}: $\gamma_{16} > 0$

[23]A moderator variable is a 'qualitative (e.g., sex, race, class) or quantitative (e.g., level of reward) variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable' (Baron & Kenny, 1986, p.1174). With regards to the testing of hypothesis 14 using Structural Equation Modeling (SEM), the residual centering approach (Little, Bovaird & Widaman, 2006) was used in which residuals were used as indicators of the latent variable interaction effect. The analysis is conducted using a two-step approach. In the first step, two respective uncentered indicators of the first-order effect variables are multiplied and the resulting product is then regressed on all first-order effect indicators. The residuals of these regression analyses are then saved. In the second step, the residuals are used as indicators of the product variable (represent the interaction effect) in the latent interaction model.

[24] $\xi_8 = \xi_1 * \xi_6$

3.5 SAMPLING AND RESEARCH PARTICIPANTS

The target population of the study is the population of disadvantaged South African learners. Testing the validity of the abridged De Goede –Burger-Mahembe learning potential structural model on the target population is not practically feasible. Given the nature of the introductory argument that served to justify the research objective of the study, it can be argued that the sample needs to consist of participants that qualify as affirmative development candidates. Moreover the sample should ideally comprise candidates that have all been enrolled on the same development programme and that have completed the same formal evaluation to assess the extent to which they have benefited from the development.

The sampling population for this research is Stellenbosch University students enrolled for the extended degree programme who are also members of the previously disadvantaged groups. A large gap between the target and sampling populations is thereby implied. The substantial gap means that even if a probability sample would have been drawn from the sampling population the sample would not have been representative of the target population. A probability sample was, however, not possible. The study employed a non-probability sampling strategy and attempted to be evenly representative of gender as well as ethnic differences to be representative of the population being observed. All students enrolled on the extended degree programme in the Economic and Management Sciences, Health Sciences, Arts and Science faculties of Stelllenbosch University were invited to participate. Sampling aspires to taking a subset or segment of the population and using it as representative of that population (Bryman & Bell, 2003). Due to the substantial gap and the fact that a non-probability method of sampling was used, it cannot be claimed that the sample is representative of the sampling or target populations. Generalisation of the study results will therefore have to occur with great circumspection.

The sample ideally should comprise candidates that have all been enrolled on the same development programme and that have completed the same formal evaluation. These requirements were not fully met in that extended degree programme students from different faculties were used in the study.

Another important concern in sampling is the size of the sample (Terre Blanch & Durrheim, 1999). The sample size must be adequate to allow inferences to be made about the population from the research findings. However, Bryman and Bell (2003) contend that the absolute rather than the relative size of a sample is what increases validation and therefore the sample must be as big as possible. The Preacher and Coffman (2006) software was used to determine the minimum sample size required to test the proposed model. The degrees of freedom were specified as 704 calculated using the formula in paragraph 3.9.4.1.2. The RMSEA was set to .05 under H_0 and RMSEA was set to .08 under Ha. The Preacher and Coffman (2006) software returned a sample size value of 300. Therefore this study aimed for a sample size of 400 extended degree programme students.

The study failed to achieve this target despite the use of incentives. The final sample consisted of 213 students. This sample consisted of 125 female (59%) and 87 male (41%) students. The majority (88%) fell in the 20 and below age category. The ethnic distribution in the sample was: Blacks (33.3%), Coloureds (43.8%), Whites (15.2%) and Indians (5.7%). Regarding highest level of qualification, the majority of respondents had matric (98.1%). The demographic sample profile of the participants is shown in Table 3.1.

The composition of the sample predominantly made up of students from previously disadvantaged groups is relevant. The unit of analysis in the present study are extended degree programme students who are members of the previously disadvantaged groups drawn from a university in the Western Cape Province of

South Africa. It is expected that the learning competencies and the competency potential determinants of *Learning performance during evaluation* should not differ.

Table 3.1

Sample Profile

Variable	Frequency	Valid Percentage (%)
Gender		
Male	87	40.8
Female	125	59
Missing	1	.2
Age of participants		
Below 20	170	88
21 – 30	22	11.3
31 – 40	1	0.5
Missing	20	
Ethnic group		
Black	70	33.3
Coloured	92	43.8
Indian	12	5.7
White	32	15.2
Missing	7	
Education		
Matric	208	98.1
Diploma	3	1.4
Degree	1	0.5
Missing	1	
Faculty		
Arts and Social Sciences	62	29.4
Sciences	42	19.9
Agri-sciences	5	2.4
Law	7	3.3
Engineering	25	11.8
Health Sciences	67	31.8
Military Sciences	3	1.4
Missing	2	

according to demographic variables but rather variance in learning should be attributed to the level of exposure to education holding other important variables constant (e.g. learning competency potential variables such as personality). Previously disadvantaged group members who have had the same exposure to education as the advantaged group members and possess the same learning competencies and competency potential variables vital for successful learning performance are expected to perform equally well. The use of previously disadvantaged group members on the extended degree programme acknowledges to a certain extent that their level of performance has been affected by their past educational exposure 'disadvantagement'. Therefore, when it came to selecting a sample, it was deemed acceptable to draw a sample that includes only participants that qualify as affirmative development candidates. It can, however, also be argued that the learning potential structural model developed in this study is applicable to any form of formal development or training. The psychological dynamics that determine the level of learning performance during eveluation that learners achieve in affirmative development programmes are not different from the process that is at work in other teaching and training contexts. The same complex nomological network of latent variables that determine learning performance in affirmative development programmes also underpins learning performance of learners in other learning contexts. The level of specific determining latent variables will most likely be different for affirmative development learners compared to non-disadvantaged learners. This line of reasoning is strengthened when it is considered that failure at learning is explained by diagnosing and identifying the latent variables that determine learning performance that have inappropriately high or low levels. In a similar vein success at learning is explained in terms of the latent variables that determine learning performance that have the values needed to achieve success. Disadvantaged learners and advantaged learners fail and succeed because of essentially the same process. The are no unique latent variables at work in either case.

3.6 DATA COLLECTION AND PROCEDURE

Participants were invited to take part in the timed information processing capacity and abstract reasoning capacity psychometric tests after making some prior arrangements with the students through the extended degree programme co-ordinators. Students who were willing to participant had to choose a day and time slot on which to take the tests. Participants were also invited to complete either the electronic or hardcopy survey. Data for the electronic survey was collected using the Stellenbosch University e-survey system. Both the electronic and hard copy questionnaires contained a covering letter which outlined the reasons for the study and the informed consent form. Participants were asked to indicate both their willingness to participate in the study as well as give consent to the researcher to access their academic results in the study. The questionnaire also contained a biographical section and the measuring instruments used to measure the latent variables under study. Confidentiality of the participants was ensured and maintained. The participants were also informed that completing both the timed psychometric tests and the questionnaire would automatically qualify them for entry into a random draw for a Kindle worth R1600.

3.7 ETHICAL CONSIDERATIONS

Ethics are typically associated with morality. The ethical considerations of research were adhered to. In this study, the Standard Operation Procedure of the Stellenbosch Research Ethics Committee (Humanities) (Standard Operating Procedure, 2013) provided the ethical considerations framework. The ethical considerations are discussed in detail in paragraphs 3.7.1 - 3.7.4 below.

3.7.1 Respect for the dignity, moral and legal rights of people

The researcher respected the dignity of the participants who participated in this study by showing respect for other people through actions and language. The researcher also demonstrated some respect to the participants by being punctual and responding to participants' requests expediently, as well as giving participants some space when they needed it (Allan, 2008). In addition, the researcher's approach was non-judgemental and refrained from imposing personal values on participants. The research participant had the right to voluntarily accept an invitation to participate in research or not. In addition participants had the right to make an informed decision on whether he/she wishes to participate in the research that included asking questions about the objective and purpose of the study, what participation in the research entails, how the research results will be disseminated and used, the right to know the identity of the researchers and who to approach when they feel that there has been an infringement of their rights, what their affiliation is, and whether or not they had to be paid or not for participation (Stellenbosch University Standard Operating Procedure, 2013).

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) also provided some additional ethical guidelines with regards to the respect for the dignity, moral and legal rights of participants. The act requires psychological researchers to obtain institutional permission from the organisation from which research participants were to be drawn. 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 for the research was obtained from Stellenbosch University.

3.7.2 Voluntary participation

Research usually intrudes into people's lives; it often requires people to reveal personal information that may be unknown to their friends and family. Participants volunteered completely to participate in the study as well as grant permission to the researcher to their academic records. This was done by way of ticking on a provision that was made in the informed consent form. Informed consent was sought after participants are made aware of what the study entails. They were informed of their rights including that they have the right to refuse to participate (Mertens, 2005), as no one should be forced to participate (Babbie, 2011).

3.7.3 Anonymity, privacy and confidentiality

Confidentiality was maintained in order to guard the participants' interests and well-being through the protection of their identity from unauthorised parties. Confidentiality and anonymity are two different terms with different meaning (Babbie, 2011). Anonymity concerns the ethical protection that participants remain nameless, their identity is protected from disclosure and remains unknown (Neuman, 2011). In the case of this study this was not possible due to the need to collate the psychological measures of *Abstract reasoning capacity* and *Information processing capacity* obtained at one point in time with non-cognitive learning competency potential measures obtained via an electronic survey and the *Learning performance during evaluatio*n measures obtained during the end of semester evaluations. Moreover the use of a prize in the form of a Kindle as an incentive to motivate students on the extended degree programme to participate neccesitated access to research participants identity. The study used student numbers allocated by the University. Confidentiality is defined as the ethical protection of those who are studied by holding the data in confidence or keeping data from the public; not releasing information in a way that may permit linking specific individuals to specific responses (Neuman, 2011). Any information obtained in connection with this study that may be identified with the participant will remain confidential and will be kept in a password secured file. Raw data will be kept for an appropriate period in order to allow for the validation of the results.

3.7.4 Non-maleficence and beneficence

The principle of non-maleficence requires that the researcher "ensures that no harm befalls research participants as a direct or indirect consequence of the research" (Wassenaar, 2006, p. 67). In the current study, no foreseen harm is expected. Beneficence alludes to compassion; taking positive action to help others and the general desire to do good to others (Beauchamp & Childress, 2009). The participants will likely derive some benefits by gaining some insights into the learning competencies that are vital for *Learning performance during evaluation*.

3.8 MEASURING INSTRUMENTS

Standardised instruments with sound psychometric attributes were used to measure each of the constructs in the proposed De Goede – Burger – Mahembe learning potential structural model. Eight questionnaires were identified through a literature review as being reliable, valid measures of the latent variables in question and applicable to this study. Each of these eight questionnaires is briefly discussed below. The measures of the *Motivation to learn, Academic self-efficacy, Conscientiousness* and *Openness to experience, Academic self-leadership, Knowledge of cognition, Cognitive regulation, Time cognitively engaged*, and *Goal orientation* latent variables were combined in a composite survey questionnaire.

3.8.1 Learning performance during evaluation

Learning performance during evaluation was assessed using the participants' average score in the recently taken Stellenbosch University examinations as well as the percentage credits passed out of the total credits enrolled for. The two scores gave an indication of the participants' current level of academic performance in the degree course that they are enrolled for. The first semester courses taken by the participants were, however, not uniform since the students were drawn from different faculties. Moreover, since students from different faculties were used it is possible that academic standards and difficulty of examinations might systematically differ accross faculties. A student on the extended degree programme who is coming from the sciences, engineering or medical sciences may not necessarily be comparable to an extended degree programme student in the faculties of Arts or Economic and Management Sciences or vice-versa due to varying levels of fluid intelligence and prior learning required to succeed in the courses. This is one of the potential limitations of the study. There was no uniform basis in terms of an examination to use to compare the students. Furthermore, no psychometric evidence on the reliability and validity of these measures were available. In addition the question needs to be asked whether the evaluations that contributed to the overall first semester marks significantly depended on the ability to transfer the insights obtained and automated via the formal course teaching. These marks may, however, reflect students' ability to rehearse, memorise and regurgitate. Inspection of the assignments and tests that contributed to the first semester overall marks in question in relation to the curriculum could have shed light on this matter. This was, however, not done. The students' overall first semester average examination score and the percentage credits passed out of the total credits enrolled for formed the two parcels that were used to operationalise *Learning performance during evaluation*.

3.8.2 Prior learning

Prior learning was measured using the extended degree programme students' grade 12 as well as the National Benchmark Test average (NBT) marks. The grade 12 and the National Benchmark Test average mark gave an indication of the participants' level of performance before they registered for their degree programme. The major advantage of using the grade 12 and National Benchmark Test average marks is that it reflects the crystallised knowledge amassed over a wide domain that the student has available at the time he/she registers as a student. This line of reasoning, however, presupposes that the grade 12 and NBT examination measures the extent to which learners have gained true insight in the learning material covered in the grade 12 curriculum and that they have automated the learning material and thus have it available in knowledge stations for subsequent transfer. It is only if significant insights are gained during the grade 12 year and these insights are successfully automated that these insights can form the basis of transfer onto novel learning material encountered during university study. No explicit evidence is available to corroborate this assumption. In addition it needs to be conceded that no formal evidence is available on the psychometric properties (i.e., reliability, construct validity and measurement bias) of the grade 12 measures. The students' grade 12 average mark and the average score achieved on the National Benchmark Tests formed the two parcels that were used to operationalise *Prior Learning*.

3.8.3 Abstract thinking capacity

Abstract thinking capacity was measured with the Concept Formation Test, which is a sub-test of the APIL-B Test Battery. This is a test that measures the individual's ability to form abstract concepts, reason hypothetically, theorise, build scenarios, and trace causes, (Taylor, 1997). The Concept Formation Test is a classificatory task where the testee is presented with sets of geometrical diagrams and has to identify a diagram, which does not share a characteristic that all the others share (Taylor, 1997).

The reliability of the Concept Formation Test scores was calculated with Kuder-Richardson-type estimates. KR-20 coefficients (with correction applied under the assumption that the item difficulties are normally distributed) ranging between .78 and .87 were obtained for the Concept Formation Test (Taylor, 1997). Each of the 30 items in the Concept Formation Test was scored by assigning either a 0 or 1 value. A score of 0 was assigned to each incorrect answer, while a score of 1 was assigned to each correct answer. Two parcels comprising the odd and even numbered correct item raw scores were used to represent the *Abstract thinking capacity* latent variable.

3.8.4 Information processing capacity

Information processing capacity was measured with the Flexibility-Accuracy-Speed-Tests. The Flexibility-Accuracy-Speed-Tests is a battery of tests that provides both measures of the speed (quickness) and the accuracy of information processing and cognitive flexibility (Taylor, 1997). This battery of tests comprise four subtests which provide measures of the speed (quickness), the accuracy and the cognitive flexibility of information processing (Taylor, 2006). The processing speed score was calculated by adding the total number of items attempted (whether correct or incorrect) over the first three sub-tests (the fourth subtest requires the testees to work with all three problem types presented in the first three subtests) (Taylor, 2006).

Taylor (1997) states that the reliability of the Information Processing Speed variable cannot be directly determined. Taylor (1997), however, states that some indication of the reliability can be obtained by inspecting the correlations between the three components that are added together to derive the speed score. These are the Series Number Attempted, Mirror Number Attempted and Transformations Number attempted. Correlation coefficients among the three components ranging between .45 and .72 have been obtained for six samples. Four item parcels made up of the correct raw scores obtained in the series, mirror, transformations and the Combined Problems Test (CPT) were used to represent the *Information processing capacity* latent variable.

3.8.5 Motivation to learn

Motivation to learn was measured using an adapted version of the Nunes (2003) 20-item motivation to learn questionnaire. This version consisted of six items. A sample item for this scale is, "I want to learn as much as I can in the current semester." The scale has sound psychometric properties with a Cronbach's alpha of .94. Participants indicated their agreement with each of the items on the scale using a 7-point Likert scale. Two parcels were formed by taking the mean of the even-numbered and the mean of the uneven-numbered items of the scale to operationalise *Motivation to learn*.

3.8.6 Academic Self-Efficacy

Academic self-efficacy was measured using the Academic Self-Efficacy scale developed by Burger (2012). It contains twelve item statements that measure an individual's perception of ability to perform in an academic situation. The scale was developed by adapting the Zimmerman and Kitsantas (2007) self-efficacy scale for self-regulated learning (SRL), termed the Self-Efficacy for Learning Form (SELF) and the Vick and Packard (2008) scale developed by adapting the Self-Efficacy subscale of the MSLQ The Burger (2012) scale is scored using a 7-point Likert scale ranging from 0 (Never) 6 (Always). The Cronbach's alpha internal consistency reliability of the scale was reported to be .91 using 460 grade 11 learners from four different schools in the Western Cape Province of South Africa (Burger, 2012). Two parcels were formed by taking the mean of the even-numbered and the mean of the uneven-numbered items of the scale to operationalise *Academic self-efficacy*.

3.8.7 Personality (Conscientiousness and Openness to experience)

The Big Five personality factors were assessed with an International Personality Item Pool (IPIP) measure. The IPIP is a measure of the Big Five personality dimensions taken from the International Personality Item Pool (Goldberg, 1999; Goldberg, 2001; Goldberg, Johnson, Eber, Hogan, Ashton, Cloninger & Gough, 2006). The scales were designed to use a lexical-type item format that is more contextualized than simple trait adjectives. The IPIP was designed to be a more precise, compact method for assessing the Big Five than are items in many standard personality measures (Goldberg, 1999). The instrument contains a total of 50 items (both positively- and negatively-keyed) that are presented in brief statements. Each personality dimension includes 10 items. The negatively worded items were reverse coded. All responses were made on a five-point scale ranging from 1 = very inaccurate to 5 = very accurate. The Cronbach alpha values for the IPIP-BFD subscales are: *Extraversion* (α = .86), *Agreeableness* (α = .81), *Neuroticism* (α = .85), *Conscientiousness* (α = .77), and *Openness to experience* (α = 0.80) (Gow, Whiteman, Pattie, & Deary, 2005; Jensen-Campbell, Rosselli, Workman, Santisi, Rios & Bojan, 2002). The scales in the IPIP have been shown to correlate highly with the corresponding NEO-PI-R domain scores, with correlations that range from .85 to .92 when corrected for unreliability (International Personality Item Pool, 2001). Due to the nature of structural model only the *Conscientiousness* and *Openness to experience* subscales were used. Two parcels were formed by taking the mean of the even-numbered and the mean of the uneven-numbered items of the *Conscientiousness* and *Openness to experience* subscales to operationalise these two latent variables.

3.8.8 Self-Leadership

Academic self-leadership was measured using the Revised Self-Leadership Questionnaire (RSLQ) developed by Houghton and Neck (2002). The RSLQ comprises nine factors namely (Houghton & Neck, 2002): self-goal setting; self-reward; self-punishment; self-observation; self-cueing; natural rewards; visualising successful performance; self-talk and evaluating belief and assumptions. The RSLQ demonstrates great factor stability and significantly high factor reliabilities. The reliabilities of the nine underlying subscales range from .74 to .93. The instrument contains 35 item statements scored using a 5-point Likert scale ranging from 1 (not at all accurate), 2 (somewhat accurate), 3 (a little accurate), 4 (mostly accurate) and 5 (completely accurate). According to Houghton and Neck (2002), the RSLQ items can be categorised in three groups namely behaviour-focused self-leadership, constructive thought self-leadership and natural reward self-leadership. Behaviour-focused self-leadership can be measured with five subscales identified as self-goal setting (5 items), self-reward (3 items), self-punishment (4 items), self-observation (4 items), and self-cueing (2 items). Natural reward self-leadership is measured with a single 5-item scale and constructive thought self-leadership is measured with three subscales comprising visualising successful performance (5-items), self-talk (3-items) and evaluating beliefs and assumptions (4-items). Items 6, 15, 24 and 30 from the self-punishment scale were excluded from the self-punishment scale as advised by Jeffery Houghton (J. Houghton, personal communication, 31 March 2011). Norris (2008) reported Cronbach's alpha coefficients of .88 for behaviour focused, .78 for natural reward, .88 for constructive thought and .93 for general self-leadership. Eight Item parcels were formed by taking the mean of the items of each of the subscales to operationalise *Self-leadership*.

3.8.9 Metacognition

The longer version of the Awareness of Independent Learning Inventory (AILI) devised by Elshout-Mohr, Meijer, van Daalen-Kapteijns and Meeus (2004) was used. The instrument was constructed for use in higher education. According to Vrugt and Oort (2008), the AILI has been shown to be a reliable and valid measure of metacognition related to academic learning tasks. A generalization study indicated that the findings could be generalized to a broader range of metacognitive components and topics of concern than were actually included in the questionnaire. A decision-study indicated that an abbreviated version of AILI would not lead to a serious loss in generalisability (Elshout-Mohr *et al.,* 2004; Meijer, Elshout-Mohr, van Daalen-Kapteijns & Meeus, 2003; Elshout-Mohr, van Daalen-Kapteijns, Meeus & Tempelaar, 2006; Vrugt & Oort, 2008). Hence the shortened version of the AILI was released, which consists of 45 items (half of the items are presented in reversed format) that measure *Knowledge of cognition* (knowledge about persons, strategies and study tasks), *Regulation of cognition* (planning, monitoring and evaluation) and responsiveness (representing metacognitive experience). The responsiveness items were left out. An example of a *Knowledge of cognition* item is: 'When students find it difficult to gain insight into the material to be studied, I know ways to solve this.' An example of a *Regulation of cognition* item is: "When I start with a text I first ask myself what I will need to do in order to study the text thoroughly.' Participants indicated their response to each item on a 1 (not at all true of me) to 7 (very true of me) scale. The Cronbach alpha coefficient for the 45 items was .88. Item parcels were formed by taking the mean of the items of each of the subscales to operationalise *Regulation of cognition* and *Knowledge of cognition*.

3.8.10 Time cognitively engaged

The Academic Engagement Scale for Grade School Students (AES-GS) constructed by Tinio (2009) was adapted and used to measure *Time cognitively engaged*. According to Tinio (2009) engagement is associated with how much the student invests in his education and the AES-GS was devised to measure the level of engagement of a learner in his or her education. Tinio (2009) administered the AES-GS to 250 sixth and seventh graders. The Academic Engagement Scale for Grade School Students (AES-GS) has a reliability of α = .89. Burger (2012) added a time component to the scale in order to measure the 'quantity' aspect of *Time Cognitively Engaged* and not only the 'quality' aspect of the construct. The scale, therefore, not only measures whether the learner is engaged cognitively with his or her study material but also whether the learner believes he/she spent enough time cognitively engaged with his or her learning tasks. Items pertaining to the time the learner spent cognitively engaged were included to see whether the learner set aside enough time, as well as made use of the time set aside in order to learn the study material. The *Time Cognitively Engaged* scale comprise 17 items measured using a 5 point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).The resultant *Time Cognitively Engaged scale* showed a reliability of α = .94 on a sample of 460 grade 11 learners from four different schools in the Western Cape Province of South Africa (Burger, 2012). Item parcels were formed by taking the mean of the items of each of the two factors obained in the EFA to operationalise *Time Cognitively Engaged*.

3.8.11 Learning goal orientation

A 13-item instrument developed and validated by Vande Walle (1997) was used to assess the *Academic learning goal orientation* of the participants. The instrument has three subscales: (a) four items that measure learning goal orientation, (b) four items that measure the proving dimension of a performance goal orientation and (c) five items that measure the avoiding dimension of a performance goal orientation. Only the learning goal orientation subscale was d in the present study. A 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree) was used for each of the items contained in the scale. Vande Walle (1997) reported Cronbach's alpha values for the instrument as: Learning goal orientation (α = .89); Proving goal orientation, (α = .85); and Avoiding goal orientation, (α = .88). Two parcels were formed by taking the mean of the even-numbered and the mean of the uneven-numbered items of the scale to operationalise *Learning goal orientation*.

3.8.12 The interaction between Prior learning and Abstract reasoning capacity

The manner in which the four indicator variables that represent the latent interaction between *Prior learning* and *Abstract reasoning capacity* were calculated when fitting the comprehensive LISREL model is explained in paragraph **3.9.5.1.7.**

3.8.13 The learning potential measurement model

Each latent variable in the abridged learning potential structural model was represented by two or more indicator variables when fitting the structural model as described in paragraphs 3.8.1 to 3.8.13 above.

3.9 STATISTICAL ANALYSIS

Item analysis, exploratory factor analysis (EFA), confirmatory factor analysis (CFA) and structural equation modelling (SEM) were used to analyse the data and to test the abridged learning potential structural model depicted in Figure 3.1. Item and exploratory factor analyses were performed using SPSS Version 21 while the LISREL version 8.80 was used to perform confirmatory factor analysis (CFA)[25] and to fit the comprehensive LISREL model.

3.9.1 Missing values

Before analysing the data for this study, the issue of missing values had to be addressed. The missing values problem is a common occurrence when self-reporting instruments are used. This problem is mostly due to non-responses (Mels, 2003). Addressing the problems of missing values entails choosing a method that does not have detrimental effects on the analysis for example through sample reduction. Furthermore, it must be ascertained that the mising values are missing at random, that is the mising observations on some variable X different from the observed scores on that variable only by chance (Kline, 2011). However, complications can arise if a systematic pattern exists in the distribution of the missing values. This may mean that incomplete cases differ from complete cases for some reason rather than randomly. Hence the way in which the missing values are handled may lead to biased results. The PRELIS module available in LISREL has the capablilities for analysing missing data patterns. Several ways of dealing with missing values exist namely: case-wise methods (listwise and pairwise deletion); single-imputation-methods such as mean substitution, group substitution, regression based imputation, random hot deck imputation and imputation by matching (Kline, 2011) and multiple imputation (MI) and full information maximum likelihood estimation (FIML) (Jöreskog & Sörbom, 2006; Mels, 2003).

[25]Prior to testing the comprehensive LISREL model, a confirmatory factor analysis (CFA) was used to evaluate the fit of the measurement model (see Figure 3.2).

3.9.1.1 Case methods

3.9.1.1.1 Listwise deletion

According to Kline (2011), two kinds of case methods exist namely listwise and pairwise deletion. The listwise deletion is the traditional way of dealing with missing data values to generate a data set that only contains only the complete data cases (Mels, 2003). Listwise deletion discards any case that is missing a measurement on the variable(s) in which the researcher is interested (Myers, 2011; Pallant, 2010). In other words, cases with missing scores on any variable are excluded from all analyses even if it is missing one piece of information and this has severe repercussions for sample size (Pallant, 2010). Listwise deletion is advantageous in that all analyses are conducted with the same number of cases. In addition, it is easy to implement and is the default in many statistical packages, including SPSS and LISREL. However, its major limitation is that the researcher may be left with a very small data set (Mels, 2003).This attracted some negative comments from Harel, Zimmerman and Dekhtyar (2008) who described listwise deletion as "a method that is known to be one of the worst available" (p. 351).

3.9.1.1.2 Pairwise deletion

Pairwise deletion discards cases on an analysis by analysis basis and only when the estimate "requires" that variable (Myers, 2011). In other words, pairwise deletion excludes the case only if they are missing the data required for the specific analysis but they will still be included in any of the analyses for which the necessary information is available (Pallant, 2010). Thus, in a multiple regression practice, this means that different participants are included in the estimation of each separate regression coefficient. This can result in biased estimates, and at times, such a practice may lead to mathematically inconsistent results (Kim & Curry, 1977). It is also a possibility that with pairwise deletion no two terms in a covariance matrix are based on the same subset of cases and this can give rise to 'out-of-bounds covariances or correlations', for this reason, pairwise deletion is not generally recommended for use in SEM (Kline, 2011).

3.9.1.2 Single-imputation-methods

The imputation by matching is arguably one of the most popular of the single-imputation methods. Imputation by matching to solve the missing value problem is usually used if the assumption of multivariate normality is not met. Imputation by matching refers to a process of substituting of real values for missing values. The substitute values replaced for a case are derived from one or more other cases that have a similar response pattern over a set of matching variables (Jöreskog & Sörbom, 1996). The ideal scenario is to use matching variables that will not be d in the confirmatory factor analysis. The items least plagued by missing values are normally identified to serve as matching variables. By default, cases with missing values after imputation are eliminated. In the mean substitution variation, the missing score is replaced with the overall sample mean; in the group-mean substitution variation, the missing score in a particluar group (e.g. female) is replaced by the group mean while the regression-based imputation technique involves replacing each missing score with a predicted score derived using multiple regression based on non-missing scores on other variables (Kline, 2011). The random hot-deck imputation method separates complete from incomplete cases and derives replacements for missing values using variables from the closest complete record (Kline, 2011).

3.9.1.3 Multiple Imputation (MI) and Full Information Maximum Likelihood estimation (FIML)

To avoid a reduction in sample size, a possible product of the use of the case-wise and single-imputation methods, alternative methods of dealing with data containing missing values can be employed. Two such methods are multiple imputation (MI) and full information maximum likelihood (FIML) (Mels, 2003), available in LISREL 8.80 (Jöreskog & Sörbom, 2006). The ideal method probably would be to use a multiple imputation procedure (Du Toit & Du Toit, 2001; Mels, 2003). The advantage of both the two multiple imputation procedures available in LISREL 8.80 is that estimates of missing values are derived for all cases in the initial sample (i.e., no cases with missing values are deleted) and the data set is available for subsequent item and dimensionality analyses, and the formation of item parcels (Du Toit & Du Toit, 2001; Mels, 2003). Although the full information maximum likelihood (FIML) estimation procedure is more efficient than the available multiple imputation procedures (Du Toit & Mels, 2002; Mels, 2003), no separate imputed data set is created which thus prevents the aforementioned preliminary analyses on the imputed data. The multiple imputation procedures available in LISREL 8.80 however, assume 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). Mels (2010) suggests that multiple imputation may be used even when the foregoing assumptions are not met. As long as the observed variables are measured on a scale comprising five or more scale values, the observed variables are not excessively skewed (even though the null hypothesis of multivariate normality has been rejected) and less than 30% of the data constitute missing values. As a result of the constraints encountered in obtaining a significantly large sample size, the multiple imputation technique was d in order to save as many data cases as possible since the current sample is marginally above the minimum required sample size of 200 for most SEM analyses (Diamantopoulos & Siguaw, 2000).

3.9.2 Item analysis

Item analyses entails eliminating items that appear to be unrelated to the total subscale score or that have a low relationship with it. The main aim of conducting item analysis is to increase the homogeneity of the components of the subscale, and in the process enhance the content validity of the subscale. The main aim of a test is to measure the same trait hence the individual item scores of the subscale should be positively correlated, with moderately high intercorrelations (Ghiselli, Campbell & Zedeck, 1981). Item analysis was conducted using the reliability-analysis procedure available in SPSS version 21. Through this procedure, the classical measurement theory item statistics such as: the item-total correlation, the squared multiple correlation, the change in subscale reliability when the item is deleted, the change in subscale variance if the item is deleted, the inter-item correlations, item mean and the item standard deviation were calculated. An item was excluded from further analyses if it had an item-total correlation value less than .3 and would result in a significant increase in the scale reliability coefficient when deleted (Pallant, 2010). The use of item response theory (IRT) item analysis in addition to the classical measurement theory item analysis procedures would have been preferable. However, due to the sophisticated procedures involved in IRT item analysis, the researcher deemed it fit to stick only to the classical measurement theory item analysis procedures. Nunnally's (1967) guidelines were used to determine levels of reliability for the scales as indicated in Table 3.2.

Table 3.2
General guidelines for interpreting reliability coefficients

Reliability coefficient value	**Interpretation**
0.9 and above	excellent
0.80 – 0.89	good
0.70 – 0.79	adequate
below 0.70	may have limited applicability

(Nunnally, 1967, p. 206)

3.9.3 Dimensionality analysis using exploratory factor analysis (EFA)

EFA is exploratory in nature and is usually performed when no a priori restrictions have been placed on the patterns of relationships between the observed measures and the latent dimensions (Brown. 2006). It is used to identify relatively independent and coherent subsets of data that are correlated with one another and denoted as factors (Tabachnick & Fidell, 2001). Most of the instruments used in the present study, are standard instruments with a predetermined factor structure that has been theoretically determined. It must be noted that the aim of the EFA in the current study was to ascertain the uni-dimensionality of each scale and not to explore the factor structure of measures, which would have been inappropriate if CFA was to follow (Hair *et al.*, 2010). To confirm the uni-dimensionality of each of the scales prior to CFA (Williams *et al.*, 2009), unrestricted principal axis factor analyses with direct oblimin rotation were performed. Principal axis factoring (PAF) was preferred over principal component factor analysis (PCA) as it only analyses common variance shared between the items comprising a subscale in contrast to PCA which analyses all the variance (Tabachnick & Fidell, 2001). Direct oblimin rotation is one of the oblique methods for conducting EFA. Oblique methods allow the factors to be correlated. This is essential in the social sciences where one expects some correlation among the factors hence oblique rotations are likely to theoretically lead to a more accurate solution (Basto & Pereira, 2012). When using oblique rotation, the *pattern matrix* is examined for factor loadings (Costello & Osborne, 2005; Tabachnick & Fidell, 2001).

The eigenvalue-greater-than-unity rule of thumb was used to determine the number of factors to extract. Although the use of this rule is the default in SPSS, there is a general consensus in literature that this is one of the least accurate methods for selecting the number of factors to retain (Velicer & Jackson, 1990). In order to increase the credibility of the factors retained, the scree-test was also used. The scree-test involves examining the graph of the eigenvalues in search for the natural bend or break point in the data where the curve flattens out (Costello & Osborne, 2005).

The decision rules that were followed to determine the number of factors to be extracted, and the items to be included in each factor when conducting exploratory factor analyses were as follows:

- ❖ The number of factors to be extracted should not be more than the number of eigenvalues greater than 1.00, according to Kaiser's (1961) criterion.
- ❖ An item not loading greater than .30 on any factor will be excluded (Field, 2005; Pallant, 2010; Tabachnick & Fidell, 2001).
- ❖ An item loading greater than .30 on more than one factor would be excluded if the difference between the higher and the lower loading was less than .25 (Nunnally & Bernstein, 1994; Tabachnick & Fidell, 2001).
- ❖ A Kaiser-Meyer-Olkin measure of sampling adequacy (KMO index) value close to 1, indicating that patterns of correlations are relatively compact and therefore factor analysis should present distinct and reliable factors (Field, 2005). The cut-off value d in this study was .7. Kaiser (as cited in Field, 2005) recommends accepting values greater than .5 as acceptable, values between .5 and .7 as mediocre, and values between .7 and .8 as good while values between .8 and .9 are great and values above .9 are superb.

3.9.4 Structural equation modelling (SEM)

Structural equation modelling, using robust maximum likelihood estimation, was used to perform a confirmatory factor analysis on the observed inter-item covariance matrix. SEM is a collection of statistical techniques that allow a set of relationships between one or more independent and dependent variables (Tabachnick & Fidell, 2001). It is a large sample technique that helps to explain the patterns of covariances found amongst the observed variables in terms of the relationships hypothesised by the measurement and structural models (Diamantopoulos & Siguaw, 2000). SEM models can be broken down into (1) the measurement which specifies the number of factors, how the various indicators are related to the latent variable (a confirmatory factor analysis model) and (2) the structural model, which specifies the relationships between the latent variables (Brown, 2006). The comprehensive LISREL model refers to the combined measurement and structural models. SEM is very beneficial in the testing and specification of complex models (Kelloway, 1998). It is also a powerful method that can be used to determine the quality of the measurement through the confirmatory factor analysis technique available in SEM. This special SEM technique is discussed next.

3.9.4.1 Confirmatory factor analysis

In the theorising phase while building the model specific connotative meaning was attached to each construct. Specific indicator variables were generated to reflect each construct as it was constitutively. This design intention is captured in a measurement model. The measurement model describes the manner in which the indicator variables are meant to reflect the specific underlying latent variables that they were earmarked to represent. The goodness-of-fit of the measurement model was tested through the use of the confirmatory factor analysis technique available in LISREL 8.80 (Jöreskog & Sörbom, 2006). Confirmatory factor analysis (CFA) serves to confirm whether a set of measures (the observed data) are in fact related to specific latent variables according to the form described in the measurement model (Blaikie, 2003) by producing a series of fit indices. These indices allow the researcher to establish how well the measurement model with its parameter estimates fits the observed data. In CFA, the number of factors/latent variables and the pattern of indicator-factor loadings are specified in advance. The pre-specified factor solution is evaluated in terms of how well it reproduces the sample covariance matrix of the measured variables (Brown, 2006). Standard CFA models have basically three characteristics namely: (1) each indicator is a continuous variable represented as having two causes, that is, a single latent variable/factor that the indicator is supposed to measure and all other unique sources of influence (omitted causes) represented by the measurement error term; (2) the measurement errors are independent of each other and of the latent variables/factors; and (3) all the associations between the latent variables/factors are assumed to covary (Kline, 2011). For the purposes of confirmatory factor analysis the measurement model was treated as an exogenous model simply due to programming advantages. The imputed data in the form of parcels was first read into PRELIS (Jöreskog & Sörbom, 1996) to compute a covariance matrix and an asymptotic covariance matrix to serve as input for the LISREL analysis. Robust maximum likelihood estimation was used to estimate the parameters set free in the model because of the lack of multivariate normality in the data.

Evaluating the fit of the measurement model by means of confirmatory factor analysis involves a five phase process. The five steps through which the SEM analysis proceeds are as follows (Hair, Black, Babin, Anderson & Tatham, 2010; Kelloway, 1998):

- ❖ Model specification
- ❖ Evaluation of model identification
- ❖ Estimation of model parameters
- ❖ Testing model fit
- ❖ Model re-specification

3.9.4.1.1 Model specification

Model specification involves determining every relationship and parameter in the model that is of interest to the researcher. The main goal of the researcher is to determine the theoretical model that generates the sample variance-covariance matrix (Schumacher & Lomax, 2004. p. 238). In SEM context, the parameters that require specification are variables that indicate the nature of the relationship between two variables. Although specification can be quite specific regarding both the magnitude and sign of parameters, parameters typically are specified as either fixed or free. Fixed parameters are not estimated from the data and their value typically is fixed at zero. Free parameters are estimated from the data and are those the researcher believes to be non-zero. The various indices of model adequacy, particularly the chi-square goodness-of-fit test, indicate the degree to which the pattern of fixed and free parameters specified in a model is consistent with the pattern of variances and co-variances from a set of observed data. The manner in which the responses of respondents to the collection of items combined in the various composite indicators are hypothesised to be related to the underlying latent learning performance is graphically depicted as a specific measurement model (see Figure 3.1).

3.9.4.1.2 Model identification

Model identification entails ensuring that the model is identified in order to ascertain that sufficient information is available to obtain a unique solution for the freed parameters to be estimated and tested in the model. Two critical conditions are necessary for model identification. Firstly, a definite scale should be established for each latent variable. This is achieved by treating each latent variable as a (0; 1) standardised variable (MacCallum, 1995). Secondly, in order to obtain a unique solution for the parameters, in structural equation modelling using LISREL, the number of independent parameters being estimated should be less than or equal to the number of non-redundant elements in the observed variance-covariance matrix (S), (Diamantopoulos & Siguaw, 2000, p. 48). This is summarised in the following equation: $\mathbf{t \leq s/2}$ where t = number of parameters to be estimated, s = the number of variances and co-variances among the manifest variables represented by the equation {(p+q)(p+q+1)} where p = the number of Y-variables representing the endogenous latent variables and q = the number of X variables representing the exogenous latent variables. In this case t= 116, p = 19, q = 21. Therefore the equation **t ≤ s/2** translates to **820.** This implies an over-identified model with 704 positive degrees of freedom.

3.9.4.1.3 Estimation of model parameters

3.9.4.1.3.1 Variable type

An important consideration in this study was whether to fit the measurement model by representing the thirteen latent variables comprising the abridged De Goede-Burger-Mahembe learning potential structural model with single items or to create item parcels. Various considerations related to the difference in psychometric characteristics, factor-solution and model-fit were taken into consideration to make this decision of whether item parcels should be used instead of single items.

Item parcelling involves combining items into small groups of items within scales or subscales (Holt, 2004). A parcel can be defined as an aggregate-level indicator comprised of the sum (or average) of two or more items, responses, or behaviours (Little, Cunningham, Shahar & Widaman, 2009). Parcels are normally created to (1) increase the stability of the parameter estimates, (2) improve the variable to sample size ratio, and (3) to remedy small sample sizes (Bandalos & Finney, 2001). Various researchers generally agree that the use of item parcels results in better fitting solutions, as measured by the root mean squared error of approximation (RMSEA), comparative fit index (CFI), and chi-square test, when items have a uni-dimensional structure (Bandalos, 2009; Little, Cunningham, Shahar & Widaman, 2009). Parcelled solutions also resulted in less bias in estimates of structural parameters under the uni-dimensionality condition than did solutions based on the individual items.

Little, Cunningham, Shahar, and Widaman (2002) list three reasons why parcelling can be advantageous over using the original items: 1) estimating large numbers of items is likely to result in spurious correlations, 2) subsets of items from a large item pool will likely share specific sources of variance that may not be of primary interest, and 3) solutions from item-level data are less likely to yield stable solutions than solutions from parcels of items.

Researchers also caution against the creation of parcels when the construct is multi-dimensional in nature (Bandalos, 2009; Little, Cunningham, Shahar & Widaman, 2009). If the latent construct is not uni-dimensional, it is likely that the item parcels are also multidimensional making it difficult to define what the latent construct actually is because the structure confounds the primary factor and systematic variance that is shared across parcels. When parcelling with multidimensional structures, the parcelling can mask many forms of model misspecification. The other caution pertaining to item parcelling is that the unstandardised parameters may be meaningful in clinical practice and that norms may be established based on the scale of the original items. However, these norms may not translate to the re-parameterised model with item parcels (Little, Cunningham, Shahar, & Widaman, 2002). Marsh, Hau, Balla, and Grayson (1998) and Yuan,

Holt (2004) recommends that researchers conducting item parcelling should:

1. Check the dimensionality of the factors to be parcelled to determine if there is a uni-dimensional or multidimensional factor structure. The factor structure should be confirmed through replication with multiple samples or with rationale review of item content.
2. Parcel items together that represent similar facets of a construct. If the factor is unidimensional, random methods of combining items can be used to create item parcels. If the factor is multidimensional, isolated parcelling strategies should be used to capture similar facets of the structure into the

same item parcel (i.e., different facets would be separated into different parcels.)

3. Check the normality/difficulty of the original items to be parcelled. If very non-normal, items should be combined in such a way as to maximise the normality of the resulting parcels. For continuous or ordered categorical items, this can be accomplished by combining items with opposite skew or distributional shape. For binary items, this can be accomplished by combining items with opposite item difficulties.
4. Parcel more items per parcel rather than more parcels, as long as the unidimensionality of each parcel can be preserved.
5. If the underlying structure to be parcelled is not known or not clear, do not parcel, as the parcelling may obscure the true underlying structure.

Operationalising the latent variables in the model with the individual items comprising the various instruments would have resulted in a model in which the number of parameters that need to be estimated exceed the available sample size. The available sample which consist of only 213 observations therefore necessitate the creation of item parcels. The most basic requirement is that the number of observations should at least have to exceed the number of parameters to be estimated (Jöreskog & Sörbom, 1996). Since this requirement has not been met the option of item parcelling was preferred. Two random parcels were created for each of the uni-dimensional scales representing a single latent construct. However, in the case of the self-leadership and metacognition latent constructs measured with different subscales, item parcels were created to reflect each of the sub-dimensions or subscales (see paragraphs 3.8.8 and 3.8.9).

3.9.4.1.3.2 Multivariate normality

The default method of estimation when fitting measurement models to continuous data (maximum likelihood), assumes multivariate normality. The inappropriate analysis of continuous non-normal variables in structural equation models can result in incorrect standard errors and chi-square estimates (Mels, 2003; Du Toit & Du Toit, 2001). The univariate and multivariate normality of the item parcels were consequently evaluated via PRELIS (Jöreskog & Sörbom, 1996).

Two possible solutions for the lack of normality in the data were investigated if the multivariate null hypothesis was be rejected. The first was to normalise the individual item parcels. If the normalization option failed to achieve multivariate normality, the use of an alternative method of estimation more suited to data not following a multivariate normal distribution was considered instead. Weighted least squares (WLS), diagonally weighted least squares (DWLS) and robust maximum likelihood (RML) are suggested to fit structural equation models to non-normal data (Du Toit & Du Toit, 2001; Jöreskog & Sörbom, 1998; Mels, 2003). Mels (2003) recommends the use of robust maximum likelihood estimation if the assumption of a multivariate normal distribution does not hold. If the normalisation has the effect of reducing the discrepancy between the observed distribution and the multivariate normal distribution, the normalised dataset will be used in the subsequent analysis.

3.9.4.1.4 Testing model fit

Model fit refers to the extent to which a hypothesized model is consistent with the data. In other words, it is the process through which the implied covariance matrix is gauged against the sample covariance matrix to determine the closeness between the two covariance matrices (Diamantopoulos & Siguaw, 2000). The aim of structural equation modelling is to determine how well the model “fits” the data of the underlying theory. More specifically the question is how well the model can account for the observed covariance matrix. If observed covariance matrix can be closely reproduced from the estimates obtained for the freed model parameters, the model fits the data. A wide variety fit indices are available to guide the researcher in this process of model fit. According to Brown (2006), the goodness of fit indices have been a subject of heated controversy with regards to recommended fit index cut-offs and this situation is further complicated by the fact that fit indices are often differentially affected by other aspects such as sample size, model complexity, estimation method, normality of data and amount and type of misspecification. Various cut-off values for these indices as well as the lack of agreement on which indices to report on might lead to conflicting information. Researchers should therefore use information with caution as model fit is one of the most important steps in the process of structural equation modelling (Diamantopoulos & Siguaw, 2000).

3.9.4.1.4.1 LISREL fit indices

A variety of fit indices are used to assess the model fit. These generally fall into three categories namely: absolute, comparative and parsimonious fit indices (Kelloway 1998). The assessment of the absolute fit of the model is concerned with the ability of the model to reproduce the actual covariance matrix. The assessment of the comparative fit of the model may be further subdivided into the assessment of comparative and parsimonious fit. The assessment of comparative fit, on the other hand, compares two or more competing models to assess which model provides the better fit to the data. The assessment of parsimonious fit is based on the recognition that one can always obtain a better fitting model by estimating more parameters. The LISREL programme version 8.80 (Jöreskog & Sörbom, 2006), reports 18 indices of model fit, of which four relate to absolute fit.

Absolute fit indices

The chi-square statistic

For the purpose of evaluating overall model fit, the minimum fit function chi-square value is traditionally used to determine the congruence or incongruence between the observed and reproduced sample covariance matrices. It provides a test of perfect fit in which the null hypothesis is that the model fits the population data perfectly. The chi-square statistic is used to test the exact fit null hypothesis (H_{01a}). This means that the model fits the data in the population perfectly and that the model can reproduce the observed covariance matrix in the population. Any discrepancy between the observed and reproduced covariance matrices in the sample is due to sampling error under the exact fit null hypothesis. A non-significant chi-square value (assuming a .05 significance level) will therefore indicate a good model fit. The normal theory chi-square statistic assumes multivariate normality and is very sensitive to sample size. Using large sample sizes might result in model rejections and in the case of small sample sizes, chi-square lacks the power to discriminate between a good fit and a poor fit (Hooper et al., 2008). The Satorra Bentler chi square that results from the use of robust maximum likelihood parameter estimation is better suited to multivariate non-normal data (Mels, 2003). The Satorra Bentler chi square is mean-adjusted by dividing the normal theory chi-square by a scaling correction to enable it to better approximate chi-square under non-normality (Brown, 2006). The use of the chi-square as a goodness-of-fit index has been affected by its known sensitivity to departures from multivariate normality (particularly excessive kurtosis), variations in sample sizes, and the assumption that the model fits perfectly in the population (Diamantopoulos & Siguaw, 2000).

Root mean square error of approximation (RMSEA)

The root mean square error of approximation (RMSEA) shows how well a model with unknown but optimally chosen parameter values fits the population covariance matrix if it is available. The RMSEA is a measure of closeness of fit and is generally regarded as one of the most informative fit indices. When assessing the RMSEA, values less than .05 are indicative of good fit, those between .05 and under .08 of reasonable fit, values between .08 and .10 indicate mediocre fit and those above .10 indicate poor fit (Diamantopoulos & Siguaw, 2000). The sample RMSEA estimate is used to test the close fit null hypothesis (H_{01a}). Failure to reject the close fit null hypothesis would mean that the position that the measurement model fits closely in the parameter is a permissible position.

Root mean square residual (RMR) and standardised root mean square residual (SRMR)

Another fit index provided by LISREL program is the root mean squared residual (RMR), which is a summary measure of fitted residuals and presents the average value of the difference between the sample covariance (variance) and a fitted (model-implied) covariance (variance). The main drawback inherent in the interpretation of the fitted residuals (and therefore the RMR statistic) is that their size varies with the unit of measurement and the RMR varies from variable to variable. This problem is resolved by concentrating on the standardised residuals, which are the fitted residuals divided by the estimated standard errors. A summary measure of standardised residuals is the standard RMR; values below .05 are indicative of acceptable fit (Diamantopoulos & Siguaw, 2000).

The goodness-of-fit (GFI) and the adjusted goodness-of-fit index (AGFI)

The goodness-of fit statistic was created by Jöreskog and Sorböm (2003) to serve as an alternative to the Chi-square. The goodness-of-fit (GFI) is an indicator of the relevant amount of variances and covariances accounted for by the model and, hence, show how closely the model comes to perfectly reproduce the observed covariance matrix. The adjusted goodness-of-fit index (AGFI) is the GFI adjusted for the degrees of freedom in the model, while the parsimony goodness-of-fit index (PGFI) makes a different type of adjustment to take model complexity into account.

The values of the GFI and AGFI should range between 0 and 1 and values greater than .90 are usually interpreted as reflecting acceptable fit. Acceptable values for the PGFI are much lower, within the .50 region (Mulaik, James, Van Alstine, Bennet, & Stilwell, 1989). Generally, the goodness-of-fit index (GFI) is recommended as the most reliable measure of absolute fit (Diamantopoulos & Siguaw, 2000).

Relative fit indices

The next set of fit indices to be discussed is the relative fit indices, which show 'how much better the model fits compared to a baseline model, usually the independence model[26]'. The relative fit indices which are also sometimes referred to as the comparative fit indices deal with the question whether the model under consideration is better than some competing model (Kelloway, 1998). With the exception of the non-normed fit index (NNFI) all the indices in this group have a range between 0 and 1, with values closer to 1 representing good fit. The NNFI can take a value greater than 1 and lower values of the PNFI are expected in relation to the non-parsimonious NFI (Diamantopoulos & Siguaw, 2000).

The normed fit index

The normed fit index (NFI) evaluates the estimated model by comparing the chi square (χ^2) value of the model to the χ^2 value of the independence model (Bentler, 1980). The NFI also indicates the percentage improvement in fit over the baseline independence model. The values of the NFI lie between 0 and 1. The major drawback of the NFI is that it tends to underestimate the fit of the model in good fitting models with small samples (Bearden, Sharma & Teel, 1982; Tabachnick & Fidell, 2001). Acceptable cut-off values of the NFI are ≥ .95 (Hooper, Coughlan & Mullen, 2008; Hu & Bentler, 1999).

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[26] The null or independence model is a model that specifies no relationships between the variables composing the model (Kelloway, 1998).

The non-normed fit index (NNFI)

The non-normed fit index (also known as the Tucker-Lewis index) adjusts the NFI by incorporating the degrees of freedom in the model (Tabachnick & Fidell, 2001). This adjustment reduces the NFI's problem of underestimating the fit in extremely good fitting models although the NNFI sometimes yield values outside the 0 and 1 range. However, in situations were small samples are used, the value of the NNFI can indicate poor fit despite other statistics pointing towards good fit (Bentler, 1990; Hooper, Coughlan & Mullen, 2008; Kline, 2005; Tabachnick & Fidell, 2007). Another problem with the NNFI is that due to its non-normed nature, values can go above 1.0 and can thus be difficult to interpret (Byrne, 1998). Researchers usually interpret NNFI values greater than .95 as reflecting acceptable fit.

The comparative fit index (CFI)

The comparative fit index assesses the fit relative to other models. The CFI is a revised form of the NFI but takes sample size into consideration. Similar to the NFI, this index also assumes a base-line model in which all latent variables are structurally unrelated. CFI values greater than .90 are indicative of good fit (Diamantopoulos & Siguaw, 2000; Tabachnick & Fidell, 2001). However, other studies have shown that a value greater than 0.90 is needed in order to ensure that mis-specified models are not accepted (Hu & Bentler, 1999). From this, a value of CFI greater than or equal to .95 is presently recognised as indicative of good fit (Hu & Bentler, 1999).

The expected cross-validation index (ECVI)

The expected cross-validation index (ECVI) expresses the difference between the reproduced sample covariance matrix derived from fitting the model on the sample at hand and the expected covariance matrix that would be obtained in an independent sample of the same size from the same population (Diamantopoulos & Siguaw, 2000). The ECVI is expected to be smaller than the value obtained for the independence model and the ECVI value associated with the saturated model in order to have a better chance of being replicated in a cross validation sample.

3.9.4.1.4.2 Interpreting the variance-covariance residuals

The essential objective of structural equation modelling is to find estimates for the freed model parameters that would minimize the difference between the estimated covariance matrix implied by the hypothesised model and the observed sample covariance matrix. Discrepancies between the two are captured in the residual covariance matrix (Byrne, 1998).

Standardised residuals are considered large when they exceed +2.58 or -2.58 (Diamantopoulos & Siguaw, 2000). Large positive residuals indicate that the model underestimates the co-variance between two variables and negative residual shows that the model overestimates the covariance between variables (Jöreskog & Sörbom, 1993). Underestimation indicates that the model needs to be modified by adding additional paths, which could better account for the observed covariances between the items. If the model tends to overestimate the observed covariances between the variables, the model should be modified by trimming paths that are associated with the particular terms (Jöreskog & Sörbom, 1993).

3.9.4.1.5 Interpretation of the measurement model parameter estimates

If the close fit null hypothesis (H_{01b}) is not rejected, or alternatively if the measurement model at least demonstrates reasonable model fit, the following null hypotheses would be tested with regards to the freed elements in **Λ**:

H_{0i}: $\lambda_{jk}=0$; i =15, 16,..., 54 j=1, 2....40 k=1, 2.....13

H_{ai}: $\lambda_{jk}>0$; i =14, 15,..., 54; j=1, 2...40; k=1, 2.....13

If the close fit null hypothesis (H_{01b}) is not rejected, or alternatively if the measurement model at least demonstrates reasonable model fit, the following null hypotheses would be tested with regards to the freed elements in Θ_δ:

H_{0i}: $\Theta_{\delta jj}=0$; i =55, 56,..., 94 j=1, 2.....40

H_{ai}: $\Theta_{\delta jj} > 0$; i =55, 56,..., 94; j=1, 2.....40

If the close fit null hypothesis (H_{01b}) is not rejected, or alternatively if the measurement model at least demonstrates reasonable model fit, the following null hypotheses would be tested with regards to the freed elements in Φ:

H_{0i}: $\phi_{jk}=0$; i =95, 96,..., 172 j=1, 2.....13; k=1, 2.....13

H_{ai}: $\phi_{jk} > 0$; i =95, 96,..., 172; j=1, 2.....13; k=1, 2.....13

3.9.4.1.6 The squared multiple correlations (R^2)

The squared multiple correlations (R^2) of the indicators depict the extent to which the measurement model is adequately represented by the observed variables (Byrne, 1998). The squared multiple correlations show the proportion of variance in an item that is explained by the underlying latent variable. A high R^2 value would indicate that variance in the indicator under discussion reflects variance in the latent variable to which it has been linked to a large degree.

3.9.4.1.7 Measurement model modification indices

Modification indices (MI) indicate the extent to which the chi-square fit statistic decreases when a currently fixed parameter in the model is freed and the model re-estimated (Jöreskog & Sörbom, 1993). Large modification index values (> 6.6349 at a significance level of .01) are indicative of parameters that, if set free, would improve the fit of the model significantly ($p < .05$) (Diamantopoulos & Siguaw, 2000; Jöreskog

& Sörbom, 1993). It is important to note that parameters with high MI values should only be freed if it makes substantive sense to do so (Kelloway, 1998). The expected change for the parameter is the expected value of the parameter if it is freed. The standardised and completely standardised expected changes are the expected values in the standardised and completely standardised solution if the parameter were freed. According to Jöreskog and Sörbom (1993), modification indices should be used in the process of model evaluation and modification (1) when the chi-square is large relative to the degrees of freedom, in which case one examines the modification indices and relaxes the parameter with the largest modification index if this parameter can be interpreted substantially (2) if it does not make sense to relax the parameter with the largest modification index, in which case one considers the second largest modification index, etc., and (3) if the signs of certain parameters are specified *a priori*, positive or negative, the expected parameter changes associated with the modification indices for these parameters can be used to exclude models with parameters having the wrong sign.

3.9.4.1.8 Discriminant validity

The latent variables comprising the abridged De Goede-Burger-Mahembe learning potential structural model are interpreted as conceptually distinct but causally related constructs. The question arises whether the scales that are used to measure these constructs reflect/acknowledge this assumption. Discriminant validity is the extent to which a latent variable is able to discriminate itself from other latent variables. It means that a latent variable is able to account for more variance in the observed variables associated with it compared to the variance from (a) measurement error or similar external, unmeasured influences; or (b) other constructs within the conceptual framework (Farrell, 2010). Discriminant validity essentially refers to the extent to which latent variables that are conceptualised to be qualitatively distinct but inter-related (i.e., correlated) constructs actually measured as distinct constructs. Discriminant validity attempts to ascertain whether the latent variables are measured in a manner that does not imply that two or more conceptually distinct latent variables correlate perfectly. If two or more latent variables would correlate to unity it would imply that they are a single construct. Theoretically one would expect the latent variables in the measurement model to correlate. The correlations between latent variables should, however, not be excessively high. If the discriminant validity is high, it means that the correlations between the latent variables are sufficiently low to warrant the conclusion that the latent variables were successfully operationalised as qualitatively distinct constructs.

According to Shiu, Pervan, Bove and Beatty (2011), the reasons for establishing discriminant validity differ according to the purpose of the research. For instance, in order to ascertain the multi-dimensional nature of a given scale there is a need to establish the discriminant validity among the sub-dimensions of the scale to ensure the multi-dimensionality of the scale. A minimum condition in assessing the psychometric properties of such a scale requires that the dimensions are all unique (i.e., not perfectly correlated). Shiu *et al.*, (2011) further affirm that the target for discriminant validity is not that the *sample* should exhibit discriminant validity among the sub-dimensions of the scale, but that discriminant validity within the proposed multi-dimensional scale needs assessment *at the population level*, taking into account the effects of sampling.

One of the reasons for assessing discriminant validity concerns the need to address multi-collinearity in causal models within structural equation modelling (SEM) (Shiu, Pervan, Bove & Beatty, 2011). Multi-collinearity poses a problem if high correlations exist among the exogenous constructs. Analogous to regression, multicollinearity produces inaccurate estimates of the regression coefficients and standard errors. According to Grewal, Cote and Baumgartner (2004), multi-collinearity (correlations between the exogenous constructs) can cause problems when it is extreme (around .95). In addition, when multicollinearity is less severe (between .6 and .8), problems can still arise if construct reliability is weak (<.7), R^2 is low (<.25), and the sample size is small (ratio less than 3:1). The authors state that even when multicollinearity ranges from .6 to .8, the problem becomes negligible when composite reliability reaches .80, R^2 attains .75 and the sample size is relatively large (ratio greater than 6:1).

3.9.4.1.8.1 Methods for the assessment of discriminant validity

Various methods for investigating discriminant validity exist. These include the paired constructs test, the average variance extracted versus shared variance test and the multi-trait-multi-method matrix (MTMM). Although various methods are discussed, the average variance extracted versus shared variance test technique and the 95% confidence interval technique for the correlation between two constructs were used in this study to ascertain discriminant validity because of their ease of application and extensive use in the social science and marketing (Farrell, 2010). Furthermore, the method relies on using structural equation modeling (SEM) which enables a researcher to account for measurement error in variables (Bollen, 1989) through the use of the CFA correlation matrix (Φ) which offers a stringent evaluation of the AVE versus squared correlation test.

3.9.4.1.8.2 The paired constructs test

The paired constructs test involves constraining the covariance (i.e., ϕ_{ij}) parameter estimate for two factors to 1.0 (constrained model) which is compared to a model where this parameter is freely estimated (unconstrained model) (Anderson & Gerbing, 1988). The correlation between the target pair of constructs is constrained to unity (Shiu, Pervan, Bove & Beatty, 2011). This test is performed and run for every possible pairing of constructs in a study and discriminant validity is ascertained if the unconstrained model with a degree of freedom less than the constrained model obtains a chi-square value that is at least 3.84 lower than the constrained model so that the two factor solution provides a statistically significantly ($p<.05$) better fit to the data (Farrell, 2010). In other words, a chi-square difference value greater than 3.84 allows for the rejection of the null hypothesis that the correlation between the pair of constructs is equal to unity at the 5% significance level.

Bagozzi, Yi and Phillips (1991) proposed a procedure to ascertain discriminant validity through the examination of the confidence intervals for the estimated correlations between pairs of constructs. If the 95% confidence interval for the correlation between two constructs does not contain unity it indicates that two constructs are distinct and therefore show discriminant validity. If the confidence intervals contains zero, it shows that the pair of constructs is totally distinct or nearly so (Bagozzi *et al.* 1991). Stated differently the discriminant validity will be investigated by calculating the 95% confidence intervals for each of the correlations in the Φ matrix using an Excel macro developed by Mels (2010). If the 95% confidence interval for any ϕ_{ij} would contain unity the discriminant validity of the scales involved would be seriously compromised.

3.9.4.1.8.3 The average variance extracted versus shared variance test

Fornell and Larcker (1981) proposed a procedure which compares the squared correlation between a pair of constructs against the average variance extracted (AVE) for each of the two constructs. If for each pair of constructs the squared correlation is smaller than the AVEs then discriminant validity is ascertained. This procedure is anchored on the basis/assumption that each construct should correlate more strongly with its own set of indicator variables than with a qualitatively distinct albeit related construct. The AVE was calculated using the formula (Diamantopoulos & Siguaw, 2000) depicted as Equation 3.10.

-------------------------[3.10]

Where

λ = indicator loadings (completely standardised factor loadings)

θ = indicator error variances (i.e. variances of the δ's or ε's

Σ = summation of the item

3.9.4.1.8.3 The multi-trait-multi-method matrix (MTMM)

The multi-trait–multi-method (MTMM) matrix permits examination of the convergent and discriminant validity of psychological measures (Campbell & Fiske, 1959). MTMM analyses are particularly important in the social sciences as indirect measurement methods are common, such as informant ratings, and resulting manifest variables may contain more variance due to method of data collection than the trait being assessed (Grimm, Pianta & Konold, 2009). The MTMM method can be used when multiple traits are examined simultaneously and each of them is assessed by a set of different measures or measurement methods (Raykov, 2011). The MTMM design entails the assessment of multiple traits crossed with multiple methods of data collection, and a systematic exploration of MTMM data enables estimation of trait-related variance and variance reflecting systematic measurement bias related to method of assessment (Grimm, Pianta & Konold, 2009). The fact that this study does not offer different measures for each construct precludes the use of the multi-trait–multi-method to investigate the discriminant validity of the measures of the latent variables comprising the learning potential structural model.

3.9.4.1.9 *Evaluating the success of operationalising the structural model*

The operationalisation of the latent variables comprising the abridged De Goede-Burger-Mahembe learning potential structural model will be considered successful if:

- The close fit null hypothesis (H_{01b}) is not rejected (p>.05) , or alternatively if the measurement model at least demonstrates reasonable model fit;
- H_{0i}: $\Theta_{\delta jj}$ =0; i =55 +1, 56,..., 94 j=1, 2.....40are rejected (p<.05);
- H_{0i}: $\Theta_{\delta jj}$ =0; i =55, 56,..., 94 j=1, 2.....40are rejected (p<.05);
- H_{0i}: ϕ_{jk} =0; i =95, 96,..., 172 j=1, 2.....13; k=1, 2.....13
- The completely standardised factor loadings (λ_{ij}) are equal to or larger than .71;
- The completely standardised error variances (θ_{ii}) are equal to or smaller than .50
- The 95% confidence intervals calculated for the inter-latent variable correlations ($ø_{ij}$) do not contain unity.

3.9.5 Fitting of the comprehensive LISREL model

Structural equation modelling (SEM) techniques allow for the specification and testing of complex "path" models that incorporate the sophisticated understanding of complex phenomena. It provides a unique analysis that simultaneously considers questions of both measurement and prediction (Kelloway, 1998). Although the steps involved in conducting SEM are almost similar to those involved when conducting CFA, SEM goes further by specifying the structural relationships among the latent variables in the model. CFA deals with the measurement model while SEM relates to the structural model. The measurement model describes how each latent variable is operationalised by corresponding manifest indicators while the structural model describes the relationships between the latent variables themselves (Diamantopoulos & Siguaw, 2000). When the measurement model and the structural model are combined in a single model the comprehensive LISREL model is obtained. The fit of the structural model cannot be directly evaluated as such. The measurement model is fitted to data and the comprehensive LISREL model is fitted to data. Inferences about the fit of the structural model are derived from a comparison of the fit of the measurement model and the comprehensive LISREL model.

A pertinent feature of the learning potential structural model hypothesised in Figure 3.1 is that *Prior Learning* is hypothesised to moderate the effect of *Abstract reasoning capacity* on *Learning performance* during evaluation.

3.9.5.1 Structural equation models of latent interactions

Theoretical models developed in the social sciences often contain latent variable interaction effects (Steinmetz, Davidov & Schmidt, 2011).This is also true of the learning potential structural model hypothesised in Figure 3.1. The testing of structural models containing interaction effects has for a long time been the Achilleshel of structural equation modeling.

The estimation of latent variable interactions has typically been conducted using similar methods used in moderated regression with observed variables. SEM essentially uses the same method as in moderated multiple regression (Kline, 2011). Both methods rely on the creation of a product interaction term. This method is also used to estimate curvilinear relations except that the curvilinear product terms are created by exponentiation where the scores (base numbers) are raised to a power or polynomial term (Kline, 2011). One of the main drawbacks with such typical analyses of interactions is the failure to adequately control for measurement errors of explanatory variables which may result in blurred interactions (Busemeyer & Jones, 1983; Steinmetz, Davidov & Schmidt, 2011). Furthermore, a problem that can occur with the calculation of a product term is extreme collinearity as correlations between the product terms and their constituent variables can be so high that the results obtained are unstable or the analysis may fail (Kline, 2011). Several approaches for addressing latent variable interaction have been proposed starting with Kenny and Judd's (1984) seminal work.

3.9.5.1.1 The Kenny and Judd (1984) approach to latent interactions

Kenny and Judd (1984) were one of the pioneers to describe a method for estimating structural equation models with product indicators. Kenny and Judd (1984) formulated a nonlinear equation for estimating latent variable interactions: $y = \mu_y + \gamma_1 \xi_1 + \gamma_2 \xi_2 + \gamma_3 \xi_1 {*} \xi_2 + \zeta$ where ξ_1 and ξ_2 are latent variables (Algina & Moulder, 2001). In the Kenny–Judd covariance structure model, the indicator variables for ξ_1 and ξ_2 are population-mean-centered and products of these deviation score indicators are used as indicators of the latent product variable $\xi_1 {*} \xi_2$ (Algina & Moulder, 2001). The scores on non-product indicators are centered before creating product indicators (Kline, 2011). One strong limitation of the Kenny–Judd method was the need to impose several nonlinear constraints on the estimates, which increased the technical complexity of the method and hampered its application (Jackman, Leite & Cochrane, 2011). Most of the SEM software programs (e.g. Mplus, Mx, the TCALIS procedure of SAS/STAT and LISREL) are not able to support non-linear constraints. Non-linear constraints have to be specified in LISREL using its matrix-based programming language not SIMPLIS (Kline, 2011). Another complication of the Kenny - Judd method is that the product variable is not normally distributed even if each of its components are normally distributed. The measurement errors for their non-product indicators are also assumed to be normally distributed but the products of the product indicators are not normally distributed, which violates the normality requirement of default maximum likelihood estimation (Kline, 2011). There is also a need for large samples when estimating even relatively small models, minimum sizes of up to 400-500 cases may be required (Kline, 2011). These considerations makes the use of the Kenny – Judd procedure impractical.

3.9.5.1.2 The constrained approach to latent interactions

The constrained approach involves the inclusion of a latent product variable in an SEM model to represent the interaction term. The main characteristic of the constrained approach in the examination of an interaction between two latent variables is the specification of nonlinear constraints to express the mathematical relationships between the product indicators and the first-order effect indicators. These constraints include a list of several complex equations to be incorporated into the syntax of the model. The inclusion of these constraints implies that the parameters of the measurement model are not freely estimated but expressed in terms of the constrained parameters of the measurement model of the first-order effect variables (Steinmetz, Davidov & Schmidt, 2011).

3.9.5.1.3 The mean centred constrained approach

The mean centred constrained approach is based on Algina and Moulder's (2001) extension of earlier models by Jöreskog and Yang (1996). Jöreskog and Yang (1996) provided a general model for the specification of constraints. Their model relied on uncentered indicators, that is, they used indicators in their original format whose means were not centered to zero. Jöreskog and Yang (1996) argued that the appropriate models for latent interaction effects typically require the inclusion of a mean structure—a feature of their model that was not included by Jaccard and Wan (1995). The critical feature of the mean-centered constrained approach proposed by Algina and Moulder was that each of the indicators of the first-order term was mean-centered, but in other respects it was like the model proposed by Jöreskog and Yang (1996).

In 2001, Algina and Moulder revised and simplified the Jöreskog-Yang model by relying on centered indicators whose means were centered to zero. By centering the indicators, the Algina-Moulder approach allowed a researcher to ignore the intercepts and latent means (at least of the first-order effect variables).

3.9.5.1.4 The unconstrained mean-centered approach proposed by Marsh, Wen, and Hau (2004; 2006)

Marsh, Wen and Hau (2004) proposed an unconstrained successor to the Kenny–Judd method, which is simpler and more easily specified. Their method consisted of dropping the constraints from the model and mean-centering the observed indicators prior to constructing the products as proposed by Algina and Moulder (2001). Similar to the Kenny–Judd method, the unconstrained approach also assumes that the latent constructs and errors are normally distributed, but the product indicators have a non-normal distribution. Furthermore, the error and disturbance terms are assumed to be independent of each other and of the latent constructs, and uncorrelated. Marsh et al. (2004) argued that an important advantage of their unconstrained approach was that it was much easier for applied researchers to implement. Importantly, their simulation results demonstrated that their unconstrained approach typically resulted in similar results to the constrained approach when the assumptions of normality imposed by the constrained approach were met, but consistently performed better than the constrained approach when normality assumptions were violated.

3.9.5.1.5 Residual centering or orthogonalising strategy

The residual centering approach (Little, Bovaird & Widaman, 2006) uses residuals as product indicators for representing latent variable interactions. This approach avoids any statistical dependence between indicators of first-order effect variables and those of the latent product variable (Steinmetz, Davidov & Schmidt, 2010). The resulting interaction model is free from constraints. A key benefit of the residual or orthogonalising strategy is that it eliminates the need to estimate a mean structure as required by the mean-centering strategy, but requires a 2-step estimation procedure in which a product term or powered term is regressed onto its respective first-order effect(s) (Chyun Lin, Wen, Marsh & Shyan Lin, 2010; Lance, 1988). In the first step, two respective uncentered indicators of the first-order effect variables are multiplied and the resulting product is then regressed on all first-order effect indicators. The residuals of these regression analyses are then saved. In the second step, the residuals are used as indicators of the product variable (represent the interaction or powered effect) in the latent interaction model. The variance of this new orthogonalised interaction term contains the unique variance that fully represents the interaction effect, independent of the first-order effect variance and general error or unreliability (Little, Bovaird & Widaman, 2006). One of the important characteristics of the residual approach is that there is unique variance common to the interaction indicator terms depending on which first-order effect indicators were used to create them. In addition, the latent interaction term is not allowed to correlate with the main effect latent variables involved in the interaction effect because the indicators of the interaction term have been orthogonalised according to the main effect latent variables (Little, Bovaird & Widaman, 2006).

The advantages of the residual or orthogonalising approach are: (1) the latent variable interaction is derived from the observed covariation pattern among all possible indicators of the interaction; (2) no constraints on particular estimated parameters need to be placed; (3) no recalculations of parameters are required; and (4) model estimates are stable and interpretable (Little, Bovaird & Widaman, 2006). The residual or orthogonalising approach was used in this study.

3.9.5.1.6 Double-mean-centering strategy to estimating latent interactions in structural equation models

The double-mean-centering combines the mean-centering and orthogonalizing strategies by first mean-centering each of the observed variables and then orthogonalizing them. The double-mean-centering strategy eliminates both the need for the mean structure and the cumbersome 2-stage estimation procedure. Furthermore, although the orthogonalizing (residual centering) and double-mean-centering strategies are equivalent when all indicators are normally distributed, the double-mean-centering strategy is superior when this normality assumption is violated (Chyun Lin, Wen, Marsh & Shyan Lin, 2010). It is also important to note that both the single- and double-mean-centering strategies also result in the same interaction and first-order effects, even if the assumption of normality is violated (Chyun Lin, Wen, Marsh & Shyan Lin, 2010). The double-mean-centering approach was used in this study.

3.9.5.1.7 Operationalising the Prior learning x Abstract reasoning capacity interaction effect latent variable when fitting the abridged structural model

The *Prior learning* latent variable was operationalised by PRIOR_1 and PRIOR_2 when fitting the abridged learning potential structural model. The *Abstract reasoning capacity* latent variable was represented by ABSTR_1 and ABSTR_2 when fitting the abridged learning potential structural model shown in Figure 3.1. The two respective uncentered indicators of the prior learning and abstract reasoning capacity were multiplied and the resulting product terms (PRIOR_1ABSTR_1; PRIOR_1ABSTR_2; PRIOR_2ABSTR_1; PRIOR_2ABSTR_2) were then regressed on all first-order effect indicators (PRIOR_1; PRIOR_2; ABSTR_1; ABSTR_2). The residuals of each of these four regression analyses were subsequently saved in the data set as a new variable. The resulting four new variables (the residuals of the four regressions analyses) were used as indicators of the latent interaction variable. The variance of this new orthogonalised interaction term contains the unique variance that fully represents the interaction effect, independent of the first-order effect variance and general error or unreliability (Little, Bovaird & Widaman, 2006).

3.9.6 Specification of the comprehensive LISREL model

The hypothesized learning potential structural model is depicted in Figure 3.1 and expressed as a matrix equation in Equation 3.7. Equation 3.7 however, does not fully specify the structural model to be fitted. Neither does Equation 3.10 fully specify the measurement model to be fitted. Equation 3.7 does not specify $\mathbf{\Phi}$ and $\mathbf{\Psi}$ and equation does not specify$\mathbf{\Theta_\delta}$.

As indicated above the latent interaction term is not allowed to correlate with the main effect latent variables from which it was formed because the indicators of the interaction term have been orthogonalised according to the main effect latent variables (Little, Bovaird & Widaman, 2006). In $\mathbf{\Phi}$ the correlation between the *Prior learning x Abstract thinking capacity latent interaction effect* and *Abstract reasoning capacity* was consequently constrained to be uncorrelated. The abridged De Goede-Burger-Mahembe structural model does not make provision for a *Prior learning* latent main effect. As is normally the case the remaining off-diagonal elements in $\mathbf{\Phi}$ were freed to be estimated indicating that the exogenous latent variables in the structural model were hypothesised to be correlated. As is normally the case the variance-covariance matrix $\mathbf{\Psi}$ was specified as a diagonal matrix. Only the variance terms in the main diagonal were therefore estimated. The structural error terms were therefore assumed to be uncorrelated. Contrary to what is normally the case, however, $\mathbf{\Theta_\delta}$ was not specified as a diagonal matrix. Due to the use of the residual centering procedure there is unique variance common to the four residual indicators used to operationalise the *Prior learning* x *Abstract thinking capacity* latent variable (Little *et al.*, 2006). The pattern of correlations between the indicator variable representing the latent interaction term in Θ_δ depend on the residual-centered indicators that were used to calculate them. Residualised indicators sharing the same original indicators were allowed to correlate inΘ_δ. PRIOR_1ABSTR_1 and PRIOR_1ABSTR_2 were therefore allowed to correlate because they all shared the uniqueness of PRIOR_1. Similarly PRIOR_2ABSTR_1 and PRIOR_2ABSTR_2 were allowed to have correlated measurement errors in Θ_δ because they all shared the uniqueness of PRIOR_2. The same logic applies to PRIOR_1ABSTR_1 and PRIOR_2ABSTR_1 sharing the uniqueness of ABSTR_1 as well as PRIOR_1ABSTR_2 and PRIOR_2ABSTR_2 sharing the uniqueness of ABSTR_2.

The comprehensive structural model was fitted in the same manner as the measurement model analysing the same moment matrix and utilising the same estimation method.

3.9.6.1 Interpreting the fit of the structural model

When the measurement model and the structural model are combined in a single model the comprehensive LISREL model is obtained. The fit of the structural model is seldom never directly evaluated as such. The measurement model is fitted to data and the comprehensive LISREL model is fitted to data. Inferences about the fit of the structural model is derived from a comparison of the fit of the measurement model and the comprehensive LISREL model. According to Vandenberg and Grelle (2009) the fit of the comprehensive LISREL model can be decomposed into two independent additive chisquare fit statistics that assess the fit of the measurement and structural models. Tomarken and Waller (2003, p. 587) stress the importance of utilising the fact that the comprehensive LISREL model and the structural model are nested within the measurement model[27]:

> … it is often the case that the measurement component of of latent variable models fits well and contributes to a high proportion of the total degree of freedom (i.e., the total number of restrictions imposed). In such cases, the result is often a well-fitting composite model that masks a poorly fitting structural component.

McDonald and Ho (2002) argue that the primary objective of a structural equation modeling study (SEM) is to test the overarching substantive hypothesis and the path-specific hypotheses as captured by the structural model[28]. McDonald and Ho (2002), Tomarken and Waller (2003) and Vandenberg and Grelle (2009) consequently advocate for obtaining a focused evaluation of the fit of the structural model by subtracting the value obtained for the chi-square statistic for the composite LISREL model from the value obtained for the chi-square statistic for measurement model (in which the comprehensive model is nested) and to interpret this chi-square difference statistic in terms of the difference in degrees of freedom. Likewise McDonald and Ho (2002) and Tomarken and Waller (2003) recommend evaluating the fit of the structural model in terms of its root mean square error of approximation (RMSEA) by calculating the difference in the population discrepency function values (F0) of the comprehensive model and the measurement model , dividing this difference by the difference in degrees of freedom and taking the square root (i.e., $\sqrt{([F0_{CM}-F0_{MM}]/(df_{CM}-df_{MM}))}$).

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[27]Anderson and Gerbing (1988) explain this position by arguing that "a model, M2, is said to be *nested within* another model, M1 , when its set of freely estimated parameters is a subset of those estimated in M1, and this can be denoted as M2 < M1 . That is, one or more parameters that are freely estimated in M1 are constrained in M2. Typically, these parameters are fixed at zero, although equality constraints may be imposed so that two or more parameters are constrained to have the same value. A *saturated* structural submodel (cf. Bentler & Bonett, 1980), Ms, can be defined as one in which all parameters (i.e., unidirectional paths) relating the constructs to one another are estimated. Note that this model is formally equivalent to a confirmatory measurement model." The researcher's comprehensive model imposes specific constraints on the saturated model Ms. The degrees of freedom of the comprehensive model are therefore greater than that of the measurement model.

[28] McDonald and Ho (2002, p. 65) use the term path model to refer to the structural relations hypothesised to exist between the latent variables and the term structural model to refer to the composite LISREL model.

McDonald and Ho (2002), Tomarken and Waller (2003) and Vandenberg and Grelle (2009) recommend that structural equation modeling studies should report the direct assessment of the fit of the structural model along with that of the comprehensive LISREL model and the measurement model. Tomarken and Waller (2003) and Vandenberg and Grelle (2009), however, acknowledge that the suggested decomposition of the fit statistics of the composite model into fit statistics for the measurement and structural models is not without criticism.

It is difficult to find fault with McDonald and Ho (2002) argument that the whole aim of an empirical explanatory study is to shed light on the validity of the overarching and path-specific substantive research hypotheses. In an SEM context it is the fit of the structural model and the significance of the structural path coefficient estimates that shed light on the validity of these hypotheses. The significance and magnitude of the structural path coefficient estimates warrant interpretation strictly speaking only if the structural model (also) fits the data at least closely. If the structural parameter estimates do not permit an accurate reproduction of the observed variance-covariance matrix, interpretation of these estimates are not justified. If the additional restrictions imposed on the composite model through the addition of the structural model to the measurement model results in deterioration in the fit of the composite model relative to that of the measurement model concerns arise as to the validity of the structural relations hypothesised by the structural model.

This study consequently adhered to the McDonald and Ho (2002), Tomarken and Waller (2003) and Vandenberg and Grelle (2009) recommendation and decomposed the fit of the comprehensive LISREL model into two independent additive chisquare fit statistics and two population discrepency function values. The fit of the structural model along with that of the comprehensive LISREL model and the measurement model was therefore directly assessed. The conditional probability of the structural model RMSEA value under the null hypothesis of close fit could, however, not be calculated.

3.9.6.2 Interpreting the structural model parameter estimates

The purpose of evaluating the structural model is to determine whether the theoretical relationships specified at the conceptualisation stage are substantiated by the data. At this stage the spotlight is on the linkages between the various endogenous and exogenous variables. According to Diamantopoulos and Siguaw (2000), four issues are of paramount significance in the evaluation of the structural model. Firstly, it is vital to assess the signs of the parameters representing the paths between the latent variables to ascertain the degree of consistence with the nature of the causal effect hypothesised to exist between the latent variables. Secondly, it is important to determine if the parameter estimates are significant ($p<0.05$) as indicated by t-values greater than $|1.96|$. Thirdly, it is important to assess the magnitudes of the estimated (standardised) parameters indicating the strength of the hypothesised relationships. Lastly, it is important to evaluate the squared multiple correlations (R^2), which indicate the amount of variance in each endogenous latent variable that is explained by the latent variables linked to it in the hypothesised structural model. The process of evaluating the structural model entails an in-depth analysis of the freed elements of the gamma (Γ) and beta (**B**) matrices.

The purpose of evaluating the structural model is to determine whether the theoretical relationships specified at the conceptualisation stage are substantiated by the data. At this stage, the focus is on the linkages between the various endogenous and exogenous variables. The process of evaluating the structural model entails an in-depth analysis of the freed elements of the Γ and **B** matrices. The fact that the comprehensive LISREL model fitted the data, or even the fact that the structural model fitted the data, constitutes insufficient evidence to conclude support for the path-specific substantive hypotheses. The fact that the structural model fitted the data merely warrants the interpretation of the structural model parameter estimates.

3.9.6.2.1 The gamma matrix

The unstandardised Γ matrix is used to assess the significance of the estimated path coefficients $\gamma_{ij,}$ expressing the strength of the influence of ξ_j (exogenous latent variables) on η_i (endogenous latent variables). The parameters are significant if the conditional probability associated with the sample parameter estimates under the stated null hypothesis is sufficiently small (i.e., if $t>|1.96|$) (Diamantopoulos & Siguaw, 2000). A significant γ estimate implies that the corresponding null hypothesis is rejected in favour of the alternative hypothesis provided the sign of the γ estimate corresponds to the effect hypothesised under the alternative hypothesis. Rejection of the path-specific null hypothesis in turn implies support for the path-specific substantive hypothesis. The strength of the statistically significant ($p<.05$) γ estimates was determined by examining the completely standardised **Γ** matrix.

3.9.6.2.2 The beta matrix

The unstandardised **B** matrix is used to assess the significance of the estimated path coefficients β_{ij}, expressing the strength of the influence of η_j on $\eta_{i.}$ The unstandardised β_{ij} estimates are also significant if the conditional probability associated with the sample parameter estimates under the stated null hypothesis is sufficiently small (i.e., if $p < 0.05$) (Diamantopoulos & Siguaw, 2000). A significant β estimate implies that the corresponding null hypothesis is rejected in favour of the alternative hypothesis provided the sign of the $\boldsymbol{\beta}$ estimate corresponds to the effect hypothesised under the alternative hypothesis. Rejection of the path-specific null hypothesis in turn implies that the path-specific substantive hypothesis is corroborated. The strength of the statistically significant ($p<.05$) β estimates was determined by examining the completely standardised **B** matrix.

3.9.6.2.3 Interpreting the structural model modification indices

It was further decided that the modification indices and completely standardized expected change values (Diamantopoulos & Siguaw, 2000) calculated for the gamma and beta matrices would be inspected to determine whether any meaningful possibilities exist to improve the fit of the comprehensive model through the addition of additional paths. Modification of the model would however only be considered if the proposed structural changes could be theoretically substantiated (Diamantopoulos & Siguaw, 2000; Henning, Theron & Spangenberg, 2004).

3.10 SUMMARY

In the present chapter the abridge model to be tested was discussed. The methodology was outlined including the statistical methods used to test the model. The different ways of dealing with method bias and measurement errors arising from failure to address latent variable interactions in SEM as well as strategies for addressing discriminant validity were also highlighted.

CHAPTER FOUR

RESULTS

4.1 INTRODUCTION

This chapter outlines the results of the data analysis described in Chapter 3. The theoretical model (Figure 3.1) derived from an in-depth study of the available literature pertaining to the learning competencies and competency potential variables that account for variance in *Classroom learning performance* and *Learning performance during evaluation* resulted in the formulation and specification of hypotheses that need to be tested. The measurement model (Figure 3.1) hypothesised relationships between specific latent variables and how these variables relate to affect *Classroom learning performance* and *Learning performance during evaluation.* Item parcels derived from random parcelling of uni-dimensional scales and uni-dimensional subscales in the case of self-leadership and metacognition were calculated in SPSS version 21. These item parcels were used to operationalise the measurement and structural models so as to test the hypothesised relationships. The operationalisation of the measurement and structural models using parcels assumes that the items in each item parcel reflect only the underlying dimension that it intends to measure. From these defined structural and measurement relationships the statistical hypotheses were formulated. Two overarching statistical hypotheses were formulated on overall measurement and structural model fit and twelve statistical hypotheses on the specific structural relations hypothesised in the structural model. An additional 260 statistical hypotheses were formulated on the specific relations hypothesised in the measurement model. Results of the statistical analysis aimed at testing these stated null hypotheses are presented in this chapter. The chapter commences with a discussion of the treatment of the missing values, which is followed by discussions of the results of item and dimensional analyses; the test of multivariate normality for the measurement model; the evaluation of the measurement and structural models; and the hypothesised relationships among the latent variables. The results of the statistical analyses are shown in separate folders on an accompanying CD.

4.2 MISSING VALUES

In order to ensure that all cases included in the selected sample formed part of the analyses, the problem of missing values had to be addressed. The missing values problem is a common occurrence when self-reporting instruments are used. In the present study, this problem was addressed through multiple imputation (Jöreskog & Sörbom, 2006). The procedure was deemed the most appropriate procedure because of the following considerations. Full information maximum likelihood (FIML) estimation procedure is considered one of the most efficient imputation procedures (Du Toit & Mels, 2002; Mels, 2003) but it does not create a separate imputed data set which prevents performing the required preliminary item, dimensionality and confirmatory factor analyses on the imputed data. The multiple imputation procedures available in LISREL 8.80 assume 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). Mels (2010), however, suggests that multiple imputation may be used even when the foregoing assumptions are not met. As long as the observed variables are measured on a scale comprising five or more scale values, the observed variables may not be excessively skewed (even though the null hypothesis of multivariate normality has been rejected) and less than 30% of the data constitute missing values. The latter assumptions were met in this study. Only 3.49% of the data constituted missing values. All the item responses were recorded on scales of 5 or more items. Inspection of the stem and leaf plots indicated that the data was not excessively skewed. Through this technique, missing values are substituted with values derived from averages via simulation (Jöreskog & Sörbom, 2006; Rubin, 1987). The multiple imputation technique was d in order to retain as many data cases as possible since the current sample was marginally above the minimum required sample size of 200 for most SEM analyses (Diamantopoulos & Siguaw, 2000). Multiple imputation was performed through a procedure available in LISREL 8.80 and all the 213 data cases were retained and used in the statistical analyses.

4.3 ITEM ANALYSIS

Item analysis using the SPSS Reliability procedure (SPSS Inc, 2013) was performed on the items of the scales used to measure the latent variables under study. The purpose of conducting item analysis was to identify and eliminate items not contributing to an internally consistent description of the latent variables measured by these scales.

4.3.1 Item analysis of the Revised Self-Leadership Questionnaire (RSLQ)

The Revised Self-leadership Questionnaire (RSLQ) (Houghton & Neck, 2002) RSLQ is a self-report measure that contains 35 items spread over 9 scales. However, 4 items comprising the self-punishment scale were excluded from the RSLQ as advised by Jeffery Houghton (J. Houghton, personal communication, 31 March 2011). Hence 31 items were used to measure self-leadership on 8 scales. The item analysis was done for each of the 8 subscales separately.

4.3.1.1 Visualising successful performance

A Cronbach alpha of .84 was obtained for the *Visualising successful performance subscale.* The corrected item-total correlation values shown in the Item-Total Statistics table give an indication of the degree to which each item correlates with the total score. Low values (less than .3) indicate that the item is measuring something different from the scale as a whole (Pallant, 2010). As indicated in Table 4.1, all the corrected item-total correlations were larger than .30 (Pallant, 2010). The item-total statistics indicated that the reliability coefficient would increase slightly if the item b33 is to be deleted, to α = .85. The item was, however, not deleted since the magnitude of the change in cronbach alpha is not substantial. The mean inter-item correlation is .51, with values ranging from .34 to .69. This suggests quite a strong relationship among items (Pallant, 2010).

Table 4.1

The reliability analysis output for the Visualising successful performance subscale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.840	.840	5

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
b1	14.91	10.453	.587	.353	.824
b10	14.88	9.783	.703	.550	.790
b19	14.85	9.842	.759	.597	.775
b27	14.86	10.310	.712	.527	.790
b33	14.88	11.595	.470	.243	.851

	Mean	**Std. Deviation**	**N**
b1	3.69	1.063	213
b10	3.71	1.067	213
b19	3.74	1.002	213
b27	3.74	.960	213
b33	3.71	.965	213

	Mean	**Minimum**	**Maximum**	**Range**	**Maximum / Minimum**	**Variance**	**N of Items**
Item Means	3.71	3.69	3.74	.05	1.01	.000	5
Item Variances	1.03	.94	1.14	.21	1.22	.010	5
Inter-Item Correlations	.51	.34	.69	.35	2.04	.014	5

4.3.1.2 Self-goal setting

A reliability coefficient of .856 was obtained for the *Self-goal setting* subscale which can be considered satisfactory (Nunnally, 1967)[29]. All the corrected item-total correlations were larger than .30 which is acceptable (Pallant, 2010). The item-total statistics indicated that the Cronbach alpha would increase slightly if item b34 is to be deleted, to α = .863. The mean inter-item correlation is .56, with values ranging from .38 to .64. This suggests quite a strong relationship among items (Pallant, 2010). The output is shown in Table 4.2.

Table 4.2

The reliability analysis output for the Self-goal setting subscale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.856	.862	5

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
b2	15.69	10.064	.710	.523	.817
b11	15.72	9.918	.709	.526	.817
b20	15.74	9.166	.772	.604	.798
b28	15.50	10.468	.641	.477	.834
b34	16.15	9.562	.561	.352	.863

	Mean	**Std. Deviation**	**N**
b2	4.01	.885	213
b11	3.98	.913	213
b20	3.96	.999	213
b28	4.20	.870	213
b34	3.55	1.143	213

[29] See Nunnally (1967) guidelines in paragraph 3.9.2

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.94	3.55	4.20	.66	1.19	.06	5
Item Variances	.94	.75	1.31	.56	1.74	.05	5
Inter-Item Correlations	.56	.38	.64	.27	1.70	.01	5

4.3.1.3 Self-talk

The *Self-talk* subscale has a high internal consistency coefficient of α = .860 which is satisfactory (Nunnally, 1967). The corrected item-total correlation indicated that the items all correlated above .30 with the total score (Pallant, 2010). All the corrected item-total correlations and squared multiple correlations were larger than .30. None of the items were flagged as problematic. The mean inter-item correlation is .51, with values ranging from .34 to .69. This suggests quite a strong relationship among items (Pallant, 2010). No items were therefore deleted. This is depicted in Table 4.3.

Table 4.3

The reliability analysis output for the Self-Talk subscale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.860	.860	3

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
b3	7.77	4.011	.713	.517	.824
b12	7.85	3.908	.772	.596	.770
b21	7.87	3.847	.722	.530	.817

	Mean	Std. Deviation	N
b3	3.98	1.077	213
b12	3.89	1.056	213
b21	3.87	1.115	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.905	3.854	3.972	.117	1.030	.004	3
Item Variances	1.185	1.119	1.257	.138	1.123	.005	3
Inter-Item Correlations	.683	.648	.710	.062	1.096	.001	3

4.3.1.4 Self-reward

The *Self-reward* subscale has a high internal consistency coefficient of α = .924 which is excellent (Nunnally, 1967). The corrected item-total correlation indicated that the items all correlated above .30 with the total score and formed part of the same construct (Pallant, 2010). All the corrected item-total correlations and squared multiple correlations were larger than .30. The mean inter-item correlation is .80, with values ranging from .78 to .82. This suggests quite a strong relationship among items (Pallant, 2010). None of the items were flagged as problematic. No items were therefore deleted. This is depicted in Table 4.4.

Table 4.4

The reliability analysis output for the Self-reward subscale

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.924	.925	3

Item-Total Statistics					
Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
b4	6.64	5.902	.830	.697	.904
b13	6.69	6.217	.834	.706	.899
b22	6.60	6.213	.874	.764	.868

	Mean	Std. Deviation	N
b4	3.32	1.361	213
b13	3.28	1.290	213
b22	3.36	1.254	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.32	3.28	3.36	.075	1.023	.001	3
Item Variances	1.71	1.60	1.86	.261	1.164	.018	3
Inter-Item Correlations	.80	.78	.82	.046	1.059	.000	3

4.3.1.5 Evaluating beliefs and assumptions

A Cronbach alpha of .793 was obtained for the Evaluating beliefs and assumptions subscale which is marginally below the critical cutoff value of .80 considered satisfactory in this study (Nunnally, 1967). All the corrected item-total correlations were larger than .30 which is acceptable (Pallant, 2010). The item-total statistics indicated that the Cronbach alpha would only increase to α = .799 if item b23 is to be deleted. The increase in alpha is not substantial and does not warrant deleting the item. All the items were retained. The mean inter-item correlation is .49, with values ranging from .33 to .58. This suggests quite a moderately strong relationship among items (Pallant, 2010).The output is shown in Table 4.5.

Table 4.5

The reliability analysis output for the Evaluating beliefs and assumptions subscale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.793	.793	4

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
b5	11.14	5.640	.598	.408	.745
b14	11.37	5.507	.671	.457	.708
b23	11.47	6.345	.481	.258	.799
b29	11.19	5.483	.670	.451	.708

	Mean	**Std. Deviation**	**N**
b5	3.92	1.015	213
b14	3.69	.980	213
b23	3.58	.951	213
b29	3.87	.987	213

	Mean	**Minimum**	**Maximum**	**Range**	**Maximum / Minimum**	**Variance**	**N of Items**
Item Means	3.76	3.58	3.92	.329	1.092	.023	4
Item Variances	.974	.91	1.05	.142	1.157	.003	4
Inter-Item Correlations	.492	.33	.58	.254	1.776	.009	4

4.3.1.6 Self-observation

The *self-observation* subscale had an internal consistency coefficient of α = .776 which is also marginally below the critical cutoff value of .80 considered satisfactory in this study (Nunnally, 1967). The corrected item-total correlation indicated that all the items correlated above .30 with the total score and formed part of the same construct (Pallant, 2010). All the corrected item-total correlations were larger than .3. None of the items were flagged as problematic. The mean inter-item correlation is .47, with values ranging from .38 to .53. This suggests a moderately strong relationship among items (Pallant, 2010).This is depicted in Table 4.6.

Table 4.6

The reliability analysis output for the Self-observation subscale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.776	.778	4

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
b7	11.54	4.391	.579	.350	.726
b16	11.57	5.123	.505	.270	.759
b25	11.41	4.780	.630	.399	.699
b31	11.59	4.564	.618	.392	.702

	Mean	**Std. Deviation**	**N**
b7	3.83	.997	213
b16	3.80	.853	213
b25	3.96	.840	213
b31	3.78	.911	213

	Mean	**Minimum**	**Maximum**	**Range**	**Maximum / Minimum**	**Variance**	**N of Items**
Item Means	3.843	3.784	3.962	.178	1.047	.007	4
Item Variances	.814	.706	.993	.287	1.407	.017	4
Inter-Item Correlations	.467	.375	.531	.157	1.419	.004	4

4.3.1.7 Focusing thoughts on natural rewards

The *Focusing thoughts on natural rewards* subscale has a somewhat questionable internal consistency coefficient of α = .708 that falls below the critical cutoff value of .80 considered satisfactory in this study (Nunnally, 1967). The corrected item-total correlation indicated that the items all correlated satisfactorily above .30 with the total score (Pallant, 2010). None of the items were flagged as problematic. The mean inter-item correlation is .33, with values ranging from .20 to .44. This suggests a moderately strong relationship among items (Pallant, 2010).This is depicted in Table 4.7.

Table 4.7

The reliability analysis output for the Focusing thoughts on natural rewards subscale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.708	.707	5

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
b8	15.29	8.158	.353	.135	.705
b17	14.95	8.294	.427	.208	.675
b26	15.17	7.305	.527	.300	.633
b32	15.26	7.711	.465	.234	.659
b35	15.03	7.060	.559	.322	.618

	Mean	**Std. Deviation**	**N**
b8	3.64	1.012	213
b17	3.98	.877	213
b26	3.75	1.014	213
b32	3.67	.984	213
b35	3.89	1.038	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.785	3.638	3.977	.338	1.093	.021	5
Item Variances	.973	.768	1.078	.310	1.403	.015	5
Inter-Item Correlations	.326	.198	.441	.243	2.228	.007	5

4.3.1.8 Self-cueing

A Cronbach alpha of .817 was obtained for the *Self-cueing* subscale. All the corrected item-total correlations and squared multiple correlations were larger than .30. None of the items were flagged as problematic. The mean inter-item correlation is .69, with values ranging from .69 to .69. This suggests quite a strong relationship among the two items (Pallant, 2010).. The output is shown in Table 4.8.

Table 4.8

The reliability analysis output for the Self-cueing subscale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.817	.818	2

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
b9	3.58	1.263	.692	.479	.
b18	3.45	1.428	.692	.479	.

	Mean	Std. Deviation	N
b9	3.45	1.195	213
b18	3.58	1.124	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.516	3.451	3.582	.131	1.038	.009	2
Item Variances	1.346	1.263	1.428	.165	1.130	.014	2
Inter-Item Correlations	.692	.692	.692	.000	1.000	.000	2

4.3.2 Item analysis of the Academic Self-efficacy

The *Academic Self-efficacy* scale has an internal consistency coefficient of α = .939. The corrected item-total correlation indicated that the items all correlated above .30 with the total score except for item c3 (Pallant, 2010). The deletion of item c3 would increase the Cronbach's alpha to α = .956. The mean inter-item correlation is .58, with values ranging from .02 to .82. This suggests quite a strong relationship among items (Pallant, 2010).It was decided to exclude the item from further analyses. This is depicted in Table 4.9.

Table 4.9

The reliability analysis output for the Academic Self-efficacy scale

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.939	.943	12

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	4.943	4.258	5.563	1.305	1.307	.140	12
Item Variances	1.581	1.143	2.353	1.209	2.058	.095	12
Inter-Item Correlations	.581	.015	.819	.804	55.060	.042	12

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
c1	54.53	114.449	.792	.686	.931
c2	54.03	116.258	.759	.637	.932
c3	**55.11**	**128.016**	**.182**	**.128**	**.956**
c4	54.82	113.122	.750	.745	.933
c5	54.57	112.727	.839	.796	.929
c6	53.98	116.608	.764	.654	.932
c7	54.50	113.874	.816	.738	.930
c8	54.32	110.803	.842	.769	.929
c9	54.21	113.080	.826	.766	.930
c10	54.53	113.543	.817	.737	.930
c11	54.69	114.090	.791	.689	.931
c12	53.79	119.372	.696	.607	.935

	Mean	Std. Deviation	N
c1	4.83	1.221	213
c2	5.33	1.164	213
c3	4.26	1.534	213
c4	4.55	1.350	213
c5	4.78	1.263	213
c6	5.39	1.138	213
c7	4.88	1.209	213
c8	5.05	1.340	213
c9	5.16	1.252	213
c10	4.84	1.242	213
c11	4.67	1.246	213
c12	5.56	1.069	213

4.3.3 Item analysis of the Learning goal orientation scale

The *Learning goal orientation scale* has an internal consistency coefficient of α = .854. The corrected item-total correlation indicated that all the items correlated with the total score (Pallant, 2010). None of the items would result in a significant increase in alpha when deleted. The mean inter-item correlation is .50, with values ranging from .35 to .61. This suggests quite a strong relationship among items (Pallant, 2010).Therefore all the items were retained. This is depicted in Table 4.10.

Table 4.10

The reliability analysis output for the Learning goal orientation scale

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.854	.856	6

Reliability Statistics

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
d1	26.77	26.590	.548	.323	.849
d2	26.52	25.609	.649	.437	.828
d3	26.10	27.499	.670	.513	.826
d4	26.30	24.992	.754	.586	.807
d5	25.98	26.585	.662	.481	.825
d6	26.26	27.355	.581	.413	.840

	Mean	**Std. Deviation**	**N**
d1	4.80	1.463	213
d2	5.08	1.416	213
d3	5.48	1.164	213
d4	5.29	1.352	213
d5	5.59	1.292	213
d6	5.31	1.307	213

	Mean	**Minimum**	**Maximum**	**Range**	**Maximum / Minimum**	**Variance**	**N of Items**
Item Means	5.258	4.803	5.587	.784	1.163	.081	6
Item Variances	1.784	1.355	2.140	.785	1.580	.076	6
Inter-Item Correlations	.498	.346	.614	.268	1.774	.008	6

4.3.4 Item analysis of the metacognitive awareness inventory (MAI)

The Metacognitive Awareness Inventory (MAI) (Schraw & Dennison, 1994) is a self-report measure that contains 52 items measuring eight dimensions that basically measure metacognitive knowledge and metacognitive regulation of cognition. The item analysis of each of the eight subscales is presented in this section.

4.3.4.1 Item analyses of the knowledge of cognition subscales

4.3.4.1.1 Declarative knowledge

The *Declarative knowledge subscale* has an somewhat unsatisfactory internal consistency coefficient of α = .748. The corrected item-total correlation indicated that the items all correlated above .30 with the total score. None of the items would result in a significant increase in alpha when deleted. The mean inter-item correlation is .27, with values ranging from .06 to .39. This suggests a somewhat weak relationship among items (Pallant, 2010).None of the items were flagged as problematic. No items were therefore deleted. This is depicted in Table 4.11.

Table 4.11

The reliability analysis output for the Declarative knowledge scale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.748	.748	8

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
e5	26.90	16.872	.484	.265	.714
e10	26.79	17.828	.471	.305	.718
e12	26.96	17.861	.391	.217	.732
e16	27.14	17.184	.515	.298	.709
e17	27.21	17.620	.430	.192	.725
e20	27.15	17.436	.486	.251	.715
e32	27.09	17.251	.442	.251	.723
e46	26.49	18.911	.329	.190	.742

	Mean	Std. Deviation	N
e5	3.92	1.052	213
e10	4.02	.901	213
e12	3.85	1.003	213
e16	3.68	.967	213
e17	3.61	.997	213
e20	3.68	.947	213
e32	3.73	1.051	213
e46	4.32	.887	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.850	3.606	4.324	.718	1.199	.056	8
Item Variances	.955	.786	1.106	.320	1.407	.015	8
Inter-Item Correlations	.274	.060	.391	.331	6.492	.006	8

4.3.4.1.2 Procedural knowledge

The *Procedural knowledge subscale* has an internal consistency coefficient of α = .534 that falls substantially below the critical cutoff value of .80 considered satisfactory in this study and which serious raises the question whether the subscale can be used in this study (Nunnally, 1967). The corrected item-total correlation indicated that the items all correlated above .30 with the total score with the exception of items e3 and e33 (Pallant, 2010). The corrected-item-total statistics of these items marginally miss the .3 level (Pallant, 2010). None of the items was deleted due to the limited number of items in this scale. Deleting these items would reduce the scale to two items. Besides, none of the items would result in a significant increase in Cronbach alpha when deleted. The mean inter-item correlation is .22, with values ranging from .09 to .29. This suggests a weak relationship among items (Pallant, 2010).This is depicted in Table 4.12.

Table 4.12

The reliability analysis output for the Procedural knowledge scale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.534	.534	4

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
e3	11.28	3.835	.292	.106	.487
e14	11.72	3.166	.364	.140	.423
e27	11.54	3.259	.341	.118	.445
e33	11.67	3.440	.293	.099	.487

	Mean	**Std. Deviation**	**N**
e3	4.12	.755	213
e14	3.69	.942	213
e27	3.86	.931	213
e33	3.74	.914	213

	Mean	**Minimum**	**Maximum**	**Range**	**Maximum / Minimum**	**Variance**	**N of Items**
Item Means	3.852	3.690	4.127	.427	1.115	.038	4
Item Variances	.791	.564	.900	.336	1.595	.024	4
Inter-Item Correlations	.217	.092	.285	.193	3.103	.004	4

4.3.4.1.3 Conditional knowledge

The *Conditional knowledge subscale* had an internal consistency coefficient of α = .573 that falls substantially below the critical cutoff value of .80 considered satisfactory in this study which serious raises the question whether the subscale can be used in this study (Nunnally, 1967). The corrected item-total correlation indicated that the items all correlated above .30 with the total score except for items e15 and e35. All the items returned very low squared multiple correlations indicating that they to a limited degree share a common source of variance. None of the items would, however, result in a significant increase in Cronbach alpha when deleted. None of the items could be flagged as isolated problematic items. All the items in a sense should be regarded as problematic. The mean inter-item correlation is .21, with values ranging from .06 to .34. This suggests a weak relationship among items (Pallant, 2010). Therefore, all the items were therefore retained. This is depicted in Table 4.13.

Table 4.13

The reliability analysis output for the Conditional knowledge scale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.573	.572	5

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
e15	15.31	6.017	.245	.077	.561
e18	15.82	5.374	.312	.127	.529
e26	15.76	4.931	.389	.167	.481
e29	15.74	5.148	.471	.238	.441
e35	15.80	5.879	.252	.101	.559

	Mean	**Std. Deviation**	**N**
e15	4.31	.840	213
e18	3.79	.964	213
e26	3.85	1.006	213
e29	3.87	.859	213
e35	3.81	.877	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.927	3.793	4.310	.516	1.136	.047	5
Item Variances	.831	.705	1.012	.306	1.434	.018	5
Inter-Item Correlations	.212	.062	.338	.276	5.443	.008	5

4.3.4.2 Item analyses of the regulation of cognition subscales

4.3.4.2.1 Planning

The *Planning subscale* had an internal consistency coefficient of α = .734 that falls marginally below the critical cutoff value of .80 considered satisfactory in this study. The corrected item-total correlation indicated that the items all correlated above .30 with the exception of items e42. The corrected-item-total statistics of item e42 marginally miss the .30 level (Pallant, 2010). None of the items would result in a significant increase in Cronbach alpha when deleted. None of the items were flagged as problematic. The mean inter-item correlation is .26, with values ranging from .06 to .45. This suggests a low to moderately strong relationship among items (Pallant, 2010). This is depicted in Table 4.14.

Table 4.14

The reliability analysis output for the Planning knowledge scale

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.734	.734	7

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
e4	22.67	13.704	.469	.326	.698
e6	22.63	14.102	.394	.186	.717
e8	22.75	13.235	.572	.356	.673
e22	23.27	13.614	.439	.244	.706
e23	22.79	14.573	.490	.273	.696
e42	22.62	15.888	.247	.109	.743
e45	23.16	13.342	.533	.302	.682

	Mean	Std. Deviation	N
e4	3.98	1.028	213
e6	4.02	1.055	213
e8	3.90	.990	213
e22	3.38	1.090	213
e23	3.86	.824	213
e42	4.03	.863	213
e45	3.49	1.017	213

	Mean	**Minimum**	**Maximum**	**Range**	**Maximum / Minimum**	**Variance**	**N of Items**
Item Means	3.861	3.384	4.033	.649	1.189	.057	6
Item Variances	.964	.685	1.202	.517	1.755	.043	6
Inter-Item Correlations	.264	.055	.452	.397	8.173	.012	6

4.3.4.2.2 Organising (Implementing strategies and heuristics)

The *Organising (Implementing strategies and heuristics)* had an internal consistency coefficient of α = .762 that also falls marginally below the critical cutoff value of .80 considered satisfactory in this study. The corrected item-total correlation indicated that the items all correlated above .30 with the total score with the exception of item e48 (Pallant, 2010). None of the items would result in a significant increase in Cronbach alpha when deleted. None of the items were flagged as problematic, all the items were retained. This is depicted in Table 4.15.

Table 4.15

The reliability analysis output for the Organising (Implementing strategies and heuristics) scale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.762	.768	10

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
e9	34.16	23.421	.413	.216	.744
e13	34.21	24.950	.320	.194	.755
e30	34.47	22.571	.583	.421	.723
e31	34.51	22.336	.479	.317	.735
e37	34.70	23.362	.316	.154	.761
e39	34.36	22.551	.567	.372	.725
e41	34.55	23.512	.408	.262	.745
e43	34.46	22.410	.536	.362	.727
e47	34.45	22.871	.406	.194	.746
e48	34.65	24.143	.290	.183	.762

	Mean	Std. Deviation	N
e9	4.12	.916	213
e13	4.07	.752	213
e30	3.81	.839	213
e31	3.77	1.009	213
e37	3.58	1.098	213
e39	3.92	.860	213
e41	3.73	.906	213
e43	3.82	.919	213
e47	3.83	1.028	213
e48	3.63	.985	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.827	3.582	4.113	.531	1.148	.029	10
Item Variances	.874	.558	1.169	.611	2.096	.032	10
Inter-Item Correlations	.257	.018	.493	.476	27.937	.011	10

4.3.4.2.3 *Monitoring subscale*

The *Monitoring subscale* had an internal consistency coefficient of α = .755 that falls marginally below the critical cutoff value of .80 considered satisfactory in this study. The corrected item-total correlation indicated that the items all correlated above .30 (Pallant, 2010). None of the items would result in a significant increase in Cronbach alpha when deleted, all the items were retained. This is depicted in Table 4.16.

Table 4.16

The reliability analysis output for the Monitoring subscale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.755	.760	7

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
e1	22.80	13.857	.497	.351	.720
e2	22.55	14.390	.469	.324	.726
e11	22.95	13.889	.512	.289	.717
e21	23.20	13.697	.414	.187	.740
e28	23.03	13.622	.509	.277	.717
e34	22.97	13.754	.401	.188	.743
e49	22.92	13.683	.527	.308	.713

	Mean	Std. Deviation	N
e1	3.93	.919	213
e2	4.19	.843	213
e11	3.79	.894	213
e21	3.54	1.066	213
e28	3.71	.952	213
e34	3.77	1.073	213
e49	3.81	.918	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.845	3.704	4.183	.479	1.129	.028	7
Item Variances	2.015	.707	8.848	8.141	12.517	9.098	7
Inter-Item Correlations	.255	.028	.498	.470	18.100	.018	7

4.3.4.2.4 Debugging subscale

The *Debugging subscale* had an internal consistency coefficient of α = .680 that falls substantially below the critical cutoff value of .80 considered satisfactory in this study and which raises the question whether the subscale can be used in this study (Nunnally, 1967). The corrected item-total correlation indicated that the items all correlated above .30 (Pallant, 2010). None of the items would result in a significant increase in Cronbach alpha when deleted. All the items were, therefore, retained. This is depicted in Table 4.17.

Table 4.17

The reliability analysis output for the Debugging scale

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.680	.681	5

Item-Total Statistics					
Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
e25	15.87	6.668	.318	.124	.680
e40	16.23	5.744	.557	.314	.572
e44	16.25	6.235	.417	.199	.637
e51	16.15	6.068	.470	.267	.613
e52	15.80	6.565	.417	.225	.637

	Mean	Std. Deviation	N
e25	4.20	.927	213
e40	3.85	.921	213
e44	3.83	.933	213
e51	3.93	.921	213
e52	4.27	.836	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	4.015	3.826	4.268	.441	1.115	.040	5
Item Variances	.822	.706	.889	.183	1.259	.005	5
Inter-Item Correlations	.299	.148	.452	.305	3.061	.010	5

4.3.4.2.5 *Evaluation strategies*

The *Evaluation subscale* had an internal consistency coefficient of α = .683 that falls substantially below the critical cutoff value of .80 considered satisfactory in this study and which raises the question whether the subscale can be used in this study (Nunnally, 1967). The corrected item-total correlation indicated that the items all correlated above .30 (Pallant, 2010). None of the items would result in a significant increase in the Cronbach alpha when deleted. None of the items were therefore flagged as problematic items. All the items were retained. This is depicted in Table 4.18.

Table 4.18

The reliability analysis output for the Evaluation strategies subscale

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.683	.689	6

Item-Total Statistics					
Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
e7	18.58	10.971	.322	.180	.677
e19	18.74	10.758	.443	.204	.632
e24	18.87	11.020	.363	.180	.660
e36	18.86	10.367	.542	.312	.600
e38	19.10	11.046	.388	.157	.651
e50	18.80	11.074	.446	.236	.633

	Mean	Std. Deviation	N
e7	4.01	1.145	213
e19	3.85	1.012	213
e24	3.72	1.065	213
e36	3.73	.976	213
e38	3.49	1.022	213
e50	3.79	.935	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.765	3.484	4.005	.521	1.150	.029	6
Item Variances	1.052	.875	1.307	.432	1.493	.023	6
Inter-Item Correlations	.273	.083	.391	.308	4.718	.007	6

4.3.5 Item analysis of the Time cognitively engaged scale

The *Time cognitively engaged scale* had a satisfactory internal consistency coefficient of α = .893. The corrected item-total correlation indicated that the items all correlated above .30 with the total score and formed part of the same construct (Pallant, 2010). The squared multiple correlations were larger than .30 except for item f14. None of the items would result in a significant increase in alpha when deleted. Therefore all the items were retained. The mean inter-item correlation is .33, with values ranging from .04 to .62. This suggests a low to moderately strong relationship among items (Pallant, 2010).This is depicted in Table 4.19.

Table 4.19

The reliability analysis output for the Time cognitively engaged scale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.893	.895	17

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
f1	61.00	75.373	.577	.518	.886
f2	60.78	76.010	.632	.572	.884
f3	60.92	76.532	.517	.410	.888
f4	60.37	77.904	.551	.447	.887
f5	60.70	77.134	.543	.460	.887
f6	60.86	77.801	.486	.329	.889
f7	60.97	75.928	.550	.407	.887
f8	60.56	76.898	.504	.447	.889
f9	60.52	77.053	.493	.354	.889
f10	60.64	75.694	.568	.539	.886
f11	61.19	78.078	.395	.360	.893
f12	60.77	76.492	.598	.519	.886
f13	60.68	75.926	.605	.529	.885
f14	60.79	78.259	.414	.287	.892
f15	60.62	75.142	.651	.549	.883
f16	60.63	76.385	.606	.478	.885
f17	60.71	76.292	.567	.425	.886

	Mean	**Std. Deviation**	**N**
f1	3.56	.963	213
f2	3.76	.838	213
f3	3.63	.946	213
f4	4.16	.769	213
f5	3.84	.848	213
f6	3.69	.858	213
f7	3.58	.952	213
f8	3.97	.931	213
f9	4.01	.952	213
f10	3.91	.947	213
f11	3.37	.989	213
f12	3.79	.840	213
f13	3.87	.878	213
f14	3.76	.935	213
f15	3.93	.890	213
f16	3.92	.835	213
f17	3.83	.895	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.798	3.366	4.164	.798	1.237	.037	17
Item Variances	.810	.591	.978	.388	1.656	.011	17
Inter-Item Correlations	.333	.037	.623	.586	16.898	.011	17

4.3.6 Item analysis of the IPIP Conscientiousness subscale

The *Conscientiousness subscale* had an internal consistency coefficient of α = .786 that falls marginally below the critical cutoff value of .80 considered satisfactory in this study. The corrected item-total correlation indicated that all the items correlated above .30 with each other and formed part of the same construct. The squared multiple correlations were larger than .30 except for items h2 and h3. None of the items would result in a significant increase in alpha when deleted. Therefore all the items were retained. The mean inter-item correlation is .27, with values ranging from -.02 to .73. This suggests a low to strong relationship among items (Pallant, 2010).This is depicted in Table 4.20.

Table 4.20

The reliability analysis output for the Conscientiousness scale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.786	.788	10

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
h1	33.19	34.713	.460	.369	.770
h2	32.80	35.650	.342	.322	.780

h3	33.43	34.030	.348	.232	.780
h4	32.78	32.616	.483	.318	.764
h5	33.40	32.091	.472	.373	.766
h6	33.17	35.606	.314	.306	.782
HR7	33.37	30.404	.466	.462	.769
HR8	33.00	29.986	.606	.647	.747
HR9	33.24	29.532	.599	.606	.747
HR10	33.12	31.570	.476	.400	.765

	Mean	Std. Deviation	N
h1	3.65	.747	213
h2	4.04	.764	213
h3	3.41	1.040	213
h4	4.06	1.010	213
h5	3.44	1.109	213
h6	3.67	.810	213
HR7	3.47	1.375	213
HR8	3.84	1.200	213
HR9	3.61	1.268	213
HR10	3.73	1.190	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.692	3.408	4.061	.653	1.191	.053	10
Item Variances	1.148	.558	1.892	1.334	3.390	.206	10
Inter-Item Correlations	.273	-.022	.730	.752	-33.552	.032	10

4.3.7 Item analysis of the IPIP Openness to experience subscale

The initial *Openness to experience* had an internal consistency coefficient of α = .728 that falls below the critical cutoff value of .80. The corrected item-total correlation indicated that the items all correlated above .30 except for items 4, 5 and 8 which were flagged as problematic in the first round of reliability analysis. Item 10, however, became problematic in the second round of analysis. These items were subsequently eliminated and the Cronbach alpha increased to α = .765. The mean inter-item correlation is .22, with values ranging from -.01 to .67. This suggests a low to moderately strong relationship among items (Pallant, 2010) which hints at the possibility of some poor items. The output is depicted in Table 4.21.

Table 4.21

The reliability analysis output for the Openness to experience scale

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.728	.737	10

Item-Total Statistics					
Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
i1	32.59	24.587	.449	.313	.698
i2	32.30	23.233	.517	.403	.685
i3	32.39	23.712	.593	.518	.679
i4	32.42	26.571	.268	.150	.723
i5	32.95	25.227	.280	.253	.724
i6	32.37	24.339	.376	.279	.708
i7	32.39	23.110	.590	.519	.676
iR8	32.81	27.319	.080	.244	.755
iR9	32.22	22.500	.462	.399	.694
iR10	32.59	24.367	.355	.371	.712

	Mean	**Std. Deviation**	**N**
i1	3.52	.892	213
i2	3.82	1.019	213
i3	3.73	.851	213
i4	3.69	.785	213
i5	3.17	1.065	213
i6	3.75	1.053	213
i7	3.72	.943	213
iR8	3.30	1.067	213
iR9	3.89	1.223	213
iR10	3.52	1.086	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.611	3.167	3.890	.724	1.229	.054	10
Item Variances	1.012	.617	1.495	.878	2.425	.067	10
Inter-Item Correlations	.219	-.103	.669	.772	-6.486	.032	10

4.3.8 Item analysis of the Nunes motivation to learn scale

The *Nunes motivation to learn scale* had a highly satisfactory internal consistency coefficient of α = .895. The corrected item-total correlation indicated that the items all correlated above .30. The squared multiple correlations were larger than .30. None of the items would result in a significant increase in alpha when deleted. Therefore all the items were retained. The mean inter-item correlation is .60, with values ranging from .37 to .71. This suggests a strong relationship among items (Pallant, 2010).This is depicted in Table 4.22.

Table 4.22

The reliability analysis output for the Nunes motivation to learn scale

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.895	.897	6

Item-Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
j1	31.33	15.524	.761	.601	.869
j2	31.54	15.844	.594	.444	.898
j3	31.51	15.043	.790	.656	.864
j4	31.30	16.221	.750	.607	.873
j5	31.46	14.891	.776	.609	.867
j6	31.18	16.591	.661	.521	.885

	Mean	Std. Deviation	N
j1	6.33	.950	213
j2	6.13	1.081	213
j3	6.15	.993	213
j4	6.36	.856	213
j5	6.21	1.030	213
j6	6.48	.883	213

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	6.282	6.131	6.488	.357	1.058	.019	6
Item Variances	.934	.716	1.171	.456	1.637	.031	6
Inter-Item Correlations	.596	.366	.712	.346	1.943	.009	6

4.4 DIMENSIONALITY ANALYSIS

In this section, the exploratory factor analysis results of the various instruments used in the study are presented.

4.4.1 Dimensional analysis of the Revised Self-Leadership Questionnaire (RSLQ)

4.4.1.1 The dimensionality analysis of the Visualising successful performance subscale

The *Visualising successful performance* scale obtained a Kaiser-Meyer-Olkin[30] measure of sampling adequacy value of .844 and the Bartlett's Test of Sphericity[31] test statistic

[30] The Kaiser-Meyer-Olkin (KMO) is a measure of sampling adequacy and reflects 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 approaches unity, or at least achieves a value bigger than .60, the correlation matrix is deemed factor analysable (Tabachnick & Fidell, 2007).

value was 428.452 (*df* = 10; p = 0.00) which allowed for the identity matrix null hypothesis to be rejected. There was therefore strong evidence that the correlation matrix was factor analysable. Kaiser (as cited in Field, 2005) recommends accepting KMO values greater than .5 as acceptable, values between .5 and .7 as mediocre, and values between .7 and .8 as good while values between .8 and .9 are great and values above .9 are superb. All the items of the *Visualising successful performance* scale were included in the dimensionality analysis as none of the items were found to be poor item in the item analysis. The correlation matrix showed that all correlations were larger than .30 and all were significant ($p < .05$) except for the correlation between b1 and b33 which was .282.

One factor was extracted, since only one factor obtained an eigenvalue greater than 1. The scree plot also suggested that a single factor should be extracted. The factor matrix indicated that all the items loaded on one factor satisfactorily as all factor loadings were larger than .50. The resultant factor structure is shown in Table 4.23. Furthermore, none of the residual correlations were larger than .05 suggesting that the factor solution provided a credible explanation for the observed inter-item correlation matrix. The uni-dimensionality assumption was thus corroborated.

Table 4.23

Factor matrix for the Visualising successful performance

	Factor
	1
b1	.641
b10	.794
b19	.853

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[31] The Bartlett's Test of Sphericity tests the null hypothesis that the correlation matrix is an identity matrix in the population (i.e., the diagonal contains 1's and all off-diagonal elements are zero's) (Tabachnick & Fidell, 2007).

b27	.793
b33	.511

4.4.1.2 The dimensionality analysis output for the Self-goal setting subscale

The *Self-goal setting* scale obtained a Kaiser-Meyer-Olkin measure of sampling adequacy value of .847 and the Bartlett's Test of Sphericity test statistic obtained a value of 477.159 (*df* = 10; p = 0.00) which allowed for the identity matrix null hypothesis to be rejected. There was therefore strong evidence that the correlation matrix was factor analysable (Kaiser as cited in Field, 2005).

Only one factor with an eigenvalue greater than 1 was obtained. The scree plot also suggested that a single factor should be extracted. The factor matrix indicated that all the items loaded on one factor satisfactorily as all factor loadings were larger than .50. The resultant factor structure is shown in Table 4.24. Furthermore only 10% of the residual correlations were larger than .05 suggesting that the factor solution provides a credible explanation for the observed inter-item correlation matrix. The unidimensionality assumption was thus corroborated.

Table 4.24

Factor matrix for the Self-goal setting subscale

	Factor 1
b2	.781
b11	.784
b20	.851
b28	.713
b34	.604

4.4.1.3 The dimensionality analysis output for the Self-talk subscale

The *Self-talk scale* achieved a Kaiser-Meyer-Olkin measure of sampling adequacy value of .728 and the Bartlett's Test of Sphericity test statistic obtained a value of 295.067 (df = 3; p = 0.00) which allowed for the identity matrix null hypothesis to be rejected. There, therefore, was sufficient evidence that the correlation matrix was factor analysable (Kaiser as cited in Field, 2005).

Only one factor with an eigenvalue greater than 1 was obtained. The scree plot also suggested that a single factor should be extracted. The factor matrix indicated that all the items loaded on one factor satisfactorily as all factor loadings were larger than .50. The resultant factor structure is shown in Table 4.25. Furthermore none of the residual correlations were larger than .05 suggesting that the factor solution provided a credible explanation for the observed inter-item correlation matrix. The uni-dimensionality assumption was thus corroborated.

Table 4.25

Factor matrix for the Self-Talk subscale

	Factor
	1
b3	.786
b12	.878
b21	.798

4.4.1.4 The dimensionality analysis output for the Self-reward subscale

The *Self-reward scale* obtained a Kaiser-Meyer-Olkin measure of sampling adequacy value of .756 and the Bartlett's Test of Sphericity test statistic onbtained a value of 490.597 (df = 3; p = 0.00) which llowed for the identity matrix null hypothesis to be rejected There, therefore, was sufficient evidence that the correlation matrix was factor analysable (Kaiser as cited in Field, 2005).

Only one factor with an eigenvalue greater than 1 was obtained. The scree plot also suggested that a single factor should be extracted. The factor matrix indicated that all the items loaded satisfactorily on one factor as all factor loadings were larger than .50. The resultant factor structure is shown in Table 4.26. Furthermore none of the residual correlations were larger than .05 suggesting that the factor solution provided a credible explanation for the observed inter-item correlation matrix. The uni-dimensionality assumption was thus corroborated.

Table 4.26

Factor matrix for the Self-Reward subscale

	Factor 1
b4	.874
b13	.880
b22	.936

4.4.1.5 The dimensionality analysis output for the Evaluating beliefs and assumptions subscale

The *Evaluating beliefs and assumptions scale* obtained a Kaiser-Meyer-Olkin measure of sampling adequacy value of .768 and the Bartlett's Test of Sphericity test statistic obtained a value of 257.813 (df = 6; p = 0.00) which allowed for the identity matrix null hypothesis to be rejected. There therefore was sufficient evidence that the correlation matrix was factor analysable (Kaiser as cited in Field, 2005).

Only one factor with an eigenvalue greater than 1 was obtained and the scree plot also suggested that a single factor should be extracted. The factor matrix indicated that all the items loaded on one factor satisfactorily as all factor loadings were larger than .50. The resultant factor structure is shown in Table 4.27. Only 16% of the residual correlations were larger than .05 suggesting that the factor solution provided a credible explanation for the observed inter-item correlation matrix. The uni-dimensionality assumption was thus corroborated.

Table 4.27

Factor matrix for the Evaluating beliefs and assumptions subscale

	Factor
	1
b5	.699
b14	.785
b23	.542
b29	.781

4.4.1.6 The dimensionality analysis output for the Self-observation scale

The *Self-observation scale* obtained a Kaiser-Meyer-Olkin measure of sampling adequacy vlaue of .774 and the Bartlett's Test of Sphericity test statistic obtained a value of 222.799 (df = 6; p = 0.00) which allowed for the identity matrix null hypothesis to be rejected. There, therefore, was sufficient evidence that the correlation matrix was factor analysable (Kaiser as cited in Field, 2005).

Only one factor with an eigenvalue greater than 1 was obtained. The scree plot also suggested that a single factor should be extracted. The factor matrix indicated that all the items loaded on one factor satisfactorily as all factor loadings were larger than .50. The resultant factor structure is shown in Table 4.28. None of the residual correlations were larger than .05 suggesting that the factor solution provided a credible explanation for the observed inter-item correlation matrix. The uni-dimensionality assumption was, therefore, corroborated.

Table 4.28

Factor matrix for the Self-Observation subscale

	Factor 1
b7	.677
b16	.584
b25	.747
b31	.731

4.4.1.7 The dimensionality analysis output for the Focusing thoughts on natural rewards scale

The *Focusing thoughts on natural rewards scale* obtained a Kaiser-Meyer-Olkin measure of sampling adequacy value of .767 and the Bartlett's Test of Sphericity test statistic obtained a value of 175.191 (*df* = 10; p = 0.00) which allowed for the identity matrix null hypothesis to be rejected. There was therefore sufficient evidence that the correlation matrix was factor analysable (Kaiser as cited in Field, 2005)

Only one factor with an eigenvalue greater than 1 was obtained. The scree plot also suggested that a single factor should be extracted. The factor matrix indicated that all the items loaded on one factor satisfactorily as all factor loadings were larger than .50 with the exception of item b8 which missed the .5 level. None of the factor loadings are really very high though indicating that all the items reflect less than 50% of the variance in the common underlying factor. This dove-tails with the results of the item analysis. The resultant factor structure is shown in Table 4.29. Only 10% of the residual correlations were larger than .05 suggesting that the factor solution provided a credible explanation for the observed inter-item correlation matrix. The uni-dimensionality assumption was, therefore corroborated.

Table 4.29

Factor matrix for the Focusing thoughts on natural rewards

	Factor
	1
b8	.420
b17	.521
b26	.660
b32	.571
b35	.695

4.4.1.8 The dimensionality analysis output for the Self-cueing scale

None of the *Self-cueing scale* items were found to be poor item in the item analysis. The correlation matrix showed that all correlations were above .5. All correlations were, however, significant ($p < .05$). The scale obtained a Kaiser-Meyer-Olkin value of .500 and the Bartlett's Test of Sphericity value of 137.388 (*df* = 1; p = 0.00) allowed for the null hypothesis to be rejected. None of the factor loadings are really very high though indicating that all the items reflect less than 50% of the variance in the common underlying factor. This dove-tails with the results of the item analysis. Although the KMO value was mediocre it provided some evidence that the correlation matrix was factor analysable (Kaiser as cited in Field, 2005). The possible reason why the KMO was low is that the scale contains only 2 items.

Only one factor with an eigenvalue greater than 1 was obtained. The scree plot also suggested that a single factor should be extracted. The factor matrix indicated that all the items loaded satisfactorily high on one factor as all factor loadings were substantially larger than .50. The resultant factor structure is shown in Table 4.30.

Furthermore none of the residual correlations were larger than .05 suggesting that the factor solution provided a credible explanation for the observed inter-item correlation matrix. The uni-dimensionality assumption was, however, corroborated.

Table 4.30

Factor matrix for the Self-cueing

	Factor
	1
b9	.832
b18	.832

4.4.2 The dimensionality analysis output for the Academic self-efficacy scale

Exploratory factor analysis was performed on the *Academic self-efficacy scale*. The KMO index and the Bartlett's test of sphericity were computed and yielded values of .937 and 2147.636 (*df* = 55; p=0.000) respectively. According to Kaiser (as cited in Field, 2005), these values are highly acceptable and shows that the correlation matrix of the Academic self-efficacy scale was factor analysable. The *Academic self-efficacy scale* was found to be uni-dimensional. Only one factor with an eigenvalue greater than 1 was obtained and this factor accounted for 66.8% of the variance. The factor loadings were all sustantially above .50 and only 29% of the residual correlations were larger than .05 suggesting that the factor solution provided a valid (i.e., permissible) explanation of the observed inter-item correlation matrix. The results are shown in Table 4.31

Table 4.31

Factor matrix for the Academic self-efficacy scale

	Factor
	1
c1	.823
c2	.761
c4	.798
c5	.878
c6	.782
c7	.853
c8	.867
c9	.845
c10	.839
c11	.820
c12	.711

4.4.3 The dimensionality analysis output for the Learning goal orientation scale

Exploratory factor analysis shows that the *Learning goal orientation scale* is factor analysable as indicated by KMO index and the Bartlett's test of sphericity values of .856 and 516.723 (df = 15; p=0.000) respectively. According to Kaiser (as cited in Field, 2005), these values are satisfactory and indicate the factor analysability of the correlation matrix of the *Learning goal orientation scale*. The *Learning goal orientation scale* was found to be uni-dimensional. Only one factor with an eigenvalue greater than 1 was obtained and this factor accounted for 50.6% of the variance. The factor loadings were all above .50 and only 26% of the residual correlations were larger than .05 suggesting that the factor solution provided a valid explanation of the observed inter-item correlation matrix. The results are shown in Table 4.32.

Table 4.32

Factor matrix for the Learning goal orientation scale

	Factor
	1
d1	.596
d2	.707
d3	.734
d4	.840
d5	.732
d6	.633

4.4.4 Dimensional analysis of the Metacognitive Awareness Inventory

4.4.4.1 The dimensionality analysis of the Declarative knowledge subscale

The *Declarative knowledge subscale* could not be proven to be uni-dimensional in the intial round of EFA. The initial round of exploratory factor analysis showed the existence of two factors. Four of the eight items appeared to be complex as they loaded on more than one factor. Items e5, e16, e17 and e20 were identified as complex items as they loaded on more than one factor and the difference between them was less than .250. These items were removed and another round of exploratory factor analysis was performed which resulted in the other items being complex. A decision was made to extract one factor and remove the item with the lowest loading. Item e46 was removed and a uni-dimensionality was achieved. This factor accounted for 29.65% of the variance. The factor loadings were all sustantially above .50 except for item e17 and e32 were were slightly below .5 and 28% of the residual correlations were larger than .05 suggesting that the factor solution provided a valid (i.e., permissible) explanation of the observed inter-item correlation matrix. The results are shown in Table 4.33.

Table 4.33

Factor matrix for the Declarative knowledge

	Factor
	1
e5	.562
e10	.601
e12	.505
e16	.598
e17	.488
e20	.581
e32	.459

4.4.4.2 The dimensionality analysis of the Procedural knowledge subscale

Exploratory factor analysis shows that the *Procedural knowledge subscale* is factor analysable as indicated by KMO index and the Bartlett's test of sphericity values of .640 and 56.689 (*df* = 6; p = 0.000) respectively. According to Kaiser (as cited in Field, 2005), these values are satisfactory and indicate the factor analysability of the correlation matrix of the *Procedural knowledge subscale*. The *Procedural knowledge subscale* was found to be uni-dimensional. Only one factor with an eigenvalue greater than 1 was obtained and this factor accounted for 22.73% of the variance. The factor loadings were above .4 and 16% of the residual correlations were larger than .05 suggesting that the factor solution provided a valid explanation of the observed inter-item correlation matrix. The results are shown in Table 4.34.

Table 4.34

Factor matrix for the Procedural knowledge

	Factor 1
e3	.431
e14	.556
e27	.493
e33	.413

4.4.4.3 The dimensionality analysis of the Conditional knowledge subscale

Exploratory factor analysis shows that the *Conditional knowledge subscale* is factor analysable as indicated by KMO index and the Bartlett's test of sphericity values of .669 and 91.153 (df = 10; p = 0.000) respectively. According to Kaiser (as cited in Field, 2005), these values are satisfactory and indicate the factor analysability of the correlation matrix of the *Conditional knowledge subscale*. The *Conditional knowledge subscale* was found to be uni-dimensional. Only one factor with an eigenvalue greater than 1 was obtained and this factor accounted for 23.52% of the variance. The factor loadings were above .3 and 30% of the residual correlations were larger than .05 suggesting that the factor solution provided a valid explanation of the observed inter-item correlation matrix. The results are shown in Table 4.35.

Table 4.35

Factor matrix for the Conditional knowledge

	Factor 1
e15	.310
e18	.429
e26	.525
e29	.699
e35	.362

4.4.4.4 The dimensionality analysis of the Planning subscale

Exploratory factor analysis shows that the *Planning subscale* is factor analysable as indicated by KMO index and the Bartlett's test of sphericity values of .781 and 269.742 (*df* = 21; p=0.000) respectively. According to Kaiser (as cited in Field, 2005), these values are satisfactory and indicate the factor analysability of the correlation matrix of the *Planning subscale* subscale. The *Planning subscale* was not found to be uni-dimensional in the initial round of EFA as item e42 is a complex item. Eliminating the item resulted in a uni-dimensional subscale. Only one factor with an eigen-value greater than 1 was obtained and this factor accounted for 33.87% of the variance. The factor loadings were all substantially above .3 and 33% of the residual correlations were larger than .05 suggesting that the rotated factor solution provided a reasonably credible explanation of the observed inter-item correlation matrix. The results are shown in Table 4.36.

Table 4.36

Factor matrix for the Planning subscale

	Factor
	1
e4	.616
e6	.429
e8	.693
e22	.522
e23	.557

4.4.4.5 The dimensionality analysis of the organising (implementing strategies and heuristics) subscale

The *Organising (implementing strategies and heuristics) subscale* could not be proven to be uni-dimensional in the intial round of EFA. The initial round of exploratory factor analysis showed the existence of three factors. Four of the 10 items appeared to be complex as they loaded on more than one factor. Items e9, e13, e37 and e41 were identified as complex items as they loaded on more than one factor and the difference between them was less than .250. These items were removed and another round of exploratory factor analysis was performed which resulted in a uni-dimensional scale. This factor accounted for 33.47% of the variance. The factor loadings were all sustantially above .50 except for item e48 and 40% of the residual correlations were larger than .05 suggesting that the factor solution provided a valid (i.e., permissible) explanation of the observed inter-item correlation matrix. The results are shown in Table 4.37.

Table 4.37

Factor matrix for the organising (implementing strategies and heuristics) subscale

	Factor 1
e30	.710
e31	.621
e39	.610
e43	.677
e47	.439
e48	.308

4.4.4.6 The dimensionality analysis of the monitoring subscale

Exploratory factor analysis shows that the *Monitoring subscale* is factor analysable as indicated by KMO index and the Bartlett's test of sphericity values of .787 and 291.396 (*df* = 21; p = 0.000) respectively. According to Kaiser (as cited in Field, 2005), these values are satisfactory and indicate the factor analysability of the correlation matrix of the *Monitoring subscale*. The *Monitoring subscale* was found to be uni-dimensional. Only one factor with an eigenvalue greater than 1 was obtained and this factor accounted for 31.53% of the variance. The factor loadings were generally above .50 except for two items which were marginally below .5 and 42% of the residual correlations were larger than .05 suggesting that the factor solution provided a valid explanation of the observed inter-item correlation matrix. The results are shown in Table 4.38.

Table 4.38

Factor matrix for the monitoring subscale

	Factor 1
e1	.594
e2	.565
e11	.593
e21	.482
e28	.589
e34	.466
e49	.622

4.4.4.7 The dimensionality analysis of the Debugging subscale

Exploratory factor analysis shows that the *Debugging subscale* is factor analysable as indicated by KMO index and the Bartlett's test of sphericity values of .732 and 159.190 (df = 10; p = 0.000) respectively. According to Kaiser (as cited in Field, 2005), these values are satisfactory and indicate the factor analysability of the correlation matrix of the *Debugging subscale*. The *Debugging subscale* was found to be uni-dimensional. Only one factor with an eigenvalue greater than 1 was obtained and this factor accounted for 31.34% of the variance. The factor loadings were generally above .50 except for item e25 which was below .5 and 30% of the residual correlations were larger than .05 suggesting that the factor solution provided a valid explanation of the observed inter-item correlation matrix. The results are shown in Table 4.39.

Table 4.39

Factor matrix for the Debugging subscale

	Factor
	1
e25	.388
e40	.711
e44	.519
e51	.602
e52	.528

4.4.4.8 The dimensionality analysis of the Evaluation strategies subscale

The *Evaluation strategies subscale* could not be proven to be uni-dimensional in the intial round of EFA. The initial round of exploratory factor analysis showed the existence of two factors. Two of the six items appeared to be complex as they loaded on more than one factor. Items e19 and e36 were identified as complex items as they loaded on more than one factor and the difference between them was less than .250. These items were removed and another round of exploratory factor analysis was performed which resulted in a uni-dimensional scale. This factor accounted for 24.43% of the variance. The factor loadings were all sustantially above .50 except for item e7 and. 16% of the residual correlations were larger than .05 suggesting that the factor solution provided a valid (i.e., permissible) explanation of the observed inter-item correlation matrix. The results are shown in Table 4.40.

Table 4.40

Factor matrix for the Evaluation strategies subscale

	Factor 1
e7	.255
e24	.501
e38	.517
e50	.628

4.4.5 The dimensionality analysis output for the Time cognitively engaged scale

The *Time cognitively engaged scale* could not be proven to be uni-dimensional. The initial round of exploratory factor analysis showed the existence of three factors. Eight of the 17 items namely items f4, f7, f8, f9, f11, f14, f15 and f16 were identified as complex items as they loaded on more than one factor and the difference between them was less than .250. These items were removed and another round of exploratory factor analysis was performed, this resulted in two factors. These two factors explained 38.4% and 11.5% of the variance respectively. The rotated factor matrix depicted in Table 4.41 shows the loading of the items on the two factors underlying the *Time cognitively engaged scale*. The identities of the two factors were subsequently determined based on the common themes emerging from the items loading on each of the two factors. Factor 1 relates to one's behaviour in class, which includes listening to the lecturer and engaging in the classroom activities. This factor was termed Time cognitively engaged (Class). Factor 2 generally relates to time and effort spent on academic activities Time cognitively engaged (Time). This can be considered a meaningful fission of the original Time –cognitively-enaged latent variable. The two factors will be used to indicate the Time cognitively engaged variable.

Table 4.41

Pattern matrix for the final EFA of the time-cognitively engaged scale

	Factor 1	Factor 2
f1	.045	**.716**
f2	.107	**.722**
f3	**.700**	-.094
f5	**.694**	-.077
f8	**.399**	.096
f10	-.049	**.795**
f12	**.733**	.024
f13	**.620**	.126
f14	-.018	**.447**
f17	**.650**	.041

4.4.6 The dimensionality analysis output for the Conscientiousness scale

The *Conscientiousness scale* failed the uni-dimensionality test. Exploratory factor analysis showed the existence of two factors. None of the items appeared to be complex items. The identified two factors explain 30% and 16.8% of the variance respectively. The rotated pattern matrix depicted in Table 4.42 shows the loading of the items on the two factors underlying the *Conscientiousness scale*. All the items loaded above .30 and only 13% of the residual correlations were larger than .05 suggesting that the rotated factor solution provided a valid explanation of the observed inter-item correlation matrix. The identities of the two factors were subsequently determined on the basis of the common themes emerging from the items loading on each of the two factors. Factor 1 relates to one's positive conscientiousness behaviour. Factor 2 generally relates to negative conscientiousness behaviour. In other words, the positively worded items loaded on Factor 1 while the negatively worded items loaded on Factor 2. The factor fission therefore seems to be a method artefact. Although the *Conscientiousness* scale has two underlying factors, based on the negative and positive wording of the items, all the items were considered to be measures of the higher-order *Conscientiousness* factor. The creation of item parcels to represent the *Conscientiousness* latent variable in the measurement model was regarded as permissible.

Table 4.42

Patternmatrix for the Conscientiousness scale

	Factor 1	Factor 2
h1	.035	**.663**
h2	-.066	**.618**
h3	.016	**.511**
h4	.153	**.552**
h5	.090	**.629**
h6	-.135	**.656**
HR7	**.698**	-.026
HR8	**.889**	-.004
HR9	**.844**	.021
HR10	**.627**	.031

4.4.7 The dimensionality analysis output for the Openness to experience scale

The initial round of EFA performed on the refined *Openness to experience scale* showed the existence of two factors. Item 5 loaded below .30 in the initial EFA analysis and was subsequently excluded. The elimination of item i5 resulted in a uni-dimensional factor structure. This factor accounted for 38.1% of the variance. The factor matrix depicted in Table 4.43 shows the loading of the items on the single factor loadings underlying the *Openness to experience scale*. All the items loaded above .30 (see guidelines in paragraph 3.9.3). However, 40% of the residual correlations were larger than .05 suggesting that the factor solution provided a somewhat tenuous explanation of the observed inter-item correlation matrix. The high percentage large residual correlations suggest a second factor. However, according to Field (2006) the number of non-redundant residuals should not exceed the level of 50% suggesting that it is within acceptable limits.

Table 4.43

Factor matrix for the revised openness to experience scale EFA

	Factor
	1
i1	.443
i2	.637
i3	.759
i6	.560
i7	.750
iR9	.481

4.4.8 The dimensionality analysis output for the Nunes Motivation to learn scale

Exploratory factor analysis shows that the Nunes Motivation to learn scale is factor analysable as indicated by KMO index and the Bartlett's test of sphericity values of .884 and 737.850 (*df* = 15; p=0.000) respectively. According to Kaiser (as cited in Field, 2005), these values are highly satisfactory and indicate the factor analysability of the correlation matrix of the Nunes Motivation to learn scale. The Nunes Motivation to learn scale was found to be uni-dimensional. Only one factor with an eigen-value greater than 1 was obtained and this factor accounted for 60% of the variance. The factor loadings were all substantially above .5 and 33% of the residual correlations were larger than .05 suggesting that the rotated factor solution provided a reasonably credible explanation of the observed inter-item correlation matrix. The results are shown in Table 4.44.

Table 4.44

Factor matrix for the Nunes Motivation to learn scale

	Factor
	1
j1	.818
j2	.624
j3	.833
j4	.808
j5	.829
j6	.714

4.5 EVALUATING THE FIT OF THE MEASUREMENT MODELS VIA CONFIRMATORY FACTOR ANALYSIS IN LISREL

Two of the latent variables in the structural model were conceptualised as multidimensional latent variables namely self-leadership and the metacognitive dimensions (knowledge of cognition and regulation of cognition). The scales used to operationalise these two latent variables therefore necessarily had to reflect the multidimensional nature of the latent variables they were meant to reflect. The item and dimnsionality analyses for the measures of these two latent variables were performed separately for each of the subscales of the instruments. To formally examine the construct validity of the measures CFA had to be performed. The findings on the CFA performed on the self-leadership scale and the metacognitive scale is discussed first. The fit of the measurement model describing the manner in which the composite indicator variables were earmarked to represent specific latent variables in the structural model is subsequently discussed.

The measurement model represents the relationship between the latent variable and its manifest indicators and is expressed by Equation 4.1:

$$\mathbf{X = \Lambda_x \xi + \delta} \text{ -- } 4.1$$

The symbol Λ_X represents the p x m matrix of factor loading coefficients (λ), which indicate the loading of the p composite indicators on their designated latent variable. The vector of latent variables is signified by the symbol ξ (ksi), whereas the symbol δ (delta) is used to indicate a vector of measurement error terms (Brown, 2006; Diamantopoulos & Siguaw, 2000). X represents a vector of composite indicator variables. Ultimately, the purpose of the confirmatory factor analysis is to determine whether the operationalisation of the latent variables comprising the measurement model in terms of item indicators was successful. The operationalisation can be considered successful if the measurement models specified in equation 4.1 can successfully reproduce the observed covariance matrix (i.e., 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 designed to reflect. Equation 4.2 describes the expression through which the reproduces covariance matrix is derived from the measurement model parameter estimates (Brown, 2006).

$$\mathbf{\Sigma = \Lambda_x \Psi \Lambda'_x + \Theta_\delta} \text{ -- } \mathbf{4.2}$$

Σ is the p x p symmetric covariance matrix for the p composite indicators.

The credibility of the measurement models was judged based on the RMSEA, p-value for the the test close fit as well as the absolute, comparative, relative and incremental fit indices. The completely standardised factor loadings are also discussed in order to evaluate the strength of the indicator factor loadings on the latent variable.

The fit of the estimated self-leadership measurement model is discussed next. A decision is made on the credibility of the measurement model parameter estimates and the parameters estimates of the fitted model are finally discussed.

4.5.1 Evaluating the fit of the RSLQ measurement model

The design of the Revised Self-leadership Questionnaire implies the measurement model expressed as Equation 4.3.

$\mathbf{X} = \mathbf{\Lambda}_x\xi + \boldsymbol{\delta}$ -- 4.3

Where $\mathbf{X}$ is a 31 by 1 colum vector of items, $\mathbf{\Lambda}_x$ is a 31 by 8 matrix of factor loadings , $\boldsymbol{\xi}$ is a 8 x 1 column vector of latent self-leadership dimensions and $\boldsymbol{\delta}$ is a 31 x 1 column vector of measurement error terms.

Confirmatory factor analysis (CFA) was performed on the items of the Revised Self-leadership Questionnaire. For the purposes of confirmatory factor analysis the measurement model was treated as an exogenous model simply due to programming advantages. The imputed data was first read into PRELIS (Jöreskog & Sörbom, 1996) to compute a covariance matrix and an asymptotic covariance matrix to serve as input for the LISREL analysis. All variables were defined as continuous. Robust maximum likelihood estimation was used to estimate the parameters set free in the model because of the lack of multivariate normality in the data.

The measurement model converged in 15 iterations. The full spectrum of fit statistics is shown in Table 4.45. An examination of the goodness-of-fit indices (discussed in detail in chapter three) shows that the model has achieved good model fit. A sample RMSEA value of .038 indicates good fit (Diamantopoulos & Siguaw, 2000). The upper bound of the 90 percent confidence interval for RMSEA (.028; .047) falls below the critical cutoff value value of .05, thereby confirming good model fit. LISREL 8.80

also explicitly tests the null hypothesis of close fit. Table 4.45 indicates that the null hypothesis of close model fit (H_{02}: RMSEA ≤ .05) is not rejected at a 5% significance level ($p > .05$). The RMR and standardised RMR values of .062 and .057 marginally miss the good model fit (< 0.05) level.

Table 4.45

Goodness-of-fit statistics for the Revised Self-leadership Questionnaire measurement model

Fit index	**Value**
Degrees of Freedom	406
Minimum Fit Function Chi-Square	680.886 (P = 0.0)
Normal Theory Weighted Least Squares Chi-Square	649.051 (P = 0.0)
Satorra-Bentler Scaled Chi-Square	530.533 (P = 0.0)
Estimated Non-centrality Parameter (NCP)	124.533
90 Percent Confidence Interval for	(69.021 ; 188.155)
Minimum fit function value	3.212
Population Discrepancy Function Value (F0)	0.587
90 Percent Confidence Interval for F0	(0.326 ; 0.888)
Root Mean Square Error of Approximation (RMSEA)	0.0380
90 Percent Confidence Interval for RMSEA	(0.0283 ; 0.0468)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.989
Expected Cross-Validation Index (ECVI)	3.352
90 Percent Confidence Interval for ECVI	(3.090 ; 3.652)
ECVI for Saturated Model	4.679
ECVI for Independence Model	45.303
Chi-Square for Independence Model with 465 Degrees of Freedom	9542.288
Independence AIC	9604.288
Model AIC	710.533
Saturated AIC	992.000
Independence CAIC	9739.488
Model CAIC	1103.049
Saturated CAIC	3155.201
Normed Fit Index (NFI)	0.944
Non-Normed Fit Index (NNFI)	0.984
Parsimony Normed Fit Index (PNFI)	0.825
Comparative Fit Index (CFI)	0.986
Incremental Fit Index (IFI)	0.986
Relative Fit Index (RFI)	0.936
Critical N (CN)	190.896
Root Mean Square Residual (RMR)	0.0615
Standardised RMR	0.057
Goodness of Fit Index (GFI)	0.835
Adjusted Goodness of Fit Index (AGFI)	0.798
Parsimony Goodness of Fit Index (PGFI)	0.684

The results of the incremental fit measures in Table 4.45 indicate that, when compared to a baseline model, the RSLQ measurement model achieved NFI (.94), NNFI (.98), CFI (.99), IFI (.99) and RFI (.94) indices exceeding .90, which represent good fit (Diamantopoulos & Siguaw, 2000; Hair *et al.*, 2010; Kelloway, 1998). Therefore, these relative indices seem to portray a positive picture of model fit. The GFI value of .84 misses the acceptable .90 level.

4.5.1.1 The unstandardised lambda-X matrix

The unstandardised lambda-X matrix provides an indication of the statistical significance of the slope of the regression of the observed variables onto their respective latent variables. It also provides an indication of the validity of the measures. In other words, if a measure is designed to provide a valid reflection of a specific latent variable, then the slope of the regression of X_i on ξ_j in the fitted measurement model has to be substantial and significant (Diamantopoulos & Siguaw, 2000). The unstandardized $\mathbf{\Lambda}_x$ matrix contains the regression coefficients of the regression of the manifest variables on the latent variables they were linked to. The regression coefficients of the manifest variables on the latent variables are significant ($p < .05$) if the t-values, as indicated in the matrix, exceed $|1.96|$. Significant indicator loadings provide validity evidence in favour of the indicators (Diamantopoulos & Siguaw, 2000). All the RSLQ manifest variables load significantly on the latent variables that they were designed to reflect (see SLEADN output file on the attached CD). In the lambda-X matrix, the t-values appear directly under the standard error estimates in brackets. Significant loadings confirm the validity of the indicators (Diamantopoulos & Siguaw, 2000).

Although the unstandardised lambda-X matrix indicate that the factor loadings are significant, Diamantopoulos and Siguaw (2000) warn against absolute reliance on the unstandardised loadings and their associated t-values. The problem is that it may be difficult to compare the validity of different indicators measuring a particular construct. This is due to the fact that indicators of the same construct may be measured on very different scales hence direct comparisons of the magnitudes of the loadings are inappropriate. Furthermore, since each latent variable has to be assigned a scale by fixing the loadings of one of its indicators to a unit, the loadings of the other indicators for that latent variable are only interpretable relative to the unit of the reference indicator. If a different indicator is used as the reference variable, the magnitudes of the loadings will change hence the magnitudes of the standardised loadings should also be inspected (Diamantopoulos & Siguaw, 2000). The standardised loadings are discussed and shown in Table 4.46

Table 4.46 gives the completely standardised factor loadings. The values shown in the completely standardised solution loading matrix represent the slopes of the regression of the standardised items on the standardised latent self-leadership dimension that the item was designed to represent. Therefore, the completely standardised loadings indicate the average change expressed in standard deviations in the item associated with one standard deviation change in the latent variable. The factor loadings of the items are generally satisfactorily large (> .50) with the exception of item 8 with a loading of .430 which is still acceptable.

Table 4.47 gives the correlations between the eight latent RSLQ dimensions. These correlations reflect the correlations between the eight RSLQ subscales, corrected for the attenuating effect of random and systematic measurement error. The correlations fall within reasonable limits, as high values (above .90) may indicate multi-collinearity (Tabachnick & Fidell, 2001).

Integrating the available evidence on the fit of the RSLQ measurement model points to good model fit. The fit statistics in Table 4.45 generally indicate a good fitting model. The model achieved close fit although both the RMR and standardised RMR values were marginally above .05. The NFI; NNFI; CFI; RFI and IFI are within the acceptable range. The GFI failed to meet the .90 level. The phi matrix shows that none of the items correlate above .90. The completely standardised factor loadings are generally acceptable.

Table 4.46

Factor loading estimates[a] for self-leadership measurement model (first-order)

Item[b]	VSP	S-GOAL	S-TALK	S-REW	EBA	S-OBS	FTNR	S-CUE
1	0.63	-	-	-	-	-	-	-
10	0.77	-	-	-	-	-	-	-
19	0.83	-	-	-	-	-	-	-
27	0.79	-	-	-	-	-	-	-
33	0.52	-	-	-	-	-	-	-
2	-	0.71	-	-	-	-	-	-
11	-	0.79	-	-	-	-	-	-
20	-	0.82	-	-	-	-	-	-
28	-	0.72	-	-	-	-	-	-
34	-	0.64	-	-	-	-	-	-
3	-	-	0.83	-	-	-	-	-
12	-	-	0.88	-	-	-	-	-
21	-	-	0.80	-	-	-	-	-
4	-	-	-	0.86	-	-	-	-
13	-	-	-	0.88	-	-	-	-
22	-	-	-	0.94	-	-	-	-
5	-	-	-	-	0.67	-	-	-
14	-	-	-	-	0.75	-	-	-
23	-	-	-	-	0.55	-	-	-
29	-	-	-	-	0.79	-	-	-
7	-	-	-	-	-	0.66	-	-
16	-	-	-	-	-	0.60	-	-
25	-	-	-	-	-	0.78	-	-
31	-	-	-	-	-	0.73	-	-
8	-	-	-	-	-	-	**0.43**	-
17	-	-	-	-	-	-	0.54	-
26	-	-	-	-	-	-	0.65	-
32	-	-	-	-	-	-	0.54	-
35	-	-	-	-	-	-	0.72	-
9	-	-	-	-	-	-	-	0.76
18	-	-	-	-	-	-	-	0.91

Note: Factor loadings < 0.50 are in bold.

VSP: Visualising Successful Performance; S-GOAL: Self-goal Setting; S-TALK: Self-talk; S-REWARD: Self-reward; EBA: Evaluating Beliefs and Assumptions; S-OBS: Self-observation; FTNR: Focusing Thoughts on Natural Rewards; S-CUE: Self-cueing.
[a]Factor loadings are completely standardised (*lamda X*); [b]Item numbers correspond to the order in Houghton, J.D., & Neck, C.P. (2002). The revised self-leadership questionnaire: Testing a hierarchical factor structure for self-leadership. *Journal of Managerial Psychology, 17*(8), 672–691. http://dx.doi.org/10.1108/02683940210450484.

Table 4.47

Inter-correlations between latent RSLQ dimensions

Dimension	VSP	S-GOAL	S-TALK	S-REWARD	EBA	S-OBS	FTNR	S-CUE
VSP	1.000							
S-GOAL	0.69	1.000						
S-TALK	0.48	0.39	1.000					
S-REWARD	0.24	0.22	0.28	1.000				
EBA	0.61	0.67	0.46	0.41	1.000			
S-OBS	0.59	0.75	0.31	0.31	0.52	1.000		
FTNR	0.60	0.71	0.34	0.47	0.62	0.61	1.000	
S-CUE	0.28	0.55	0.23	0.24	0.29	0.41	0.45	1.000

Note: $N = 213$.
Correlations are below the diagonal. VSP: Visualising Successful Performance; S-GOAL: Self-goal Setting; S-TALK: Self-talk; S-REWARD: Self-reward; EBA: Evaluating Beliefs and Assumptions; S-OBS: Self-observation; FTNR: Focusing Thoughts on Natural Rewards; S-CUE: Self-cueing.

4.5.2 Goodness-of-fit of the Metacognitive Awareness Inventory measurement model

The design of the Metacognitive Awareness Inventory implies the measurement model expressed as Equation 4.4.

$$\mathbf{X} = \boldsymbol{\Lambda}_x\boldsymbol{\xi} + \boldsymbol{\delta} \text{ --- } \quad 4.4$$

Where **X** is a 52 by 1 colum vector of items, Λ_x is a 52 by 8 matrix of factor loadings , ξ is a 8 x 1 column vector of latent metacognitive dimensions and δ is a 44 x 1 column vector of measurement error terms.

Table 4.48

Goodness-of-Fit statistics for the Metacognitive Awareness Inventory measurement model

Fit index	Value
Degrees of Freedom	874
Minimum Fit Function Chi-Square	1722.042 (P = 0.0)
Normal Theory Weighted Least Squares Chi-Square	1847.170 (P = 0.0)
Satorra-Bentler Scaled Chi-Square	1515.114 (P = 0.0)
Estimated Non-centrality Parameter (NCP)	641.114
90 Percent Confidence Interval for NCP	(536.988 ; 753.083)
Minimum fit function value	8.123
Population Discrepancy Function Value (F0)	3.024
90 Percent Confidence Interval for F0	(2.533 ; 3.552)
Root Mean Square Error of Approximation (RMSEA)	0.0588
90 Percent Confidence Interval for RMSEA	(0.0538; 0.0638)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.00209
Expected Cross-Validation Index (ECVI)	8.241
90 Percent Confidence Interval for ECVI	(7.750 ; 8.769)
ECVI for Saturated Model	9.340
ECVI for Independence Model	75.356
Chi-Square for Independence Model with 465 Degrees of Freedom	15887.501
Independence AIC	15975.501
Model AIC	1747.114
Saturated AIC	1980.000
Independence CAIC	16167.398
Model CAIC	1103.049
Saturated CAIC	16167.398
Normed Fit Index (NFI)	0.905
Non-Normed Fit Index (NNFI)	0.954
Parsimony Normed Fit Index (PNFI)	0.836
Comparative Fit Index (CFI)	0.957
Incremental Fit Index (IFI)	0.957
Relative Fit Index (RFI)	0.897
Critical N (CN)	137.315
Root Mean Square Residual (RMR)	0.0692
Standardised RMR	0.0745
Goodness of Fit Index (GFI)	0.716
Adjusted Goodness of Fit Index (AGFI)	0.679
Parsimony Goodness of Fit Index (PGFI)	0.632

An examination of the goodness-of-fit indices of the Metacognitive Awareness Inventory shows that the model has achieved reasonable model fit. An RMSEA value of .059 indicates reasonable fit with the data (Diamantopoulos & Siguaw, 2000). LISREL also explicitly tests the null hypothesis of close fit. Table 4.48 indicates that the null hypothesis of close model fit (H_{02}: RMSEA ≤ .05) is rejected at a 5% significance level ($p > .05$). The RMR and standardised RMR values of .069 and .075 miss the good model fit (< .05) level.

The results of the incremental fit measures indicate that, when compared to a baseline model, the Metacognitive Awareness Inventory measurement model achieved NFI (.91), NNFI (.95), CFI (.96), IFI (.96) and RFI (.90) indices exceeding .90, which indicates good fit (Diamantopoulos & Siguaw, 2000; Hair *et al*., 2010; Kelloway, 1998). Therefore, these relative indices seem to portray a reasonably positive picture of model fit. The GFI failed to reach the .90 level indicative of good model fit.

An examination of the magnitude and statistical significance of the slope of the regression of the eight observed variables of the MAI indicates that all the MAI manifest variables load significantly on the latent variables that they were designed to reflect (see METAN output file on the attached CD). The t-values appear directly under the standard error estimates in brackets in the lambda-X matrix. Significant loadings confirm the validity of the indicators (Diamantopoulos & Siguaw, 2000). The output was not formally presented in the thesis due to the size of the lambda-X matrix which spreads over four pages. Since Diamantopoulos and Siguaw (2000) advised against an over reliance on the unstandardised lambda-X estimates the completely standardised factor loadings were also inspected and discussed.

Table 4.49

Completely standarised factor loading estimates[a] for Metacognitive Awareness Inventory measurement model (first-order)

Item	DK	PK	CK	PLAN	STRAT	MONITOR	DEBUG	EVALUATE
5	0.53	-	-	-	-	-	-	-
10	0.57	-	-	-	-	-	-	-
12	0.53	-	-	-	-	-	-	-
16	0.58	-	-	-	-	-	-	-
17	0.48	-	-	-	-	-	-	-
20	0.61	-	-	-	-	-	-	-
32	0.49	-	-	-	-	-	-	-
3	-	0.40	-	-	-	-	-	-
14	-	0.46	-	-	-	-	-	-
27	-	0.50	-	-	-	-	-	-
33	-	0.50		-	-	-	-	-
15	-		**0.35**	-	-	-	-	-
18	-	-	0.41	-	-	-	-	-
26	-	-	0.49		-	-	-	-
29	-	-	0.50		-	-	-	-
35	-	-	0.55		-	-	-	-
4	-	-	-	0.52	-	-	-	-
6	-	-	-	0.54	-	-	-	-
8	-	-	-	0.66	-	-	-	-
22	-	-	-	0.49	-	-	-	-
23	-	-	-	0.59	-	-	-	-
45	-	-	-	0.63	-	-	-	-
30	-	-	-	-	0.70	-	-	-
31	-	-	-	-	0.63	-	-	-
39	-	-	-	-	0.66	-	-	-
43	-	-	-	-	0.64	-	-	-
47	-	-	-	-	0.44	-	-	-
48	-	-	-	-	**0.30**	-	-	-
1	-	-	-	-	-	0.59	-	-
2	-	-	-	-	-	0.56	-	-
11	-	-	-	-	-	0.61	-	-
21	-	-	-	-	-	0.51	-	-
28	-	-	-	-	-	0.58	-	-
34	-	-	-	-	-	0.51	-	-
49	-	-	-	-	-	0.61	-	-
25	-	-	-	-	-	-	**0.38**	-
40	-	-	-	-	-	-	0.70	-
44	-	-	-	-	-	-	0.54	-
51	-	-	-	-	-	-	0.61	-
52	-	-	-	-	-	-	0.56	-
7	-	-	-	-	-	-	-	0.44
24	-	-	-	-	-	-	-	0.49
38	-	-	-	-	-	-	-	0.44
50	-	-	-	-	-	-	-	0.52

Note: Factor loadings < 0.40 are in bold.
DK: Declarative knowledge; PK: Procedural knowledge; CK: Conditional knowledge; PLAN: Planning; STRAT: Organising; MONITOR: Monitoring; DEBUG: Debugging; EVALUATE: Evaluation. [a]Factor loadings are completely standardised (*lambda X*); [b]Item numbers correspond to the order in Schraw, G., & Dennison, R.S. (1994). Assessing metacognitive awareness. *Contemporary Educational Psychology, 19*, 460-475.

Table 4.49 gives the completely standardised factor loadings. The factor loadings of the items are generally substantial (> 0.30). This means that all items to a reasonable degree represent the dimension they were designed to reflect.

Table 4.50 gives the correlations among the eight Metacognitive Awareness Inventory dimensions. The correlations are, however, a cause for concern as they are above .90 which may indicate the problem of multi-collinearity (Tabachnick & Fidell, 2001). Moreover some of the values are inadmissable in that they exceed unity. This seriously erodes confidence in the results obtained for the Metacognitive Awareness Inventory CFA.

Table 4.50

Inter-correlations between latent Metacognitive Awareness Inventory dimensions

Dimension	DK	PK	CK	PLAN	STRAT	MONITOR	DEBUG	EVALUATE
DK	1.000							
PK	1.10	1.000						
CK	1.02	1.29	1.000					
PLAN	0.80	0.96	0.91	1.000				
STRAT	0.77	1.03	0.95	0.70	1.000			
MONITOR	0.83	1.07	1.07	1.04	0.87	1.000		
DEBUG	0.76	1.06	1.00	0.68	0.89	0.82	1.000	
EVALUATE	0.93	1.20	1.10	1.11	0.90	1.15	0.92	1.000

Note: $N = 213$.
DK: Declarative knowledge; PK: Procedural knowledge; CK: Conditional knowledge; PLAN: Planning; STRAT: Organising; MONITOR: Monitoring; DEBUG: Debugging; EVALUATE: Evaluation.

Integrating the available evidence on the fit of the MAI measurement model points to a model that fits the data resonably well. The fit statistics in Table 4.48 generally indicate a good fitting model except that the model failed to achieve close fit and that both the RMR and standardised RMR values were above .05. The NFI; NNFI; CFI;

RFI and IFI are within the acceptable range. The GFI failed to meet the .90 level. The phi matrix shows that some of the items are correcting highly above .90 which raises the issue of possible multi-collinearity among the item parcels. The completely standardised factor loadings are generally acceptable.

4.6 ASSESSMENT OF UNIVARIATE AND MULTIVARIATE NORMALITY OF THE DE GOEDE-BURGER-MAHEMBE STRUCTURAL MODEL COMPOSITE INDICATOR VARIABLE DATA

Maximum likelihood estimation is the default procedure used to estimate model parameters in the process of fitting a measurement model to continuous data. This method of estimation assumes that data follows a multivariate normal distribution. Since the results indicate that the problem of lack of univariate and multivariate normality still had to be addressed, robust maximum likelihood etimation method was used to resolve this problem.

The multivariate normality of the composite item parcels in this study was evaluated via PRELIS. Table 4.51 indicates that the 30 out of the 40 indicator variables failed the test of univariate normality ($p < .05$). The chi-square value for skewness and kurtosis indicates that 30 of the 40 indicator variables failed the test of univariate normality ($p < .05$). Furthermore, the null hypothesis that the data follows a multivariate normal distribution also had to be rejected (^{2}= 972.631; $p < .05$). Since the quality of the

Table 4.51

Test of univariate normality for continuous variables before normalisation

	Skewness		Kurtosis		Skewness and Kurtosis	
	Z-SCORE	P-VALUE	Z-SCORE	P-VALUE	CHI-SQUARE	P-VALUE
VSP	-5.257	0.000	3.350	0.001	38.863	0.000
SGOAL	-5.226	0.000	2.913	0.004	35.797	0.000
STALK	-4.541	0.000	1.136	0.256	21.912	0.000
SREW	-2.057	0.040	-5.093	0.000	30.168	0.000
EBA	-5.170	0.000	3.152	0.002	36.665	0.000
SOBS	-2.190	0.028	-0.568	0.570	5.121	0.077
FTNR	-3.364	0.001	1.072	0.284	12.465	0.002
SCUE	-2.730	0.006	-2.140	0.032	12.030	0.002
SEFF_1	-1.232	0.218	0.224	0.823	1.568	0.457
SEFF_2	-0.332	0.740	-0.535	0.593	0.396	0.820
LGO_1	-5.581	0.000	2.566	0.010	37.735	0.000
LGO_2	-4.119	0.000	1.407	0.159	18.948	0.000
DK	-3.164	0.002	1.431	0.152	12.059	0.002
PK	-2.879	0.004	0.666	0.505	8.730	0.013
CK	-1.680	0.093	-1.235	0.217	4.348	0.114
PLAN	-2.982	0.003	0.440	0.660	9.083	0.011
STRAT	-3.340	0.001	2.178	0.029	15.895	0.000
MONITOR	-2.203	0.028	-0.729	0.466	5.383	0.068
DEBUG	-2.613	0.009	-1.027	0.304	7.881	0.019
EVALUATE	-2.277	0.023	0.277	0.782	5.262	0.072
TCOG_1	-1.653	0.098	0.847	0.397	3.449	0.178
TCOG_2	-2.633	0.008	-1.131	0.258	8.209	0.017
CONSC_1	-3.035	0.002	0.835	0.404	9.911	0.007
CONSC_2	-2.253	0.024	-0.666	0.505	5.521	0.063
OPEN_1	-2.233	0.026	0.333	0.739	5.098	0.078
OPEN_2	-3.189	0.001	0.208	0.835	10.212	0.006
MOT_1	-7.892	0.000	5.344	0.000	90.850	0.000
MOT_2	-6.907	0.000	3.760	0.000	61.844	0.000
CRRATIO	4.331	0.000	-3.311	0.001	29.715	0.000
LEARNP	-2.562	0.010	-0.622	0.534	6.951	0.031
ABSTR_1	-0.276	0.782	-2.185	0.029	4.850	0.088
ABSTR_2	-1.146	0.252	-3.262	0.001	11.957	0.003
SERIES	0.786	0.432	0.546	0.585	0.916	0.633
MIRROR	-3.366	0.001	2.325	0.020	16.732	0.000
TRNS	-0.122	0.903	-1.535	0.125	2.372	0.305
CPT	-0.542	0.588	0.080	0.936	0.300	0.860
RES_1	0.925	0.355	2.627	0.009	7.757	0.021
RES_2	6.028	0.000	4.425	0.000	55.926	0.000
RES_3	1.103	0.270	2.503	0.012	7.482	0.024
RES_4	4.763	0.000	3.450	0.001	34.586	0.000

solution obtained in structural equation modelling is to a large extent dependent on multivariate normality, it was decided to normalise the variables through PRELIS. Table 4.52 indicates that the null hypothesis stating that the data follows a multivariate normal distribution was also rejected (^{2} = 972.631; $p < .05$). PRELIS was subsequently employed to normalise the data.

Table 4.52

Test of Multivariate Normality for Continuous Variables before Normalisation

Skewness			Kurtosis		Skewness	and	Kurtosis
Value	Z-score	P-value	Value	Z-score	P-value	Chi-square	P-value
459.605	28.261	0.000	1853.321	13.188	0.000	972.631	0.000

Table 4.53 indicates that the normalisation procedure succeeded in rectifying the univariate normality problem on 36 out of the 40 indicator variables. The p-values of the 36 item parcels increased quite substantially as can be seen in Table 4.53. The univariate normality null hypothesis had to be rejected for 4 of the 40 item parcels. Normalising the data typically does improve the symmetry and kurtosis of the indicator variable distributions. The chi-square also improved from 972.631 to 476.725. Table 4.54 indicates that although the normalisation procedure employed using PRELIS succeeded in improving the univariate normality of 36 indicator variables, the null hypothesis of multivariate normality still had to be rejected hence it was decided to use robust maximum likelihood estimation to derive estimates for the freed measurement model model parameters. Table 4.54 indicates that the chi square of the normalised data improved but the null hypothesis of multivariate normality (^{2} = 476.725, $p < .05$) still had to be rejected.

Table 4.53

Test of univariate normality for continuous variables after normalisation

	Skewness		Kurtosis		Skewness and Kurtosis	
	Z-SCORE	P-VALUE	Z-SCORE	P-VALUE	CHI-SQUARE	P-VALUE
VSP	-0.238	0.812	-0.528	0.598	0.335	0.846
SGOAL	-0.510	0.610	-0.772	0.440	0.857	0.652
STALK	-1.659	0.097	-2.399	0.016	8.507	0.014
SREW	-0.434	0.664	-2.575	0.010	6.820	0.033
EBA	-0.238	0.812	-0.366	0.714	0.191	0.909
SOBS	-0.352	0.725	-0.830	0.406	0.813	0.666
FTNR	-0.139	0.889	-0.328	0.743	0.127	0.939
SCUE	-0.793	0.428	-1.695	0.090	3.501	0.174
SEFF_1	-0.205	0.837	-0.345	0.730	0.161	0.923
SEFF_2	-0.267	0.789	-0.445	0.656	0.270	0.874
LGO_1	-0.220	0.826	-0.102	0.919	0.059	0.971
LGO_2	-0.343	0.731	-0.458	0.647	0.328	0.849
DK	-0.023	0.981	-0.148	0.882	0.023	0.989
PK	-0.134	0.894	-0.096	0.923	0.027	0.987
CK	-0.197	0.844	-0.254	0.799	0.104	0.950
PLAN	-0.104	0.917	-0.082	0.934	0.018	0.991
STRAT	-0.116	0.908	-0.105	0.917	0.024	0.988
MONITOR	-0.065	0.948	-0.050	0.960	0.007	0.997
DEBUG	-0.262	0.793	-0.368	0.713	0.204	0.903
EVALUATE	-0.160	0.873	-0.238	0.812	0.082	0.960
TCOG_1	-0.062	0.950	-0.009	0.993	0.004	0.998
TCOG_2	-0.141	0.888	-0.038	0.970	0.021	0.989
CONSC_1	-0.070	0.945	0.024	0.681	0.005	0.997
CONSC_2	-0165	0.869	-0.143	0.886	0.048	0.977
OPEN_1	-0.193	0.847	-0.183	0.855	0.071	0.965
OPEN_2	-0.668	0.504	-1.037	0.300	1.520	0.468
MOT_1	-2.264	0.024	-2.361	0.018	10.701	0.005
MOT_2	-2.507	0.012	-2.424	0.015	12.159	0.002
CRRATIO	-0.557	0.577	-0.501	0.617	0.561	0.755
LEARNP	-0.027	0.978	0.026	0.979	0.001	0.999
ABSTR_1	-0.037	0.971	-0.045	0.964	0.003	0.998
ABSTR_2	-0.318	0.751	-0.577	0.564	0.434	0.805
SERIES	-0.017	0.986	0.038	0.970	0.002	0.999
MIRROR	-0.005	0.996	-0.023	0.981	0.001	1.000
TRNS	0.154	0.878	-0.250	0.802	0.086	0.958
CPT	0.049	0.961	-0.024	0.981	0.003	0.998
RES_1	0.000	1.000	0.097	0.923	0.009	0.995
RES_2	0.000	1.000	0.097	0.923	0.009	0.995
RES_3	0.000	1.000	0.097	0.923	0.009	0.995
RES_4	0.000	1.000	0.097	0.923	0.009	0.995

Table 4.54

Test of Multivariate Normality for Continuous Variables after Normalisation

Skewness			Kurtosis			Skewness and	Kurtosis
Value	Z-score	P-value	Value	Z-score	P-value	Chi-square	P-value
411.797	19.074	0.000	1797.319	10.625	0.000	476.725	0.000

4.7 OVERALL MEASUREMENT MODEL FIT

The operationalisation of the latent variables comprising the De Goede-Burger-Mahembe learning potential structural model as described in paragraph 3.8 implies the measurement model expressed as Equation 3.11.

The LISREL programme, version 8.80 (Jöreskog & Sörbom, 2006) was used to perform a confirmatory factor analysis on the overall measurement model to determine the fit of the model. The robust maximum likelihood estimation method was used to produce the estimates due to the failure of the data to satisfy the multivariate normality assumption. The overall measurement model fit indices are briefly discussed in this section since they have been discussed in detail chapter three. The fit statistics are shown in Table 4.55.

The chi-square statistic is the traditional measure for overall model fit in co-variance structure models. It provides a test of perfect fit in which the null hypothesis is that the model fits the population data perfectly. A statistically significant chi-square leads to the rejection of the null hypothesis, implying imperfect fit and possible rejection of the model. Thus the null hypothesis tested by the chi-square test is **H_0: $\Sigma = \Sigma(\Theta)$** (Diamantopoulos & Siguaw, 2000). The p-value associated with the Satorra-

Table 4.55

Goodness-of-fit statistics for the overall measurement model

Fit index	**Value**
Degrees of Freedom	659
Minimum Fit Function Chi-Square	1101.598 (P = 0.0)
Normal Theory Weighted Least Squares Chi-Square	1051.780 (P = 0.0)
Satorra-Bentler Scaled Chi-Square	952.433 (P = 0.0)
Estimated Non-centrality Parameter (NCP)	293.433
90 Percent Confidence Interval for NCP	(215.299; 379.567)
Minimum fit function value	5.196
Population Discrepancy Function Value (F0)	1.384
90 Percent Confidence Interval for F0	(1.016; 1790)
Root Mean Square Error of Approximation (RMSEA)	0.0458
90 Percent Confidence Interval for RMSEA	(0.0393; 0.0521)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.859
Expected Cross-Validation Index (ECVI)	6.011
90 Percent Confidence Interval for ECVI	(5.643; 6.418)
ECVI for Saturated Model	7.736
ECVI for Independence Model	70.194
Chi-Square for Independence Model with 780 Degrees of Freedom	14801.206
Independence AIC	14881.206
Model AIC	1274.433
Saturated AIC	1640.000
Independence CAIC	15055.658
Model CAIC	1976.601
Saturated CAIC	5216.260
Normed Fit Index (NFI)	0.936
Non-Normed Fit Index (NNFI)	0.975
Parsimony Normed Fit Index (PNFI)	0.791
Comparative Fit Index (CFI)	0.979
Incremental Fit Index (IFI)	0.979
Relative Fit Index (RFI)	0.924
Critical N (CN)	167.138
Root Mean Square Residual (RMR)	0.0445
Standardised RMR	0.0553
Goodness of Fit Index (GFI)	0.801
Adjusted Goodness of Fit Index (AGFI)	0.753
Parsimony Goodness of Fit Index (PGFI)	0.644

Bentler scaled chi-square returned a value of 952.433 ($p = .0$) which indicates a significant test statistic ($p < .05$). This suggests that there is a significant discrepancy between the covariance matrix implied by the measurement model and the observed covariance matrix, thus rejecting the following exact fit null hypothesis (H_{01a}) :

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

H_{a1a}: RMSEA > 0

The root mean square error of approximation (RMSEA) value is .0458 which indicates good model fit (Diamantopoulos & Siguaw, 2000). LISREL 8.80 also provides a 90% confidence interval for the RMSEA (0.0393; 0.0521) indicating that the hypothesis of close fit is not rejected since the interval includes the RMSEA value. The LISREL programme also tests the null hypothesis of close fit, (H_{01b} RMSEA ≤ .05) by calculating the conditional probability of observing the sample value of .0458 under the assumption that H_0: RMSEA < .05 is true in the population. A probability value of .859 is returned in Table 4.55. The close fit null hypothesis (depicted below) is therefore not rejected.

H_{01b}: RMSEA ≤ .05

H_{a1b}: RMSEA > .05

The root mean squared residual (RMR) and the standardised RMR values below .05 are indicative of acceptable fit (Diamantopoulos & Siguaw, 2000). In this case the values of the RMR and standardised RMR were .0445 and .0553 respectively. These values indicate of good although the standardised RMR value marginally misses the .05 level indicative of good model fit.

The absolute fit indices generally indicated that the covariances predicted from the parameter estimates reproduce the sample covariances (Diamantopoulos & Siguaw, 2000). The values of the GFI = .80 and AGFI = .75 miss the .90 level indicative of good model fit. However, the PGFI value of .64 is within a reasonable range. Acceptable values for the PGFI are much lower, within the .50 region (Mulaik, James, Van Alstine, Bennet, & Stilwell, 1989).

The relative fit indices displayed in Table 4.47 indicate that the NFI = .94, NNFI = .98, CFI = .98, Relative Fit Index = .92, and Incremental Fit Index = .98. These indices generally indicate a good fit of the model over the independence model as acceptable values are above .90 (Diamantopoulos & Siguaw, 2000).

The critical N (CN) statistic. Shows a value of CN = 167.14 which is below the generally suggested minimum threshold of 200 for structural equation modeling studies (Diamantopoulos & Siguaw, 2000). However, according to Diamantopoulos and Siguaw (2000), both the value of the CN statistic and the cut-off point has been challenged in the literature and therefore the CN statistic has to be interpreted with caution.

4.7.1 The unstandardised lambda-X matrix for the overall measurement model

An examination of the statistical significance of the slope of the regression of the observed variables of the overall measurement model indicates that all the measurement model item parcels load significantly on the latent variables that they were designed to reflect with the exception of one of the item parcels (RES_2) of the interaction term (see BMP2N.OUT file on the attached CD). Generally, the t-values obtained for the interaction term are slightly higher than 1.96 and range from 2.278 to 3.048. Since Diamantopoulos and Siguaw (2000) advised against overly depending on the unstandardised lambda-X estimates, the completely standardised factor loadings were also studied and discussed.

4.7.2 The completely standardised factor loading matrix

The values shown in the completely standardised solution factor loading matrix (see Table 4.56) represent the regression slopes of the regression of the standardised indicator variables on the standardised latent variables. The completely standardised loadings therefore indicate the average change expressed in standard deviations in the indicator variable associated with one standard deviation change in the latent variable (Diamantopoulos & Siguaw, 2000). The standardised factor loadings appear to be satisfactorily large with the exception of OPEN_2 the second item parcel for *Openness to experience* which obtained an inadmissable value thatexceeds unity. The item parcels SREW (.367) and STALK (.476) for the self-reward subscale of the Revised Self-leadership Questionnaire; and two item parcels for the interaction term RES_2 (.122) and RES_4 (.292) were low in comparison with the other completely standardised item parcel values which were generally above .5. This to some degree erodes confidence in the operationalisation.

Table 4.56

Completely standardised lambda-X matrix for the item parcels

	SLEADER	SEFFICAC	LGOAL	MREGUL	MKNOW	TCOGNIT
VSP	0.689					
SGOAL	0.821					
STALK	0.476					
SREW	0.367					
EBA	0.655					
SOBS	0.675					
FTNR	0.665					
SCUE	0.505					
SEFF_1		0.956				
SEFF_2		0.982				
LGO_1			0.838			
LGO_2			0.854			
DK					0.790	
PK					0.862	
CK					0.844	
PLAN				0.821		
STRAT				0.747		
MONITOR				0.989		
DEBUG				0.707		
EVALUATE				0.788		
TCOG_1						0.868
TCOG_2						0.886

Table 4.56 (continued)

	CONSCIEN	OPENNES	MOTIVATI	LPERFORM	ABSTRACT	ABSPRIO	INFOPRO
CONSC_1	0.802						
CONSC_2	0.937						
OPEN_1		0.586					
OPEN_2		1.030					
MOT_1			0.953				
MOT_2			0.879				
CRRATIO				0.710			
LEARNP				0.736			
ABSTR_1					0.861		
ABSTR_2					0.839		
SERIES							0.757
MIRROR							0.815
TRNS							0.772
CPT							0.896
RES_1						0.643	
RES_2						0.122	
RES_3						0.514	
RES_4						0.292	

Note: SLEADER, Self-leadership; LGOAL, Learning goal; MREGUL, Metacognitive regulation; TCOGNIT, Time cognitively engaged; LPERFORM, Learning performance; SEFFICAC, Self-efficacy; MKNOW, Metacognitive knowledge; CONSCIEN, Conscientiousness; OPENNES, Openness to experience; ABSTRACT, Abstract thinking capacity; ABSPRIO, interaction term for abstract thinking capacity and prior learning; INFOPRO, Information processing capacity; MOTIVATI, Learning motivation.

4.7.3 The theta-delta matrix

The total variance in the indicator variable could be decomposed into variance due to variance in the latent variable the indicator variable was meant to reflect (ξ_j), variance due to variance in other systematic latent effects the indicator variable was not designed to reflect and random error. The latter are reflected in the δ_i terms. The measurement error terms δ_i do not differentiate between systematic and random sources of error or non-relevance variance. The square of the completely standardised factor loadings λ (see Table 4.56) could be interpreted as the proportion of systematic-relevant indicator variable variance which corresponds to the squared multiple correlations for X-variables in Table 4.58.The completely standardised theta-delta (θ_δ) shown in Table 4.57 reflect the proportion of non-relevant item parcel variance.

Table 4.57

Completely standardised theta-delta matrix

VSP	SGOAL	STALK	SREW	EBA	SOBS
.525	.326	.773	.865	.571	.544
FTNR	**SCUE**	**SEFF_1**	**SEFF_2**	**LGO_1**	**LGO_2**
.558	.745	.087	.037	.298	.271
DK	**PK**	**CK**	**PLAN**	**STRAT**	**MONITOR**
.375	.258	.287	.327	.441	.193
DEBUG	**EVALUATE**	**TCOG_1**	**TCOG_2**	**CONSC_1**	**CONSC_2**
.500	.380	.246	.215	.357	.122
OPEN_1	**OPEN_2**	**MOT_1**	**MOT_2**	**CRRATIO**	**LEARNP**
.657	-.061	.092	.227	.496	.459
ABSTR_1	**ABSTR_2**	**SERIES**	**MIRROR**	**TRNS**	**CPT**
.258	.296	.427	.336	.404	.197
RES_1	**RES_2**	**RES_3**	**RES_4**		
.587	.985	.736	.915		

4.7.4 Squared multiple correlations for item parcels

The squared multiple correlations (R^2) (see Table 4.58) of the indicators depict the extent to which the measurement model is adequately represented by the observed variables (item parcels) (Byrne, 1998). In other words, the squared multiple correlations show the proportion of variance in an indicator that is explained by the underlying latent variable. A high R^2 value would indicate that variance in the indicator under discussion reflects variance in the latent variable to which it has been linked to a large degree. The rest of the variance not explained by the latent variable can be ascribed to systematic and random measurement error (Diamantopoulos & Siguaw, 2000). The R^2 values range from 0.00 to 1.00 and also serve as reliability indicators Bollen (as cited in Byrne, 1998, p.104). An examination of the R^2 values shown in Table 4.58 reveals above average correlations except for variables VSP (Visualising successful performance); STALK (Self-talk); SREW (self-reward); EBA (Evaluating beliefs and asumptions); SOBS (Self-observation), FTNR (focusing thoughts on natural rewards); SCUE (Self-cue) dimensions of self-leadership. The openness to experience item parcel (OPEN_1) and the indicators of the interaction term (RES_1; RES_2; RES_3 and RES_4) were also very low.

Table 4.58

Squared multiple correlations for X – variables

VSP	SGOAL	STALK	SREW	EBA	SOBS
.475	.674	.227	.135	.429	.456
FTNR	**SCUE**	**SEFF_1**	**SEFF_2**	**LGO_1**	**LGO_2**
.442	.255	.913	.963	.702	.729
DK	**PK**	**CK**	**PLAN**	**STRAT**	**MONITOR**
.625	.742	.713	.673	.559	.807
DEBUG	**EVALUATE**	**TCOG_1**	**TCOG_2**	**CONSC_1**	**CONSC_2**
.500	.620	.754	.785	.643	.878
OPEN_1	**OPEN_2**	**MOT_1**	**MOT_2**	**CRRATIO**	**LEARNP**
.343	1.061	.908	.773	.504	.541
ABSTR_1	**ABSTR_2**	**SERIES**	**MIRROR**	**TRNS**	**CPT**
.742	.704	.573	.664	.596	.803
RES_1	**RES_2**	**RES_3**	**RES_4**		
.413	.015	.264	.085		

4.7.5 Examination of measurement model residuals

Standardised residuals are considered large when they exceed +2.58 or -2.58 (Diamantopoulos & Siguaw, 2000). Large positive residuals indicate that the model underestimates the co-variance between two variables and negative residual shows that the model overestimates the covariance between variables (Jöreskog & Sörbom, 1993). In the present study, the measurement model standardised residuals comprised 28 negative and 21 positive residuals. This indicates that the measurement model tends to slightly overestimate the variance in and covariance between the composite indicator variables.

21 large positive standardised residuals and 28 large negative standardised residuals indicate 49 out of 820 (5.98%) observed variance and covariance terms in the observed sample covariance matrix being poorly estimated by the derived model parameter estimates. This small percentage indicated good model fit. An inspection of the variables associated with these standardised residuals reveals no clear specific suggestions for possible model modification.

4.7.6 Measurement model modification indices

Modification indices indicate an approximation of the extent to which the chi-square fit statistic decreases when a currently fixed parameter in the model is freed and the model re-estimated (Brown, 2006; Jöreskog & Sörbom, 1993). According to Brown (2006), the modification indices are analogous to the chi-square difference (with a single degree of freedom) of nested models. According to the measurement model modification indices, consideration should be given to the possibility of a number of cross-loadings between items and factors other than those they were designed to measure. For example, as indicated in Table 4.59, fit would increase if item SCUE *(self-cue)* and PLAN (*Planning subscale of the Metacognitive Awareness Inventory)* loaded on the CONSCIEN *(conscientiousness)* dimension; RES_2 and DEBUG load on LPERFORM; LGO_1 and LGO_2 item parcels of the *Learning goal orientation scale* load on ABSTRACT *(Abstract thinking capacity)*; DK load on the interaction effect term ABSPRIO and having item parcels DK; CK load on SLEADER; SREW; LGO_1;

PLAN; STRAT; OPEN_2; CRRATIO; LEARNP load on SEFFICAC; FTNR load on LGOAL; DK; CRRATIO and LEARNP load on MREGUL; DEBUG and CONSC_2 load on MKNOW; EBA; CONSC_2; CRRATIO and LEARNP load on TCOGNIT. However, the magnitudes of the expected completely standardised parameter changes (i.e., the expected factor loading estimates that would be obtained if the currently fixed parameters would be set free) associated with the fixed parameters in this matrix do not warrant setting any of these parameters free, with a few exceptions. However, to justify freeing the identified items, a convincing theoretical argument would have to be offered to explain why the items should be regarded as also reflecting latent dimensions. A close look at the item parcels identified above shows that, although the modification indices point to the direction of including the items as indicators of the latent variables that they are also loading on, it does not make theoretical sense to do so since the parcels would be made to load on a theoretically different latent variable (see Table 4.59).

Table 4.59

Modification indices for lambda-X

	CONSCIEN	**OPENNES**	**MOTIVATI**	**LPERFORM**	**ABSTRACT**	**ABSPRIO**
VSP	2.794	3.316	0.334	0.377	1.221	0.114
SGOAL	3.402	6.435	1.726	2.429	0.923	0.420
STALK	0.240	2.460	3.568	0.181	0.181	0.005
SREW	2.372	3.410	5.020	0.407	0.184	0.011
EBA	7.950	2.160	5.284	0.777	1.401	0.698
SOBS	1.800	1.102	0.039	0.006	0.047	1.944
FTNR	2.339	1.200	0.130	2.669	4.754	1.242
SCUE	18.317	5.138	0.195	0.042	2.659	0.539
SEFF_1	0.664	0.202	0.067	0.002	1.299	0.072
SEFF_2	0.650	0.206	0.079	0.002	1.321	0.071
LGO_1	0.285	4.826	2.187	0.278	12.630	0.039
LGO_2	0.414	5.441	0.846	0.271	12.497	0.042
DK						
PK	0.328	0.000	2.328	0.689	0.082	0.031
CK	2.237	2.050	1.009	0.709	0.331	5.968
PLAN	11.810	2.317	0.114	5.789	0.504	0.215
STRAT	3.063	1.690	0.150	3.305	1.592	0.078

MONITOR	1.030	0.305	0.103	1.884	0.010	1.031
DEBUG	0.247	1.241	1.088	10.162	0.433	0.227
EVALUATE	0.311	1.479	1.729	0.063	0.574	0.008
TCOG_1	0.787	0.031	1.747	0.140	0.525	3.381
TCOG_2	0.667	0.029	2.334	0.141	0.522	3.346
CONSC_1	- -	1.572	2.221	2.480	5.394	0.107
CONSC_2	- -	1.695	2.411	2.645	5.739	0.142
OPEN_1	0.499	- -	0.033	0.439	0.119	1.464
OPEN_2	0.586	- -	0.054	1.090	0.115	0.999
MOT_1	4.124	0.000	- -	0.808	0.497	0.158
MOT_2	3.073	0.000	- -	0.753	0.503	0.100
CRRATIO	2.353	1.329	3.604	- -	4.719	2.787
LEARNP	2.424	1.436	3.519	- -	4.212	2.776
ABSTR_1	0.504	0.570	1.271	0.078	- -	0.025
ABSTR_2	0.505	0.554	1.297	0.090	- -	0.066
SERIES	0.215	0.086	0.165	0.964	0.287	0.010
MIRROR	0.229	0.854	0.065	0.078	7.024	0.126
TRNS	0.010	0.099	0.590	0.980	0.444	1.409
CPT	0.660	0.561	0.245	0.106	1.401	0.268
RES_1	0.207	0.633	0.858	0.256	0.004	- -
RES_2	0.008	2.811	0.078	7.176	0.115	- -
RES_3	0.366	0.424	0.465	0.295	0.009	- -
RES_4	0.073	0.094	0.585	1.837	0.139	- -

Table 4.59 (continued)

Modification indices for lambda-X

	SLEADER	SEFFICAC	LGOAL	MREGUL	MKNOW	TCOGNIT	INFOPRO
VSP		1.919	1.345	0.652	0.778	0.095	1.665
SGOAL		2.778	0.006	3.528	3.700	1.423	0.952
STALK		2.913	0.568	0.390	1.396	0.242	0.111
SREW		11.395	2.719	4.774	3.933	0.550	0.029
EBA		0.185	0.049	5.639	3.486	8.679	0.422
SOBS		3.015	0.283	0.006	0.013	0.301	1.051
FTNR		2.455	8.922	1.027	0.274	3.937	0.114
SCUE		1.574	0.869	0.063	0.073	0.179	4.565
SEFF_1	4.422	- -	0.662	1.991	2.517	0.480	0.048
SEFF_2	4.780	- -	0.795	2.082	2.571	0.528	0.049
LGO_1	0.024	7.304	- -	- -	- -	2.063	2.271
LGO_2	0.019	4.654	- -	- -	0.457	3.694	2.291
DK	22.834	0.613	2.028	18.630	- -	0.263	5.921
PK	0.011	1.117	0.014	0.018	- -	1.730	0.230
CK	13.029	0.211	0.727	0.523	- -	3.076	2.791
PLAN	0.004	8.019	5.821	- -	4.246	0.014	0.076
STRAT	0.713	13.745	6.195	- -	1.845	1.221	0.498
MONITOR	0.120	0.104	0.804	- -	4.586	1.980	1.571
DEBUG	0.411	1.574	2.321	- -	26.374	1.596	1.871

EVALUATE	0.551	3.406	0.033	- -	0.036	0.072	0.155
TCOG_1	1.935	0.017	3.237	3.783	0.519	- -	1.127
TCOG_2	2.461	0.014	3.326	- -	1.498	- -	1.104
CONSC_1	1.243	1.006	0.366	1.423	2.005	3.616	1.222
CONSC_2	2.608	1.106	1.850	- -	23.162	12.178	1.381
OPEN_1	0.002	5.376	6.160	0.440	2.795	0.309	0.388
OPEN_2	0.001	12.084	- -	0.466	3.046	0.237	0.293
MOT_1	1.189	2.742	0.767	0.140	0.085	0.999	3.757
MOT_2	1.027	2.823	0.739	0.140	0.097	0.725	4.497
CRRATIO	0.933	12.768	1.675	7.136	5.441	10.563	0.242
LEARNP	0.913	12.785	1.676	6.801	5.367	10.423	2.873
ABSTR_1	0.511	0.307	0.014	0.529	0.938	0.176	- -
ABSTR_2	0.472	0.327	0.011	0.551	1.002	0.191	- -
SERIES	1.032	0.865	2.294	0.023	0.083	0.099	- -
MIRROR	0.044	4.787	0.825	0.214	0.306	0.820	- -
TRNS	0.740	4.538	1.350	0.200	0.056	0.072	- -
CPT	0.072	0.856	0.984	0.026	0.243	0.108	- -
RES_1	5.673	0.024	0.163	0.286	0.007	0.261	0.050
RES_2	0.532	0.632	1.077	0.214	1.075	0.585	1.136
RES_3	6.505	0.115	0.016	0.069	0.070	0.769	0.028
RES_4	1.558	2.351	3.991	0.867	1.517	1.511	0.028

4.8 DISCRIMINANT VALIDITY

The method proposed by Farrell (2010) for assessing the discriminant validity of two or more factors was used. This method involves comparing the average variance extracted (AVE) of each construct with the shared variance between the constructs. The AVE indicates the average proportion of variance in the indicator variables accounted for by the latent variable that the indicator variables were designed to represent (Diamantopoulos & Sigauw, 2000). If the AVE for each construct is greater than its shared variance with any other construct, discriminant validity is supported. In this case, the shared variance estimate metacognitive knowledge and regulation of cognition is greater than the average variance extracted estimate for the constructs (see Table 4.60). However, the use of 95% confidence intervals utilising an Excel macro developed by Scientific Software International (Mels, 2010) indicated that all the latent variables show discriminant validity as none of the confidence intervals include unity (see Table 4.61).

4.9 DECISION ON THE SUCCESS OF THE OPERATIONALISATION

The measurement model showed good fit. All the indicator variables loaded statistically significantly ($p < .05$) on the latent variables they were tasked to reflect. Although the second item parcel for *Openness to experience* (OPEN_2) loaded significant, it had an inadmissibly high value that exceeds unity in the completely standardised solution matrix. The item parcels SREW (.367) and STALK (.476) for the self-reward subscale of the Revised Self-leadership Questionnaire; and two item parcels for the interaction term RES_2 (.122) and RES_4 (.292) were low in comparison with the other completely standardised item parcel values which were generally above .5. Despite the insignificant loading of the RES_2 residualised indicator variable of the latent interaction term it was decided to retain the indicator when fitting the structural model. The squared multiple correlations (R^2) of the openness to experience item parcel (OPEN_1) and the indicators of the interaction term (RES_1; RES_2; RES_3 and RES_4) were also very low. The measurement model residuals indicate that the measurement model tends to slightly overestimate the variance in and covariance between the composite indicator variables. The modification indices suggested that SCUE *(self-cue)* and PLAN (*Planning subscale of the Metacognitive Awareness Inventory)* loaded on the CONSCIEN *(conscientiousness)* dimension; RES_2 and DEBUG load on LPERFORM; LGO_1 and LGO_2 item parcels of the *Learning goal orientation scale* load on ABSTRACT *(Abstract thinking capacity)*; DK load on the interaction effect term ABSPRIO and having item parcels DK; CK load on SLEADER; SREW; LGO_1; PLAN; STRAT; OPEN_2; CRRATIO; LEARNP load on SEFFICAC; FTNR load on LGOAL; DK; CRRATIO and LEARNP load on MREGUL; DEBUG and CONSC_2 load on MKNOW; EBA; CONSC_2; CRRATIO and LEARNP load on TCOGNIT. With regards to discriminant validity, a shared variance estimate for metacognitive knowledge and regulation of cognition is greater than the average variance extracted estimate for the constructs (see Table 4.60). However, the 95% confidence intervals indicated that all the latent variables show discriminant validity as none of the confidence intervals include unity. It is therefore concluded that the operationalisation of the latent variables comprising the measurement model was generally successful. It therefore will be possible to derive an unambiguous verdict on the fit of the structural model from the fit of the comprehensive LISREL model.

Table 4.60

Inter-correlations between latent dimensions, average variance extracted (AVE) and shared variance estimates.

	SLEADER	SEFFICAC	LGOAL	MREGUL	MKNOW	TCOGNIT	CONSCIEN	OPENNES	MOTIVATI	LPERFORM	ABSTRACT	ABSPRIO	INFOPRO
SLEADER	**.39**	.20	.38	.52	.40	.34	.14	.15	.28	.005	.008	.08	.002
SEFFICAC	.45	**.94**	.41	.27	.27	.29	.16	.04	.23	.001	.05	.02	.02
LGOAL	.62	.64	**.71**	.48	.44	.35	.24	.12	.36	.01	.0001	.05	.004
MREGUL	.72	.52	.69	**.63**	.85	.64	.27	.14	.49	.02	.01	.04	.00
MKNOW	.63	.52	.66	.92	**.69**	.56	.24	.13	.44	.00	.00	.01	.00
TCOGNIT	.58	.54	.59	.80	.75	**.77**	.26	.13	.42	0.0	.00	.04	.01
CONSCIEN	.38	.40	.49	.52	.49	.51	**.76**	.06	.22	.00	.00	.00	.05
OPENNES	.39	.19	.35	.38	.36	.36	.24	**.70**	.12	.01	.01	.04	.01
MOTIVATI	.53	.48	.60	.70	.66	.65	.47	.34	**.84**	.00	.002	.00	.00
LPERFORM	-.07	-.01	-.10	-.13	.02	-.07	.08	.11	-.004	**.52**	.07	.00	.13
ABSTRACT	-.09	.22	.03	-.09	-.06	.01	.07	.10	-.049	.27	**.72**	- -	.23
ABSPRIO	.29	.13	.22	.19	.11	.20	.09	.19	.02	.05	- -	**.19**	.05
INFOPRO	.05	.15	.06	.03	.01	.10	.22	.11	.05	.36	.48	..22	**.66**

Note: $N = 213$

Correlations are below the diagonal; squared correlations are above the diagonal and average variance extracted (AVE) estimates are presented on the diagonal (in bold). SLEADER, Self-leadership; LGOAL, Learning goal; MREGUL, Metacognitive regulation; TCOGNIT, Time cognitively engaged; LPERFORM, Learning performance; SEFFICAC, Self-efficacy; MKNOW, Metacognitive knowledge; CONSCIEN, Conscientiousness; OPENNES, Openness to experience; ABSTRACT, Abstract thinking capacity; ABSPRIO, interaction term for abstract thinking capacity and prior learning; INFOPRO, Information processing capacity; MOTIVATI, Learning motivation.

Table 4.61

95% confidence interval for sample phi estimates

	SLEADER	SEFFICAC	LGOAL	MREGUL	MKNOW	TOCGNIT	CONSCIEN	OPENNES	MOTIVATI	LPERFORM	ABSTRACT	ABSPRIO
SLEADER												
SEFFICAC	.313 - .563											
LGOAL	.484 - .724	.516 - .732										
MREGUL	.603 - .801	.403 - .622	.570 - .787									
MKNOW	.506 - .726	.396 - .631	.532 - .752	.854 - .952								
TCOGNIT	.431 - .698	.423 - .634	.451 - .698	.705 - .868	.640 - .830							
CONSCIEN	.232 - .516	.272 - .518	.341 - .610	.394 - .633	.365 - .599	.373 - .623						
OPENNES	.226 - .529	.226 - .529	.175 - .505	.226 - .522	.203 - .503	.211 - .500	.337 - .591					
MOTIVATI	.403 - .634	.403 - .634	.468 - .703	.600 - .774	.557 - .746	.533 - .749	.090 - .386	.193 - .477				
LPERFORM	-.230 - .089	-.230 - .089	-.264 - .078	-.277 - .015	-.131 - .168	-.223 - .092	.109 - .259	-.054 - .265	-.154 - .146			
ABSTRACT	-.235 - .065	-.235 - .065	-.125 - .174	-.224 - .057	-.202 - .082	-.142 - .161	-.075 - .210	-.034 - .223	-.194 - .098	.097 - .420		
ABSPRIO	.045 - .500	.045 - .500	-.012 - .436	-.010 - .381	.640 - .830	-.026 - .403	-.127 - .301	-.016 - .379	-.155 - .198	-.169 - .267	- -	
INFOPRO	-.106 - .198	-.106 - .198	-.104 - .226	-.117 - .183	.365 - .599	-.053 - .247	.066 - .366	-.033 - .251	-.106 - .205	.202 - .506	.366 - .585	.008 - .415

Note. SLEADER, Self-leadership; LGOAL, Learning goal; MREGUL, Metacognitive regulation; TCOGNIT, Time cognitively engaged; LPERFORM, Learning performance; SEFFICAC, Self-efficacy; MKNOW, Metacognitive knowledge; CONSCIEN, Conscientiousness; OPENNES, Openness to experience; ABSTRACT, Abstract thinking capacity; ABSPRIO, interaction term for abstract thinking capacity and prior learning; INFOPRO, Information processing capacity; MOTIVATI, Learning motivation.

4.10 COMPREHENSIVE LISREL MODEL FIT

The De Goede-Burger-Mahembe learning potential structural model was earlier expressed as Equation 3.8.

The structural model describes the relationships between the latent variables themselves. When assessing the structural model, the focus on the hypothesised relationships between the exogenous and endogenous variables with the goal of ascertaining the significance and magnitude of the proposed relationships. To determine whether the obtained path coefficient estimates may be regarded as credible estimates the fit of the comprehensive LISREL model first needs to be determined. If the comprehensive LISREL is able to reproduce the observed covariance matrix to such a degree of accuracy that H_{02} cannot be rejected, and given that the measurement model close fit null hypothesis **(H_{01b})** could not be rejected, the interpretation of the structural model parameter estimates would be warranted. Strictly speaking this conclusion is, however, only warranted if it can be shown that the fit of the structural model is acceptable. To determine this, the fit of the comprehensive model has to be decomposed into independent additive non centrality chi-squares for the measurement and the structural models separately (Vandenberg &Grelle, 2009). The details pertaining to the purposes of the various fit indices have been discussed in chapter three; hence the comprehensive model fit indices are presented briefly. The results of the decomposition of the chi square and population discrepency function values are discussed in paragraph 4.10.2.

The LISREL program version 8.80 (Jöreskog & Sörbom, 2006) was used to determine the fit of the comprehensive model. The robust maximum likelihood estimation method was used to produce the estimates. An admissible solution of parameter estimation was reached after 34 iterations. Some of the indices provided by the

LISREL programme are presented in Table 4.62. The path diagram of the fitted comprehensive LISREL model is depicted in Figure 4.1.

Table 4.62

Goodness-of-fit statistics for the structural model

Fit index	Value
Degrees of Freedom	704
Minimum Fit Function Chi-Square	1338.714 (P = 0.0)
Normal Theory Weighted Least Squares Chi-Square	1275.051 (P = 0.0)
Satorra-Bentler Scaled Chi-Square	1155.764 (P = 0.0)
Estimated Non-centrality Parameter (NCP)	451.764
90 Percent Confidence Interval for NCP	(362.414; 549.004)
Minimum fit function value	6.315
Population Discrepancy Function Value (F0)	2.131
90 Percent Confidence Interval for F0	(1.710; 2.590)
Root Mean Square Error of Approximation (RMSEA)	0.0550
90 Percent Confidence Interval for RMSEA	(0.0493; 0.0607)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.0744
Expected Cross-Validation Index (ECVI)	6.546
90 Percent Confidence Interval for ECVI	(6.125; 7.005)
ECVI for Saturated Model	7.736
ECVI for Independence Model	70.194
Chi-Square for Independence Model with 780 Degrees of Freedom	14801.206
Independence AIC	14881.206
Model AIC	1387.764
Saturated AIC	1640.000
Independence CAIC	15055.658
Model CAIC	1893.674
Saturated CAIC	5216.260
Normed Fit Index (NFI)	0.922
Non-Normed Fit Index (NNFI)	0.964
Parsimony Normed Fit Index (PNFI)	0.832
Comparative Fit Index (CFI)	0.968
Incremental Fit Index (IFI)	0.968
Relative Fit Index (RFI)	0.913
Critical N (CN)	146.684
Root Mean Square Residual (RMR)	0.0673
Standardised RMR	0.103
Goodness of Fit Index (GFI)	0.769
Adjusted Goodness of Fit Index (AGFI)	0.731
Parsimony Goodness of Fit Index (PGFI)	0.660

The p-value associated with the Satorra-Bentler Scaled χ^2 value in 1155.764 (p = 0.0) (0.0) indicates a significant test statistic ($p<0.05$). This implies that the comprehensive model is not able to reproduce the observed covariance matrix (Kelloway, 1998) to a degree of accuracy that can be explained in terms of sampling error only. The exact fit null hypothesis H_{02a} is therefore rejected.

The sample RMSEA estimate is .055, which marginally misses the good fit category. The LISREL program also tests the null hypothesis of close fit H_{02b}. The conditional probability of observing the sample RMSEA estimate under H_{02b} is .074. This indicates that the stance that the comprehensive model shows close fit in the parameter is a permissible position. The value of the standardised RMR is .10 which misses the good fit category, as acceptable values should be lower than .05. Since this value exceeds .05, it raises some doubts regarding the model's fit.

Generally, the goodness-of-fit index (GFI) is recommended as the most reliable measure of absolute fit (Diamantopoulos & Siguaw, 2000). In this case, the value of the GFI (.77) indicates satisfactory fit (Diamantopoulos & Siguaw, 2000).

The relative fit indices show 'how much better the model fits compared to a baseline model, usually the independence model (Diamantopoulos & Siguaw, 2000). In this case the NFI(.92), NNFI (.96), CFI (.97), IFI (.97) and RFI (.91) generally indicate a good fit of the model over the independence model as indicated by values above .90 (Diamantopoulos & Siguaw, 2000).

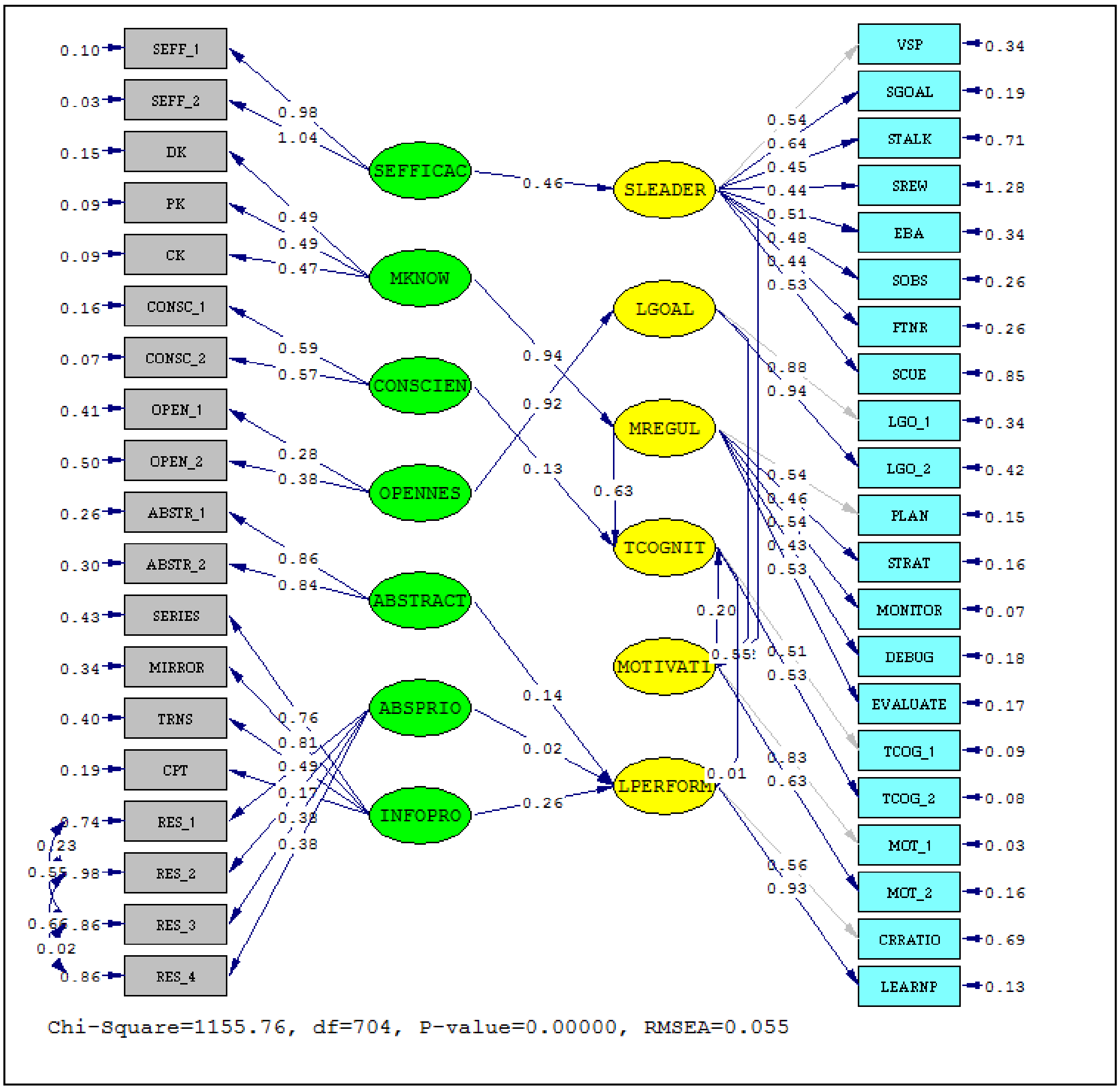

Figure 4.1. The fitted De Goede-Burger-Mahembe learning potential comprehensive model

Note: SLEADER, Self-leadership; LGOAL, Learning goal; MREGUL, Metacognitive regulation; TCOGNIT, Time cognitively engaged; LPERFORM, Learning performance; SEFFICAC, Self-efficacy; MKNOW, Metacognitive knowledge; CONSCIEN, Conscientiousness; OPENNES, Openness to experience; ABSTRACT, Abstract thinking capacity; ABSPRIO, interaction term for abstract thinking capacity and prior learning; INFOPRO, Information processing capacity; MOTIVATI, Learning motivation.

4.10.1 Examination of comprehensive model residuals

In the present study, the comprehensive model standardised residuals comprised 26 negative and 102 positive residuals (see Appendix B).

```
-14|5
-13|
-12|
-11|
-10|
- 9|
- 8|
- 7|
- 6|4
- 5|5
- 4|8430
- 3|8873222211000
- 2|888777664433333222111111111111100000
- 1|9999888888888887777777766666665555444444444433333333222222222211111111000+10
- 0|99999999999888888888888888877777777777777777666666666666666655555555555555+78
 0|1111111111111111111122222222222222222222333333333333333333333333334444444444+00
 1|00000000000000000001111111111111112222222222233333333333333333334444444444555+35
 2|000000000111111122222222233333333344444444455556666777888888888999
 3|00000011111111222223333333444455555556667888888999
 4|000011111122233444556 7889
 5|003569
 6|24666
```

Figure 4.2. The distribution of the residuals in the stem-and-leaf

102 large positive standardised residuals and 26 large negative standardised residuals indicate 128 observed variance and covariance terms in the observed sample covariance matrix being poorly estimated by the derived comprehensive model parameter estimates. An inspection of the variables associated with these standardised residuals revealed no clear specific suggestions for possible model modification.

The distribution of the residuals in the stem-and-leaf (in Figure 4.2) is positively skewed implying that the model is underestimating the observed variance and covariance terms. This suggests that important paths are lacking in the model. An examination of the Q-plot (in Figure 4.3) reveals a clear deviation from the dotted line; thereby providing further evidence that specification of the model is somehow problematic.

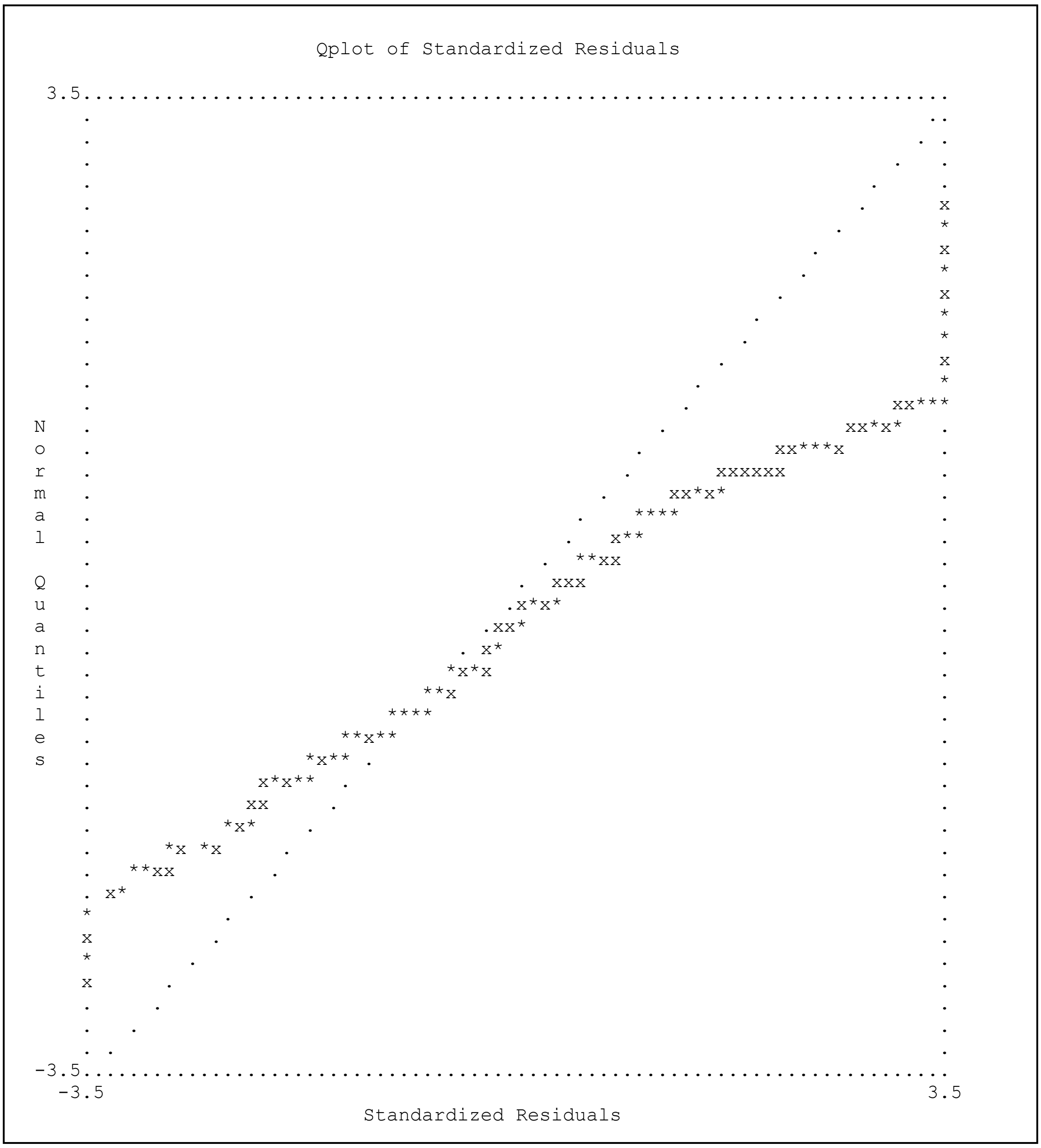

Figure 4.3. Q-plot of standardised residuals

4.10.2 Decomposing the comprehensive LISREL model

The composite model whose fit has been evaluated in paragraphs 4.10.1 is a composite of the measurement model defining the structural relations between the composite indicator variables and the latent variables included in the study (Figure 4.1) and the structural model defining the structural relations that have been hypothesised between the latent variables (Figure 3.1). Interest is primarily on the structural model. The structural model is, however, never directly empirically tested. The comprehensive model is tested. Because of this fact the measurement model is normally fitted first (as was also the case in this study) to attempt to ensure that unambigious inferences about the fit of the structural model can be derived from the fit of the comprehensive model. If the comprehensive models shows poor fit for example is it because of problems in the structural model or because of problems in the measurement model? According to Vandenberg and Grelle (2009), researchers who take this approach often overlook the fact that the final fit of the comprehensive model may be decomposed into independent additive non centrality chi-squares for the measurement and the structural models separately. According to Vandenberg and Grelle (2009), this is possible because the structural model is nested within the measurement model and the measurement model is nested within the comprehensive model.

Since the interest of the study is first and foremost on the structural model but the fit of the structural model cannot be directly acertained by fitting the structural model as such to data inferences on its fit needs to be derived from the fit of the comprehensive and measurement models. A well fiting measurement model and a well fitting comprehensive model is, however no guarantee that the structural model fits well. The danger exists that the well fitting comprehensive and measurement models may mask a poor fitting structural model (Vandenberg & Grelle, 2009) because of the fact that the measurement model imposes fewer restrictions and therefore contributes a larger proportion of the total degree of freedom of the comprehensive model (Vandenberg & Grelle, 2009). The concern therefore exists that the comprehensive model fits maybe acceptable soley because of good measurement model fit, despite poor structural model fit model, because of the dominance of the measurement model in the comprehensive model. In other words, the interpretation of the measurement and comprehensive models are highly dependent of each other. (McDonald & Ho, 2002; Tomarken & Waller, 2003). Because of this interdependence unwarranted inferences about the fit of the structural model can be derived from the fit of the comprehensive model.

The effect of the additional parameters being estimated in the structural model can be ascertained by *post hoc* analysis separating the measurement and structural models in the comprehensive model. To determine the contribution of the structural model to the fit of the comprehensive model, the difference in Satorra-Bentler chi-square values obtained for the comprehensive and the measurement models was firstly calculated. The scaled Satorra-Bentled chi-square difference was calculated (Satorra & Bentler, 2001, p. 511). The probability of observing this chi-square difference under the null hypothesis of no difference in fit in the parameter was subsequently determined. The question is therefore whether the additional parameters that were estimated in the structural model (and for which degrees of freedom were sacrificed) produced a statistically significant improvement in model fit. In addition the RMSEA of the structural model was calculated by subtracting the population discrepancy function value (F_0) of the measurement model from that obtained by the comprehensive model, dividing the difference by the difference in the degrees of freedom of the two models and taking the square root (Steiger, date unknown). A significant Satorra-Bentler Scaled χ^2 difference value (205.3767353) (p=.36746E-22) was found while the RMSEA value of .009191 indicates good model fit. The conclusion is therefore that the structural model does not show exact fit but that the model shows good close fit. The researcher is not aware of a procedure to test the significance of the structural model RMSEA value infered from the difference in the F_0 values of the comprehensive and measurement models. Thus the conclusion is that the restrictions constituting the structural/model are meaningful and interpretable (Vandenberg & Grelle, 2009). The results are indicated in Table 4.55. The acceptable close fit obtained for the structural model on the sample warrants the interpretation of the structural model parameter estimates.

4.10.3 Structural model parameter estimates

The purpose of evaluating the structural model is to determine whether the theoretical relationships specified at the conceptualisation stage are substantiated by the data. At this stage the spotlight is on the structural linkages between the various endogenous and exogenous latent variables and between the various endogenous latent variables. According to Diamantopoulos and Siguaw (2000), four issues are of paramount significance in the evaluation of the structural model. Firstly, it is vital to assess the signs of the parameters representing the paths between the latent variables to ascertain the degree of consistence with the nature of the causal effect hypothesised to exist between the latent variables. Secondly, it is important to determine if the parameter estimates are significant ($p < .05$) as indicated by t-values greater than $|1.96|$. Thirdly, it is important to assess the magnitudes of the estimated parameters indicating the strength of the hypothesised relationships. Lastly, it is important to evaluate the squared multiple correlations (R^2), which indicate the amount of variance in each endogenous latent variable that is explained by the latent variables linked to it in the hypothesised structural model. The process of evaluating the structural model entails an in-depth analysis of the freed elements of the gamma (Γ) and beta (Β) matrices.

Table 4.63

Fit of comprehensive and measurement nested models

HYPOTHESIS	SATORRA-BENTLER CHI SQUARE	NORMAL THEORY CHI-SQUARE	DF	cd	SCALED DIFFERENCE IN S-B CHI-SQUARE	PROB S-B CHI-SQUARE DIFF	PROB SCALED S-B CHI-SQUARE DIFF	PROB NORMAL THEORY CHI-SQUARE DIFF	**F0**	**RMSEA**
COMPREHENSIVE MODEL	1155.764	1275.051	704						2.131	0.055018
MEASUREMENT MODEL	952.433	1051.78	659						1.384	0.045827
STRUCTURAL MODEL	203.331	223.271	45	1.087129	205.3767353	5.32302E-22	**2.36746E-22**	1.81873E-25		0.009191

4.10.4 The gamma matrix

The unstandardised Γ matrix is used to assess the significance of the estimated path coefficients γ_{ij}, expressing the strength of the influence of ξ_j (exogenous latent variables) on η_i (endogenous latent variables). The gamma parameters are significant if $t > |1.96|$ ($p < .05$) (Diamantopoulos & Siguaw, 2000). A significant γ estimate implies that the corresponding null hypothesis is rejected in favour of the alternative hypothesis. It is important to note that a significant gamma path coefficient estimate does not imply a causal effect. When using correlational data obtained via an *ex post facto* research design, it is not possible to isolate the empirical system sufficiently enough to label the relationship among the variables as strictly causal (Cliff, 1988). An *ex post facto* design of this nature, therefore, precludes the drawing of causal inferences from significant paths coefficients (Theron, Spangenberg & Henning, 2004). The gamma matrix is presented in Table 4.64.

Table 4.64

The gamma matrix of path coefficients for the structural model

VARIABLE	ABSTRACT	INFOPRO	CONSCIEN	SEFFICAC	MKNOW	ABSPRIO	OPENNES
LPERFORM	0.140	0.260				0.025	
	(0.100)	(0.117)				(0.108)	
	1.400	2.22*				0.228	
TCOGNIT			0.128				
			(0.069)				
			1.86				
SLEADER				0.461			
				(0.076)			
				6.03*			
MOTIVATI							
MREGUL					0.938		
					(0.070)		
					13.37*		
LGOAL							0.918
							(0.086)
							10.65

Note: Completely standardised path coefficients in bold; standard error estimates in brackets; t-values ≥│1.96│indicate significant parameter estimates; *p < .05. SLEADER, Self-leadership; LGOAL, Learning goal; MREGUL, Metacognitive regulation; TCOGNIT, Time cognitively engaged; LPERFORM, Learning performance; SEFFICAC, Self-efficacy; MKNOW, Metacognitive knowledge; CONSC, Conscientiousness; OPEN, Openness to experience; ABSTR, Abstract thinking capacity; ABSPRIO, interaction term for abstract thinking capacity and prior learning; INFOPRO, Information processing capacity; MOT, Learning motivation.

4.10.5 The beta matrix

The unstandardised **B** matrix (see Table 4.65) is used to assess the significance of the estimated path coefficients β_{ij}, expressing the strength of the influence of η_j on η_i.. The beta parameters are significant if $t >$ │1.96│ ($p < 0.05$) (Diamantopoulos & Siguaw, 2000). A significant β estimate implies that the corresponding null hypothesis is rejected in favour of the alternative hypothesis.

Table 4.65

The beta matrix of path coefficients for the structural model

VARIABLE	LPERFORM	TCOGNIT	SLEADER	MOTIVATI	MREGUL	LGOAL
LPERFORM		**0.008** (0.078) 0.102				
TCOGNIT				**0.197** (0.057) 3.47*	**0.628** (0.080) 7.89*	
SLEADER						
MOTIVATI			**0.218** (0.063) 3.45*			**0.548** (0.068) 8.03*
MREGUL						
LGOAL						

Note: Completely standardised path coefficients in bold; standard error estimates in brackets; t-values ≥│1.96│indicate significant parameter estimates; *p < .05. SLEADER, Self-leadership; LGOAL, Learning goal; MREGUL, Metacognitive regulation; TCOGNIT, Time cognitively engaged; LPERFORM, Learning performance; SEFFICAC, Self-efficacy; MKNOW, Metacognitive knowledge; CONSC, Conscientiousness; OPEN, Openness to experience; ABSTR, Abstract thinking capacity; ABSPRIO, interaction term for abstract thinking capacity and prior learning; INFOPRO, Information processing capacity; MOT, Learning motivation.

4.10.6 Relationships between latent variables

In this section the results obtained on the relationships postulated in the form of hypotheses in Chapter three are presented. The evaluations of the relationships are based on the t-values displayed in the gamma and beta matrices in Tables 4.64 and 4.64 respectively.

Hypothesis 3: *Abstract reasoning capacity* (ξ_1) positively affects *Learning performance during evaluation* (η_1)

The t-value of the link between *Abstract reasoning capacity* (ξ_1) and *Learning performance during evaluation* (η_1) is less than 1.96 (see Table 4.64). There is no significant relationship *Abstract reasoning capacity* (ξ_1) and *Learning performance during evaluation*. Therefore H_{03}: $\gamma_{11} = 0$ is not rejected which suggests that the proposed relationship between these two latent variables was not supported.

Hypothesis 4: *Information processing capacity* positively influences *Learning Performance during evaluation*

The t-value of the link between *Information processing capacity* and *Learning Performance during evaluation* is greater than 1.96 (see Table 4.64). A significant ($p < .05$) positive relationship is therefore evident between *Information processing capacity* and *Learning Performance during evaluation*. H_{04}: $\gamma_{12} = 0$ can be rejected in favour of H_{a4}: $\gamma_{12} > 0$, which suggests that the proposed relationship between these two latent variables was supported.

Hypothesis 5: *Self-leadership* positively affects *Motivation to learn*

The relationship between *Self-leadership* and *Motivation to learn* was supported as the t-value of the link between the two variables is greater than 1.96 (see Table 4.65). A significant ($p < 0.05$) positive relationship is therefore evident between *Self-leadership* and *Motivation to learn*. H_{05}: $\beta_{43} = 0$ can be rejected in favour of H_{a5}: $\beta_{43} > 0$, which suggests that the proposed relationship between these two latent variables was supported.

Hypothesis 6: *Conscientiousness* positively affects *Time-engaged-on-task*

The t-value of the link between *Conscientiousness* and *Time-engaged-on-task* is less than 1.96 (see Table 4.64). A non significant ($p < 0.05$) relationship is therefore evident between *Conscientiousness* and *Time-engaged-on-task*. H_{06} is therefore not rejected, which suggests that the proposed relationship between these two latent variables was not supported.

Hypothesis 7: *Motivation to learn* positively influences *Time-engaged-on-task*

The t-value of the link between *Motivation to learn* and *Time-engaged-on-task* is greater than 1.96 (see Table 4.65). A significant ($p < 0.05$) positive relationship is therefore evident between *Motivation to learn* and *Time-engaged-on-task*. H_{07}: $\beta_{24} = 0$ can be rejected in favour of H_{a7}: $\beta_{24} > 0$, which suggests that the proposed relationship between these two latent variables was supported.

Hypothesis 8: *Self efficacy* positively influences *Self-leadership*

The t-value of the link between *Self efficacy* and *Self-leadership* is greater than 1.96 (see Table 4.64). A significant ($p < 0.05$) positive relationship is therefore evident between the two constructs. H_{08}: $\gamma_{34} = 0$ can be rejected in favour of H_{a8}: $\gamma_{34} > 0$, which suggests that the proposed relationship between *Self efficacy* and *Self-leadership* was supported.

Hypothesis 9: *Knowledge about cognition* positively influences *Regulation of cognition*

t-value of the link between *Knowledge about cognition* and *Regulation of cognition* is greater than 1.96 (see Table 4.64). H_{09}: $\gamma_{55} = 0$ can be rejected in favour of H_{a9}: $\gamma_{55} > 0$, which suggests that the proposed relationship between these two latent variables was supported.

Hypothesis 10: *Regulation of cognition* positively influences *Time-engaged-on-task*

The t-value of the link between *Regulation of cognition* and *Time-engaged-on-task* is greater than 1.96 (see Table 4.65). A significant ($p < 0.05$) positive relationship is therefore evident between these two constructs. H_{010}: $\beta_{25} = 0$ can be rejected in favour of H_{a10}: $\beta_{25} > 0$, which suggests that the proposed relationship between *Regulation of cognition* and *Time-engaged-on-task* was supported.

Hypothesis 11: *Learning goal orientation* affects *Motivation to learn*

The t-value of the link between *Learning goal orientation* and *Motivation to learn* is greater than 1.96 (see Table 4.65). A significant ($p < 0.05$) positive relationship is therefore evident between these two constructs. H_{011}: $\beta_{46} = 0$ can be rejected in favour of H_{a11}: $\beta_{46} > 0$, which suggests that the proposed relationship between *Learning goal orientation* and *Motivation to learn* was supported.

Hypothesis 12: *Time-engaged-on-task* affects *Learning performance*

The t-value of the link between *Time-engaged-on-task* and *Learning performance* is less than 1.96 (see Table 4.65). A non significant ($p < 0.05$) relationship is therefore evident between *Time-engaged-on-task* and *Learning performance*. H_{012}: $\beta_{12} = 0$ can therefore not be rejected which suggests that the proposed relationship between these two latent variables was not supported.

Hypothesis 13: *Openness to experience* positively affects *Learning goal orientation*

The t-value of the link between *Openness to experience* and *Learning goal orientation* is greater than 1.96 (see Table 4.64). A significant ($p < 0.05$) positive relationship is therefore evident between *Openness to experience* and *Learning goal orientation*. H_{013}: $\gamma_{67} = 0$ can therefore be rejected in favour of H_{a13}: $\gamma_{67} > 0$, which suggests that the proposed relationship between these two latent variables was supported.

Hypothesis 14: *Prior learning* moderates the relationship between *Abstract reasoning capacity* and *Learning performance during evaluation*

The moderating effect of *Prior learning* (indicated by the interaction term ABSPRIO) on the relationship between *Abstract reasoning capacity* and *Learning performance during evaluation* was not supported. The t-value associated with the structural path running from the latent *Prior learning* x *Abstract thinking capacity* interaction effect to *Learning performance during evaluation* is less than 1.96 (see Table 4.64). It is therefore evident that *Prior learning* is not a significant moderator of the relationship between *Abstract reasoning capacity* and *Learning performance during evaluation.* H_{013}: $\gamma_{67} = 0$ can therefore not be rejected, which suggests that the proposed latent interaction effect was not supported.

4.10.7 Squared multiple correlations for Structural Equations

An examination of the R^2 values shown in Table 4.66 reveals above average correlations for most of the variables except for SLEADER (Self-leadership) and LPERFORM (learning performance during evaluation). The low proportion of variance that the model explains in *Learning performance during evaluation* is a cause of concern. Future research will have to focus on rectifying this shortcoming. Suggestions in this regard are made in Chapter 5. The R^2 value for learning motivation (MOTIVATI) was somewhat low but within acceptable levels.

Table 4.66

Squared multiple correlations for structural equations

SLEADER	LGOAL	MREGUL	TCOGNIT	MOTIVATI	LPERFORM
.213	.843	.880	.652	.416	.127

4.10.8 The beta and gamma modification indices

The modification index values calculated for beta and gamma are shown in Tables 4.67 and 4.68 respectively. The beta and gamma modification indices reveal currently fixed paths that, if freed, would statistically significantly ($p < .01$) improve the fit of the comprehensive model. The theoretical meaningfulness of the proposed paths are critical in considering the possibility of freeing currently fixed parameters. According to Jöreskog and Sörbom (1993, p. 127), "one examines the modification indices and relaxes the parameter with the largest modification index *if this parameter can be interpreted substantively*. If it does not make sense to relax the parameter with the largest modification index, one considers the second largest modification index etc. If the signs of certain parameters are specified a priori, positive or negative, the expected parameter changes associated with the modification indices for these parameters can be used to exclude models with parameters having the wrong sign."

Table 4.67

Modification indices for gamma

VARIABLE	ABSTRACT	INFOPRO	CONSCIEN	SEFFICAC	MKNOW	ABSPRIO	OPENNES
MOTIVATI	0.637	0.003	7.329	4.466	65.994	4.204	- -
LPERFORM	- -	- -	0.160	0.040	0.329	- -	0.067
TCOGNIT	1.463	1.013	- -	4.096	- -	2.012	2.064
SLEADER	8.208	0.168	12.373	- -	58.715	9.688	55.062
MREGUL	0.139	0.458	2.134	0.965	- -	3.616	2.591
LGOAL	1.928	0.987	6.215	5.736	0.057	1.510	- -

SLEADER, Self-leadership; LGOAL, Learning goal; MREGUL, Metacognitive regulation; TCOGNIT, Time cognitively engaged; LPERFORM, Learning performance; SEFFICAC, Self-efficacy; MKNOW, Metacognitive knowledge; CONSCIEN, Conscientiousness; OPENNES, Openness to experience; ABSTRACT, Abstract thinking capacity; ABSPRIO, interaction term for abstract thinking capacity and prior learning; INFOPRO, Information processing capacity; MOTIVATI, Learning motivation.

The modification indices for B were also inspected for large modification index values (> 6.6349 at a significance level of 0.01) ($p < 0.01$) (Diamantopoulos & Siguaw, 2000; Jöreskog & Sörbom, 1993). The larger modification indices are highlighted.

An examination of the beta and gamma modification indices shows possible additions that are at first glance appealing. The modification indices suggest that regulation of cognition and learning goal orientation could affect self-leadership. The The suggestion of a path between *Regulation of cognition* and *Self-leadership* makes theoretical sense. *Regulation of cognition* also incorporates an element of self-monitoring which hinges self-regulation a component of *Self-leadership*. It is also possible to create a path between *Self-leadership* and *Learning goal orientation*. One of the dimensions of self-leadership is goal setting. An individual through his/her individually initiated self-influence chooses to be either learning goal oriented or performance goal oriented through their study behaviour habits. Hence this empirical recommendation also makes theoretical sense. The expected change is significant and positive in both cases. However, freeing the path with the largest modification index can affect the remaining modification indices. On the other hand, Diamantopoulos and Siguaw, 2000 caution against falling for the temptation of freeing these parts for the reason that data driven modifications are susceptible to capitalisation on chance in that 'idiosyncratic characteristics' of the sample may influence the particular modifications that may be performed. Future studies should consider incorporating the modification index recommendations provided it makes theoretical sense and validate the revised model on a fresh sample.

Table 4.68

Modification indices for beta

VARIABLE	MOTIVATI	LPERFORM	TCOGNIT	SLEADER	MREGUL	LGOAL
MOTIVATI	- -	0.830	29.003	- -	43.136	- -
LPERFORM	0.203	- -	- -	0.448	0.054	0.854
TCOGNIT	- -	0.208	- -	0.435	- -	0.332
SLEADER	10.060	1.333	34.927	- -	63.913	41.290
MREGUL	8.948	3.124	0.680	16.557	- -	3.708
LGOAL	7.252	5.637	0.763	3.012	1.341	- -

SLEADER, Self-leadership; LGOAL, Learning goal; MREGUL, Metacognitive regulation; TCOGNIT, Time cognitively engaged; LPERFORM, Learning performance; SEFFICAC, Self-efficacy; MKNOW, Metacognitive knowledge; CONSCIEN, Conscientiousness; OPENNES, Openness to experience; ABSTRACT, Abstract thinking capacity; ABSPRIO, interaction term for abstract thinking capacity and prior learning; INFOPRO, Information processing capacity; MOTIVATI, Learning motivation.

4.10.9 POWER ASSESSMENT

According to Diamantopoulos and Siguaw (2000), statistical power refers to the probability of rejecting the null hypothesis that the model fits the data given that the null hypothesis is false. When testing whether a model fits exactly or closely the probability of making a Type 1 error is emphasised, that is rejecting a correct model. In the present study, the close fit null hypothesis was not rejected. This indicates that the the position that the model is able to closely reproduce the population covariance matrix is a permmissible position. The question however is whether the decision not to reject (H_{02}) was the correct decision. An RMSEA result indicates that if the null hypothesis is true (that is the model is correct in the population), then the probability of incorrectly rejecting it is low (that is less than five times out of 100 if α= 0.05) (Diamantopoulos & Siguaw, 2000). However, another error that can occur is not to reject an incorrect model. This type of error is known as a Type II error and the probability associated with it is denoted as β. The probability of making a Type II error therefore refers to the probability of not rejecting the null hypothesis given that the null hypothesis is false. The probability of avoiding a Type II error is, therefore, 1- β and it is this probability that indicates the power of the hypothesis test. Thus the power of the test indicates how likely it is that a false null hypothesis (that is the incorrect model) is rejected.

The analysis of statistical power is relevant once a decision on the exact and close fit null hypotheses has been reached to assist in deciding how likely it is that the decision to reject the specific hypothesis was wrong. Especially in small samples ascribing the decision not to reject the close fit null hypothesis to good model fit can be challenged by the alternative explanation that the statistical power was too low to reject H_{02} even when it is false, this is not relevant here. The power of the test is a function of the degrees of freedom (v) in the model calculated using the formula ½ $[(p + q)(p + q + 1)-t]$ which is 704. Here p = the number of indicator variables for the y-variables, q = the number of indicator variables for the exogenous variable and t = the number of parameters to be estimated. The higher the degrees of freedom, the greater the power of the test (Diamantopoulos & Siguaw, 2000). MacCallum, Browne, and Sugawara (1996) assembled power tables but only makes provision for degrees of feedom ≤ 100 and N ≤ 500. In the present study, syntax developed by Preacher and Coffman (2006) in R and available at http://www.quantpsy.org/rmsea/rmsea.htm was d to determine the statistical power of the test of close fit. For this purpose a significance level of .05; a sample size of 213; and 704 degrees of freedom were specified. The null hypothesis of the RMSEA was set to .05 while the alternative hypothesis for the RMSEA was set to .08. The Preacher and Coffman (2006) software returned a power value of unity. This boosts confidence in the comprehensive LISREL model given the decision not to reject the close fit null hypothesis.

4.11 SUMMARY

This chapter explored the psychometric properties of the instruments used to measure the constructs under investigation. Item and dimensional analyses were conducted to determine the psychometric properties of the measures as well as identify and eliminate poor items. In the case of the Revised Self leadership Questionnaire and the Metacognitive Awareness Inventory, confirmatory factor analyses were also conducted to confirm the measurement structure underlying the measures of these two latent variables. The overall measurement and structural model fit indices were determined and their implications briefly discussed. Several fit indices were d to test model fit. The results, generally, reflect a good fit of both the measurement and the comprehensive LISREL models. The null hypothesis of close fit was not rejected in both the measurement and comprehensive LISREL models. The bulk of the fit statistics indicate good fit and the small percentage of large modification indices calculated for lambda-X matrices also indicate a good fit. The latent dimensions correlate moderately with each other in the sample with the exception of the correlations of learning performance; abstract thinking capacity; the interaction term and information processing capacity; with the rest of the constructs.

No excessively high correlations exist. Confidence intervals calculated to determine discriminant validity did not include unity for any of the correlations in the phi matrix. However, the shared variance estimate of metacognitive knowledge and regulation of cognition is greater than the average variance extracted estimate for the constructs. The Preacher and Coffman (2006) R power calculation syntax software indicated a power value of unity thereby boosting confidence in the decision on the comprehensive LISREL model. With regards to the fit of the nested comprehensive and measurement models, a non significant Satorra-Bentler Scaled was obtained while the RMSEA value indicates good model fit. Thus the conclusion is that the restrictions constituting the structural/comprehensive model are meaningful and interpretable.

CHAPTER FIVE

DISCUSSION OF RESEARCH RESULTS, CONCLUSION AND RECOMMENDATIONS FOR FUTURE RESEARCH

5.1 INTRODUCTION

The previous chapters focused on the introduction of the research problem, the literature on the learning competencies and competency potential latent variables that impact on both *Classroom learning performance* and *Learning performance during evaluation*. The review of the literature in Chapter two showed that *Classroom learning performance* and *Learning performance during evaluation* directly and indirectly depend on an array of cognitive and non-cognitive learning competency potential latent variables. The overarching substantive research hypothesis and subsequent path specific substantive research hypotheses presented in Chapter three were tested using structural equation modeling. The results were presented in the Chapter four and are now the subject of discussion in the present chapter. The objective of the present study was to answer the question, what other cognitive and non-cognitive learning competencies and learning competency potential latent variables besides those contained in the De Goede (2007) and Burger (2012) learning potential models directly or indirectly explain variance in *Learning performance during evaluation*? The specific objectives of the study consequently were to:

- Elaborate and integrate the De Goede (2007) and the Burger (2012) learning potential models in a manner that circumvents the problems and shortcomings of these models by developing an extended explanatory learning performance structural model that explicates additional cognitive and non-cognitive learning competency potential latent variables that affect *Learning performance during evaluation* and that describes the manner in which these latent variables combine to affect *Learning performance during evaluation*;
- Test the model's absolute fit; and

- Evaluate the statistical significance of the hypothesised structural paths in the model.

Before determining the fit of the measurement and structural models, item and exploratory factor analyses were performed on the measures used in the study. The main purpose of conducting item analysis was to determine the reliability coefficients of the scales as well as to identify items which were not correlating well with the other items in the scale before combining items into linear composites to represent the latent variables when fitting the proposed model to the data. This was accomplished through the use of the item statistics estimates provided as part of the output from the reliability analysis procedure available in SPSS version 21. Items correlating below .3 with the total score (Pallant, 2010) as well as items that would result in a significant increase in the Cronbach alpha were eliminated from the study. Exceptions to this rule were made in cases such as that of the *Conditional knowledge* and *Procedural knowledge scales* for *Metacognitive knowledge* in which most of the items correlated with the total scale above 0.2 but were lower than .3 (see Table 4.12 and Table 4.13). This decision was taken to retain as many of the items as posible since the reliability coefficients were already low and would not increase significantly even after deleting the items. Most of the scale reliabilities ranged from adequate (at least α = .70) to excellent reliability coefficients (above α = .90) (Nunnally, 1967) except for three subscales of the Metacognitive Awareness Inventory. These scales are the *Evaluation subscale* (α = .683); *Debugging subscale* (α = .680); *Conditional knowledge subscale* (α = .573); Procedural *knowledge subscale* (α = .534). The reliability coefficients of these scales fall substantially below the critical cutoff value of .80 (Nunnally, 1967).

After conducting item analyses the scales were subjected to exploratory factor analysis to determine whether the scales or subscales were uni-dimensional. The issue of of uni-dimensionality was essential since items parcels were calculated to represent the constructs under investigation due to sample size restrictions. The current sample size of 213 was not large enough to enable the use of individual items. Researchers have advised against randomly parceling items derived from scales which are not uni-dimensional (Bandalos, 2009; Little, Cunningham, Shahar & Widaman, 2009). When parcelling scales which are not uni-dimensional, it is recommended to parcel them in terms of their subscales or sub-dimensions (Bandalos, 2009; Little, Cunningham, Shahar & Widaman, 2009). The study adhered to this recommendation. In the process of ascertaining uni-dimensionality in the scales, complex items were eliminated to enhance discriminant validity. Most of the scales were found to be uni-dimensional with the exception of the Time-cognitively engaged scales which showed two factors (see Table 4.41). The Conscientiousness scale also exhibited two factors, based on the negative and positive wording of the items (see Table 4.42). Nevertheless, the higher-order factor was used in further analyses including the creation of item parcels for the overall measurement model.

In addition to item and dimensionality analyses, confimatory factor analyses was conducted to determine the factor structure of the Revised Self-Leadership Questionnaire and the Metacognitive Awareness Inventory. The goodness-of-fit properties of the measurement models of these two measures ranged from good model fit in the case of the Revised Self-Leadership Questionnaire to reasonable fit for the Metacognitive Awareness Inventory as indicated in Table 4.45 and Table 4.48 respectively.

5.2 ASSESSMENT OF MODEL FIT

5.2.1 Measurement model

The measurement model fit assesses the extent to which a hypothesised model fits the data and provides information on the validities and reliabilities of the observed indicators (Diamantopoulos & Siguaw, 2000).

The p-value associated with the Satorra-Bentler scaled chi-square returned a value of 952.433 ($p = 0$) which indicates a significant test statistic ($p < .05$). The Chi-square value shows that the model does not show exact fit. This suggests that there is a significant discrepancy between the covariance matrix implied by the measurement model and the observed covariance matrix, thus rejecting the exact fit null hypothesis (H_{01a}) indicated by the following hypothesis:

H_{01a}: RMSEA = 0

H_{a1a}: RMSEA > 0

The LISREL programme also tests the null hypothesis of close fit, (H_{01b} RMSEA ≤ .05) by calculating the conditional probability of observing the sample value of .0458 under the assumption that H_0: RMSEA < .05 is true in the population. A probability value of .859 is returned in table 4.54. The close fit null hypothesis (depicted below) is therefore rejected.

H_{01b}: RMSEA ≤ .05

H_{a1b}: RMSEA > .05

Most of the indicator variables loaded statistically significantly ($p < .05$) on the latent variables they were tasked to reflect. Although the OPEN_2 parcel for *Openness to experience* loaded statistically significantly it had an inadmissably high value in the completely standardised solution. The SREW (.367) and STALK (.476) parcels for the self-reward and self-talk subscales of the Revised Self-leadership Questionnaire as well as RES_2 (.122) and RES_4 (.292) item parcels for the interaction term were low in comparison with the other completely standardised item parcel values which were generally above .5. The squared multiple correlations (R^2) of (OPEN_1) (*Openness to experience*) and (RES_1; RES_2; RES_3 and RES_4) (the indicators of the interaction term) were also very low. The measurement model residuals indicate that the measurement model tends to slightly overestimate the variance in and covariance between the composite indicator variables. The measurement model standardised residuals comprised 28 negative and 21 positive residuals. This indicates that the measurement model tends to somewhat overestimate the covariance between variables.

With regards to the measurement model discriminant validity, the method proposed by Farrell (2010) which involves comparing the average variance extracted (AVE) of each construct with the shared variance between the constructs was used. In this case, the shared variance estimate for metacognitive knowledge and regulation of cognition is greater than the average variance extracted estimate for the constructs (see Table 4.60). Nonetheless, the use of 95% confidence indicated that all the latent variables show discriminant validity as none of the confidence intervals include unity (see Table 4.61).

A decision on the success of the operationalisation of the measurement was made that the measurement model showed good model fit. This was based on the findings discussed above on goodness of fit indices displayed in Table 4.55 as well as the completely standardised factor loadings; the squared multiple correlations (R^2); measurement model residuals; modification indices and assessment of discriminant validity. Despite the insignificant loading of the RES_2 residualised indicator variable of the latent interaction term it was decided to retain the indicator when fitting the structural model. It was therefore decided that judging from the measurement model fit, it will be possible to derive an unambiguous verdict on the fit of the structural model from the fit of the comprehensive LISREL model.

5.2.2 Comprehensive LISREL model

The structural model describes the relations among the latent variables. The structural model fit generally shows a reasonable model fit with the data. The exact fit null hypothesis of the structural model was rejected since the Satorra-Bentler Scaled Chi-Square returned a value of 1155.764 (P = 0.0).

H_{02a}: RMSEA = 0

H_{a2a}: RMSEA > 0

If the overarching structural model substantive research hypothesis would be interpreted to mean that the structural model provides an approximate description of the psychological process that determines learning performance, the substantive research hypothesis translates into the following close fit null hypothesis. Since a probability value of 0.0744 is returned in Table 4.54. The close fit null hypothesis (depicted below) is therefore rejected.

H_{02b}: RMSEA ≤ .05

H_{a2b}: RMSEA > .05

The remaining fit indices generally indicated acceptable fit although the standardised RMR value of .10 missed the good fit category. The GFI value missed the acceptable fit level while the relative fit indices indicated a good fit of the structural model over the independence model as indicated by values above .90 (Diamantopoulos & Siguaw, 2000).

Further examination of the structural model residual distribution showed that the distribution of the standardised residuals was positively skewed implying that the model was underestimating the observed covariance terms. The 102 large positive standardised residuals and 26 large negative standardised residuals indicate 128 observed covariance terms in the observed sample covariance matrix being poorly estimated by the derived model parameter estimates (see Figure 4.2). An examination of the Q-plot revealed a clear deviation from the dotted line, thereby providing further evidence that the models did not fit perfectly (see Figure 4.3).

An examination of the R^2 values shown in Table 4.66 reveals above average correlations for most of the variables except for STALK (Self-talk); SREW (self-reward); EBA (Evaluating beliefs and asumptions); SOBS (Self-observation), FTNR (focusing thoughts on natural rewards); SCUE (Self-cue) dimensions of self-leadership and the CRRATION item parcel for learning performance.

An examination of the beta and gamma modification indices shows possible additions that could have been implemented to modify the structural model. These were not implemented to maintain the theoretically driven relationships among the variables. Future studies should consider incorporating the modification indices recommendations provided it makes theoretical sense and hence validate the model on a fresh sample.

The interest of the study is on the fit of the structural model. The fit of the structural model cannot be directly acertained by fitting the structural model as such to data. Inferences on its fit were therefore derived from the fit of the comprehensive and measurement models. To determine the contribution of the structural model to the fit of the comprehensive model, the difference in the Satorra-Bentler chi-square values obtained for the comprehensive and the measurement models was firstly calculated. The probability of observing the scaled Satorra-Bentled chi-square difference was calculated (Satorra & Bentler, 2001, p. 511) under the null hypothesis of no difference in fit in the parameter was subsequently determined. In addition the RMSEA of the structural model was calculated. A significant Satorra-Bentler Scaled χ^2 difference value (205.3767353) (p=.36746E-22) was found while the RMSEA value of .009191 indicates good model fit. The conclusion is therefore that the structural model does not show exact fit but that the model shows good close fit. The acceptable close fit obtained for the structural model in the sample warrants the interpretation of the structural model parameter estimates.

5.2.3 Power assessment

An analysis of statistical power using syntax developed by Preacher and Coffman (2006) in R programme was made. For this purpose a significance level of .05; a sample size of 213; and 704 degrees of freedom were specified. The null hypothesis of the RMSEA was set to .05 while the alternative hypothesis for the RMSEA was set to

.08. The Preacher and Coffman (2006) software returned a power value of unity which further provide some confidence in the comprehensive model.

5.3 ASSESSMENT OF MODEL HYPOTHESES

The overarching structural model substantive research hypotheses was dissected into 12 more detailed, path-specific substantive research hypotheses. The findings on the hypotheses are discussed below.

Hypothesis 3: *Abstract reasoning capacity* (ξ_1) positively affects *Learning performance during evaluation* (η_1)

The t-value of the link between *Abstract reasoning capacity* (ξ_1) and *Learning performance during evaluation* (η_1) is less than 1.96 (see Table 4.64). This indicates that there is no significant relationship between *Abstract reasoning capacity* (ξ_1) and *Learning performance during evaluation*. Therefore H_{03}: $\gamma_{11} = 0$ is not rejected which suggests that the proposed relationship between these two latent variables was not supported. The association of *Abstract reasoning capacity* and *Learning performance during evaluation* is consistent with previous findings by De Goede (2007) and De Goede and Theron (2010). Although differences in the operationalisation of the *Learning Performance* between the present study and the De Goede (2007) exist, the same conclusion of lack of support for this relationship holds.

Hypothesis 4: *Information processing capacity* positively influences *Learning Performance during evaluation*

The t-value of the link between *Information processing capacity* and *Learning Performance during evaluation* is greater than 1.96 (see Table 4.64). A significant ($p < .05$) and positive relationship (.260) is therefore evident between *Information processing capacity* and *Learning performance during evaluation*. H_{04}: $\gamma_{12} = 0$ can be rejected in favour of H_{a4}: $\gamma_{12} > 0$, which suggests that the proposed relationship between these two latent variables was supported. The application of newly acquired knowledge in solving new work-related problems is, however, transfer at work and thus dependent on information processing capacity, the speed, accuracy and cognitive flexibility with which the information is processed. Information processing capacity facilitates the choice of the strategy to use which in turn is affected by 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 maybe relevant to the problem, and of the speed and efficiency of any other system used in the total activity (Taylor, 1992; Underwood, 1978). This finding is consistent with the De Goede (2007) and De Goede and Theron (2012) findings that *information processing capacity* positively affects *learning performance.*

Hypothesis 5: *Self-leadership* positively affects *Motivation to learn*

The relationship between *Self-leadership* and *Motivation to learn* was supported as the t-value of the link between the two variables is greater than 1.96 (see Table 4.65). A significant ($p < 0.05$) and positive relationship (.218) is therefore evident between *Self-leadership* and *Motivation to learn*. H_{05}: $\beta_{43} = 0$ can be rejected in favour of H_{a5}: $\beta_{43} > 0$. This is consistent with the findings reported by Burger (2012) in a study involving grade 11 learners, who had completed their first semester (term 1 and 2) of grade 11 at selected schools in the Western Cape province. This finding makes theoretical and practical sense as self-leadership theory can be classified as a motivational theory in which motivation is a function of behavioural, cognitive and natural reward strategies that influence the initiation, direction, intensity and persistence of behaviour (Manz, 1992; Prussia, Anderson & Manz, 1998). Self-leadership is a self-influence process through which people seek to direct their cognitions and actions in order to reach desired goals (Manz, 1986; Manz & Neck, 2004), it gives the student or trainee some intrinsic impetus to manouvre towards attaining self-set objectives and in the process provides the energy, direction, and maintenance of objective-directed behaviours vital for successful learning performance.

On a slightly different note, this finding provides further evidence to critics about the conceptual distinction between self-leadership and motivation. Some authors have questioned the uniqueness of self-leadership strategies, because they are founded upon, and operate within, the context of other established theories of self-regulation, motivation and self-influence (Guzzo, 1998; Markham & Markham, 1995, 1998). However, Houghton *et al.* (2012, p. 220), in response to these criticisms, emphasised that self-leadership is a normative or prescriptive model rather than a deductive or descriptive theory. Normative theories, such as self-leadership, are prescriptive and emphasise *how* something should be done, whereas descriptive theories seek to explain the basic operation of various phenomena without giving normative information for applying an approach. The conceptual distinction between self-leadership and other theories has been a subject of persistent debates (see Neck & Houghton, 2006, for a review). It therefore remains important to consider the possibility that specific self-leadership strategies are distinct from general dimensions that may underlie their operation. Whilst self-leadership consists of a particular set of behavioural and cognitive strategies that are based upon, and related to, other theories of personality, motivation, and self-influence, such as self-regulation theory and social cognitive theory, self-leadership strategies remain distinct from these approaches (Neck & Houghton, 2006).

Hypothesis 6: *Conscientiousness* positively affects *Time cognitively engaged*

The t-value of the link between *Conscientiousness* and *Time-cognitively-engaged* is less than 1.96 (see Table 4.64). A non significant ($p < .05$) relationship is therefore evident between *Conscientiousness* and *Time-cognitively-engaged*. H_{06} is therefore not rejected. . This finding is surprising since students who are engaged show some sustained behavioural involvement in the task at hand and, in addition to task involvement, the engaged students exert intense effort and concentration as well as display some positive emotions such as enthusiasm, curiosity, optimism and interest (Skinner & Belmont, 1993). Individuals, who score high on *Conscientiousness* generally set high standards for themselves, are more likely to be willing to work hard on tasks (Chen, Casper & Cortina, 2001). Diligent and conscientious students make an effort to engage with their study material. These students direct their energy towards mastering the learning task using various metacognitive and self-monitoring strategies in an attempt to ultimately transfer existing knowledge to resolve novel problems. This finding is not consistent with the finding reported by Burger (2012).

Hypothesis 7: *Motivation to learn* positively influences *Time cognitively engaged*

The t-value of the link between *Motivation to learn* and *Time cognitively engaged* is greater than 1.96 (see Table 4.65). A significant ($p < .05$) and positive relationship (.197) is therefore evident between *Motivation to learn* and *Time cognitively engaged*. H_{07}: $\beta_{24} = 0$ can be rejected in favour of H_{a7}: $\beta_{24} > 0$, which suggests that the proposed relationship between these two latent variables was supported. Motivated trainees take a more active role in training and get more from the experience compared to individuals who are not motivated (Nunes, 2003). These students are likely to be cognitively engaged and put in a lot of effort to truly understand a topic as well as continue studying over a long period of time. Hence a students' cognitive engagement represents a motivated behaviour associated with students' persistence on difficult tasks and the usage of cognitive strategies (Pintrich & Schrauben, 1992). This finding is consistent with Burger's (2012) conclusion that *learning motivation* serve as the force that brings an individual's intention to learn into action.

Hypothesis 8: *Self efficacy* positively influences *Self-leadership*

The t-value of the link between *Self efficacy* and *Self-leadership* is greater than 1.96 (see Table 4.64). A significant ($p < .05$) and positive relationship (.461) is therefore evident between the two constructs. H_{08}: $\gamma_{34} = 0$ can be rejected in favour of H_{a8}: $\gamma_{34} > 0$, which suggests that the proposed relationship between *Self efficacy* and *Self-leadership* was supported. The self-efficacy quality and the ensuing behaviours are consistent with those of individuals who believe in their ability to complete a task as well as have a self-driven influence to initiate and implementing strategies that are goal-directed and ultimately lead to higher learning performance. The *self-efficacy* belief is a key factor in regulating behaviour leading to human competence (Pintrich, 1999; Pintrich & De Groot, 1990). Self-efficacy regulates the way in which an individual perceives his or her competence. This perception influences an individual's ability to complete a task and a set, attainable goal (Pajares & Schunk, 2001). Generally, in a training situation, individuals with a high degree of self-efficacy are likely to exert considerable effort to master the program content, persevere in the face of difficulties, demonstrate intrinsic motivation when engaged in task performance, and are less likely to feel disappointed in the face of failure. These findings are consistent with other previous study findings (Burger, 2012; Pintrich & De Groot, 1990; Schunk & Zimmerman, 1997).

Hypothesis 9: *Knowledge about cognition* positively influences *Regulation of cognition*

A strong (.938) positive and significant relationship exists between *Knowledge about cognition* and *Regulation of cognition* as the t-value of the link between the two constructs is greater than 1.96 (see Table 4.64). H_{09}: $\gamma_{55} = 0$ can be rejected in favour of H_{a9}: $\gamma_{55} > 0$, which suggests that the proposed relationship between these two latent variables was supported. The bigger an individual's *Knowledge about cognition* base the more likely that individual will be to strategies such as planning, organising, regulating and monitoring cognitive resources for increased efficiency during learning. When the learner detects through *Regulation of cognition* via strategies such as self-monitoring that a skill has not been adequately learnt and rehearsed, a good learner is likely to allocate some more time on the skills. The relationship between *Knowledge about cognition* and *Regulation of cognition* affirms the intial conceptualisation of the two as part of one construct although *Knowledge about cognition* appears to be more of a competency potential variable while Regulation *of cognition* is a learning competency.

Hypothesis 10: *Regulation of cognition* positively influences *Time cognitively engaged*

The t-value of the link between *Regulation of cognition* and *Time-cognitively-engaged* is greater than 1.96 (see Table 4.65). A significant ($p < .05$) and positive relationship (.628) is therefore evident between these two constructs. H_{010}: $\beta_{25} = 0$ can be rejected in favour of H_{a10}: $\beta_{25} > 0$, which suggests that the proposed relationship between *Regulation of cognition* and *Time cognitively engaged* was supported. The student's ability to make use of *meta-cognitive regulation of cognition* strategies implies that the individual is willing to spend some time on the task, grappling and engaging with the task using difference metacognitive and self-monitoring strategies such as planning strategies and the allocation of resources, monitoring of progress and the effectiveness of strategies and eventually evaluating their own learning. The confirmation of the relationship between *Regulation of cognition* and *Time cognitively engaged* has some important implications for the student's ability to manage and use their study time productively.

Hypothesis 11: *Learning goal orientation* affects *Motivation to learn*

The t-value of the link between *Learning goal orientation* and *Motivation to learn* is greater than 1.96 (see Table 4.65). A significant ($p < .05$) and positive relationship (.548) is therefore evident between these two constructs. H_{011}: $\beta_{46} = 0$ can be rejected in favour of H_{a11}: $\beta_{46} > 0$, which suggests that the proposed relationship between

Learning goal orientation and *Motivation to learn* was supported. *Learning goal orientation* was shown in the current study to positively influence *Learning motivation*. Individuals with a high *Learning goal orientation* persist, escalate effort, and report enjoying the challenge as well as believe in the power of effort and hard work in the enhancement of ability. These individuals are likely to display higher levels of *Learning motivation* and accept mistakes or setbacks as learning opportunities that is likely to result in further motivation. Learning oriented individuals react to challenges with positive effect, pride, and intrinsic motivation (Dweck & Leggett, 1988). This is due to their optimism, maintenance of task interest and persistence in task performance (Dweck, 1999).

Hypothesis 12: *Time cognitively engaged* affects *Learning performance*

The t-value of the link between *Time-cognitively-engaged* and *Learning performance* is less than 1.96 (see Table 4.65). A non significant ($p < .05$) relationship is therefore evident between *Time-cognitively-engaged* and *Learning performance*. H_{012}: $\beta_{12} = 0$ can therefore not be rejected which suggests that the proposed relationship between these two latent variables was not supported. This result is not consistent with Burger's (2012) finding on the association between the two latent variables. *Time-cognitively-engaged*, which takes into account the amount of time spent on a learning task as well as the effort exerted by the individual, was found to positively influence *Learning Performance*. Indeed hard work characterised by an investment of time on a task, grappling with the task using various metacognitive regulative skills is lkely to lead to positive academic performance. The ability to set aside some time on the task itself shows to a certain extent the individual's *Self-leadership* and *Conscientiousness* as far as achieving their academic goals is concerned.

It can, however be argued that hard work and low hours spent on the task will not necessarily translate to success if the cognitive ability is lacking and/or the interpretation of the learning task is misunderstood. The latter is especially a potentially powerful explanation for the lack of a significant relationship, especially if the measures of *Learning performance during evaluation* truly assessed the ability of transfer post-learning knowledge. It is possible that many students still harbour the misperception that the essence of learning is memorisation. Human behaviour is cognitively mediated. The expectancy theory of motivation (Vroom, 1964) attests to this by stressing the critical moderating role that accuracy of role perception plays in the effect of effort on performance.

In addition it needs to be recalled that the original unabridged De Goede-Burger_Mahembe learning potential structural model made provision for a Prior learning moderator variable that moderates the effect of *Time cognitively engaged* on Transfer of knowledge. In addition it needs to be recalled that in the original unabridged model the effect of *Time cognitively engaged* on *Learning performance during evaluation* was mediated by *Transfer of knowledge* and *Automisation*.

Hypothesis 13: *Openness to experience* positively affects *Learning goal orientation*

The t value of the link between *Openness to experience* and *Learning goal orientation* is greater than 1.96 (see Table 4.64). A significant ($p < .05$) and positive relationship (.918) is therefore evident between *Openness to experience* and *Learning goal orientation*. H_{013}: $\gamma_{67} = 0$ can be rejected in favour of H_{a13}: $\gamma_{67} > 0$, which suggests that the proposed relationship between these two latent variables was supported. Personality theory suggests that employees who are open to experience value training as an opportunity to learn new skills (Goldstein & Ford, 2002; Kanfer, 1990, Lievens, Harris, Van Keer, & Bisqueret, 2003). In view of the role of openness to experience in training proficiency, it is expected that individuals with a high openness to experience personality are likely to be pre-occupied with increasing competence as well as construe ability as an incremental skill that can be incessantly improved by acquiring knowledge and perfecting competencies (Wood & Bandura, 1989).

Hypothesis 14: *Prior learning* moderates the relationship between *Abstract reasoning capacity* and *Learning performance during evaluation*

The moderating effect of Prior learning (indicated by the interaction term ABSPRIO) on the relationship between *Abstract reasoning capacity* and *Learning performance during evaluation* was not supported. The t-value of the link of this relationship is less than 1.96 (see Table 4.64). It is therefore evident that Prior learning is not a significant moderator of the relationship between *Abstract reasoning capacity* and *Learning performance during evaluation.* H_{a14}: $\gamma_{67} = 0$ can therefore not be rejected in favour of H_{a14}: $\gamma_{67} > 0$, which suggests that the proposed moderating role of *Prior learning* on the relationship between *Abstract reasoning capacity* and *Learning performance during evaluation* was not supported. *Abstract thinking capacity* is synonymous with the ability to think flexibly and to understand abstract relations (Preusse, Van der Meer, Deshpande, Krueger & Wartenburger, 2011) and is vital for solving novel problems as well as the acquisition of new knowledge (Cattell, 1971). *Learning performance during evaluation* involves the adaptation of knowledge and skills to address problems somewhat different from those already encountered. The *Transfer of knowledge* component expressed in *Learning performance during evaluation* like *Learning performance in the classroom* and general *Transfer of knowledge* involves the use of previously gained insight, *Prior Learning*, to find meaningful structure in a novel, initially meaningless, stimulus set. Transfer in essence is creative cognitive problem-solving. Hence it is expected that the larger the individual's store of *Prior Learning* the better and easier it is to adapt as well as use the available knowledge to resolve novel problems and ultimately influence *Learning Performance during Evaluation*. The current finding is therefore disappointing given the persuasiveness of the theoretical argument underlying this hypothesis.

Two of the residualised indicators of the latent interaction effect showed low factor loadings. The concern therefore exists that the current finding can possibly be attributed to the low validity of these two indicators. These two indicators are part of the four indicators calculate through the Little *et al*., (2004; 2006) residual centering approach. The question that arises pertains to whether or not the random and non-random measurement errors have been fully controlled for through the use of this method.

5.4 LIMITATIONS OF THE STUDY

Although most of the limitations or shortcomings in the research methodology have already been discussed throughout the text, some of the more important limitations will be highlighted again. First, the study findings cannot be generalised to the broader population of students without further replication. The sample that was used consisted of students on the extended degree programme. Furthermore, the participants were drawn from a single university in the Western Cape Province of South Africa, while it is vital to test the model using participants drawn from a heterogenous sample that is representative of the multicultural society of South Africa. Besides a bigger sample size has the advantage of enhancing the statistical power of the study. The proposed learning potential structural model was therefore tested on a non-probability sample comprising learners from the extended degree programme. The use of the non-probability sampling procedure precludes the drawing of a conclusion that the sample is representative of the target population. Furthermore to sampling limitation, due to the affirmative action perspective from which this study stems one would want to argue that the sample needs to consist of only participants that qualify as affirmative development candidates. In this study 15.2% of the participants were White students who are commonly regarded as the formerly 'advantaged students.' Although the number is small compared to the student group of participants, it still remains a limitation of the study that the sample was not totally from a disadvantaged affirmative action background. Therefore, replication of this research on other samples and in different developmental contexts is therefore encouraged.

The second limitation relates to the measuring instruments used in this study. The instruments used are self-report measures. Self-report measures run the risk of social desirability. Social desirability refers to the risk that respondents may be tempted to attempt to manipulate the answers in order to create a more favourable impression when completing such instrument. This, in turn, impacts on the reported levels of the constructs investigated and it influences the results (Elmes, Kantowitz & Roediger, 2003). Furthermore, the question is left open as to whether the reported results pertain to the individuals' actual experiences, or mainly illustrate their perceptions. In other words, the respondents' perceptions may differ from the actual state of being causing them to rate themselves higher (or lower) on the constructs due to a false perception. This limitation is especially a concern in this type of study as in a competitive environment such as that of the extended degree programme students. These students may be tempted to create a more favourable impression in order to appear on par with their competent peers already in the main stream degree programme. Method bias was somewhat less of an issue in the current study as the self-report measures were complemented with data from psychometric tests and in the structural model that was tested the criterion latent variable *Learning performance during evaluation* was not obtained via self-report measures but was tested objectively using the first semester average mark and the credits passed over total credits ratio.

It should, thirdly, be noted again that good model fit in SEM does not imply causality. Even though the structural model being evaluated hypothesised specific causal paths between the latent variables comprising the model, good model fit and significant path coefficients constitute insufficient evidence to conclude that these causal hypotheses have been confirmed. In the final analysis this is not due to limitations in the analysis technique as such but rather due to the *ex post facto* nature of the study that precludes the experimental manipulation of the relevant latent exogenous and endogenous variables (Kerlinger & Lee, 2000).

With regards to the learning performance data itself, a decision was made to use the average semester mark as an indication of learning performance and the average grade 12 mark to indicate *Prior Learning*. This may have served as a limitation as the best option would have been to represent the *Learning Performance* of each learner using that learner's full range of subject marks from both semesters. Furthermore, the fact that these students write different examinations and assignments and come from different programmes is also a weakness of the study.

The validity of some of the composite indicator variables also gave reason for concern. OPEN_2 (for the *Openness to experience*); obtained an inadmissible value that exceeds unity; SREW (.367) and STALK (.476) for the self-reward and self-talk subscales of the Revised Self-leadership Questionnaire as well as the RES_2 (.122) and RES_4 (.292) item parcels for the interaction term were low in comparison with the other completely standardised item parcel values which were generally above .5. The squared multiple correlations (R^2) of (OPEN_1) (*Openness to experience*) and (RES_1; RES_2; RES_3 and RES_4) (the indicators of the interaction term) were also very low.

5.5 SUGGESTIONS FOR FUTURE RESEARCH

Future research should examine the relationship between *Time cognitively engaged* and *Learning performance during evaluation*. Essentially *Time cognitively engaged* represents exerted learning effort. Expectancy theory (Vroom, 1964) suggests that the effect of effort on performance is moderated by ability and acuracy of role perceptions. In the learning contect this suggests that the effect of *Time cognitively engaged* on *Transfer of knowledge* and *Automisation* should be moderated by the *Accuracy of the learning role perception* and by the *Prior learning* and *Fluid intelligence* of the learner. The latter should probably be understood as an interaction in itself that interacts with effort or *Time cognitively engaged*.

This line of reasoning points to the urgent need to find appropriate ways of operationalising the *Transfer of knowledge* and *Automisation* latent variables. These two variables constitute the core of *Classroom learning performance*. As argued earlier the APIL-B scales are not appropriate to measure these two variables in an actual learning context. The APIL-B creates its own learning context that is radically different from the actual learning context in which the study is conducted.

In addition future learning potential structural models will have to formally acknowledge that *Post-development learning* or crystalised knowledge is the outcome of *Transfer of knowledge* and *Automatisation*. It is *Post-development learning* that in interaction with Abstract thinking capacity determines *Learning performance during evaluation* as yet again transfer of knowledge.

Future research should in addition consider the possibility of expanding the theoretical model by formally incorporating environmental variables that may impact on learning such as training design and *Environmental unfavourableness*. The latter theme is especially relevent to affirmative development. Disadvantaged individuals could be expected to find themselves in less than optimal living and studying conditions. In terms of this line of reasoning the ability of overcome the adversity inherent in their current position then becomes an important factor that will determine whether they will achieve success when offered an affirmative development opportunity (possibly based on cognitive learning potential). The *Psychological capital* of the learner (Prinsloo, 2013) could possibly play an important role in the ability of the learner to rise above adversity inherent in their current position.

Students' expectancies, that is, notions concerning effort-performance and performance-outcome perceptions as causes of behaviour also have particular relevance in training situations. These can be expected to affect the *Learning motivtion* of the learner (Nunes, 2003). Furthermore, *Locus of control* is likely to positively influence learning performance. Individuals with an *Internal locus of control* believe that learning performance and events that occur in the classroom setting are contingent on their own behaviour and are therefore under personal control while externals believe that learning outcomes are beyond personal control and therefore attribute the cause of those learning outcomes to luck, fate or the action of others (Noe, 1986). *Internal locus of control* could affect *Learning goal orientation* and through that *Learning motivation*.

A multi-group comparison with the main stream students is vital for the validation of the model. It is vital to ensure that the measurement and structural models would fit equally well when comparing the two groups of students. Multiple group analysis in structural equation modelling is very useful because it allows one to compare multiple samples across the same measurement instrument or multiple population groups (e.g., males vs. females) for any identified structural equation model. Vandenberg and Grelle (2009) presents a seemingly convincing argument of the importance to examine alternative model specifications (AMS) practices as applied to confirmatory factor analysis and structural equation modelling.

5.6 PRACTICAL IMPLICATIONS OF FINDINGS

The major contribution of the present study relates to the role of industrial psychology in the formulation of credible and valid psychological explanations of learning performance, to bring about positive change in the performance achieved by learners in affirmative development programmes. The aim of these programmes in turn is to assist in transforming the profile of the South African workforce in the private sector without compromising on productivity. In South Africa, reports have been made that almost 80% of learners registered for SETA learnerships do not complete their training (Letsoalo, 2007). Others, for example Alexander (2006), gave examples of skills development programmes where up to 90% of learners did not complete their training. Although there may be many underlying factors contributing towards the dissatisfaction and poor performance of learners, a frequently cited reason is the poor recruitment and selection of learners into skills development programmes (Letsoalo, 2007).

The model presented in this study offers a plausible explanation of the learning performance of the previously disadvantaged group members who are on the extended degree programme. It therefore allows educators and training development practitioners to derive solutions on how to reduce the high number of drop-outs in different training programmes through selection as well as to derive solutions on how to promote successful learning once admitted onto the programmes.

Selection into affirmative development opportunities represents an attempt to improve the level of *Learning performance during evaluation* of learners admitted to affirmative development opportunities. Effective selection into affirmative development opportunities is possible fundamentally because variance across learners in *Classroom learning performance* and ultimately variance across learners in *Learning performance during evaluation* are not random events. Rather variance across learners in *Classroom learning performance* and ultimately variance across learners in *Learning performance during evaluation* is systematically determined by an array of latent variables characterising the learner and characterising the learning environment. In addition these determining latent variables combine in a specific manner to determine the level of *Classroom learning performance* and ultimately the level of *Learning performance during evaluation* that each learner achieves. Although prediction is possible without the benefit of an explanatory model that identifies the determinants of learning performance and that describes how these determinants combine to determine the level of learning performance that each learner achieves (Sutton, 1998) a valid understanding of the identity of the determinants of learning performance in conjunction with a valid understanding of how they combine to determine the level of learning performance achieved should nonetheless allow a theoretically better grounded prediction of *Learning performance during evaluation*. The following practical recommendations can be made help predict *Classroom learning performance* and *Learning performance during evaluation.*

Information processing capacity is the only learning competency potential latent variable that has been found, in this study, to affect *Learning Performance in the Classroom* directly. To successfully filter out those that will not benefit from affirmative development opportunities practitioners and educators should test the students or trainees' information processing capacity. Information processing capacity, as defined by Taylor (1994), represents the speed, accuracy and flexibility with which information is proccessed. *Information processing capacity is assessed* in terms of these three components that are extremely important for successful learning namely: (1) the speed with which information of a moderate difficulty level is processed (i.e. processing speed); (2) the accuracy with which information of a moderate difficulty level is processed (i.e. processing accuracy) and (3) the cognitive flexibility with which a problem-solving approach, which is appropriate to the problem, is selected (De Goede & Theron, 2010). The cognitive flexibility, with which an individual selects a problem-solving approach, appropriate to the problem from a personal 'toolkit' of cognitive strategies is a fundamental characteristic of intelligent behaviour (Hunt, 1980; Taylor, 1997). Individuals who keep on following an inappropriate strategy are regarded as having a lesser capacity to process information. *Information processing capacity* is an extremely important attribute which should be included in the selection of students and trainees for admission to tertiary institutions, affirmatice development programmes and trainee development programmes. To my mind, it should also be a component of the National Benchmark tests used to select students for tertiry education. Educators and Training managers should come up with some coaching programmes to educate the students and trainees on the need to process information quickly, accurately and to be cognitively flexible in the application of the concepts that have been learnt.

Academic self-leadership has also emerged as an important learning competency. Although *Academic self-leadership* does not affect classroom learning performance directly, it relates with a learner or trainees' motivation to learn and self-efficacy to create the intrinsic motivation required to engage in learning performance related behaviours. In addition to its influence in academic settings, self-leadership has also been linked to more specific personal work outcomes, such as enhanced individual innovation and creativity potential (Curral & Marques-Quinteiro, 2009; DiLiello & Houghton, 2006), entrepreneurship (D'Intino, Goldsby, Houghton & Neck, 2007) and productivity (Birdi *et al.*, 2008). Studies show that self-leading employees are better adjusted, more confident (Stajkovic & Luthans, 1998) and enjoy greater career success (Murphy & Ensher, 2001; Raabe, Frese & Beehr, 2007). These findings suggest the need to develop this competency among students or trainees educators and managers alike can rely on self-leadership rather than on external leadership as it has been traditionally applied. Self-leadership is considered pivotal to individuals' enthusiasm for, commitment toward and performance in organisations. Organisations therefore may do well in training employees in general self-leadership strategies to create more individual-dependent positive behaviours.

A combination of a good *Academic self-leadership* skill with metacognitive regulation of cognition is likely to ultimately create a good student or trainee. This is achieved through the students' use of individually-initiated behaviour and self-monitoring in implementing metacognitive regulation strategies when they encounter difficult learning problems. The strategies that are at their disposal include: organising and transforming information, sub-goal setting and planning, seeking information, keeping records and self-monitoring, environmental structuring, creating consequences, rehearsing and memorising, seeking peer, teacher, or adult assistance, reviewing notes, tests or textbooks. The successful application of the self-leadership and metacognitive regulation of cognition is likely to lead to an enlarged metacognitive knowledge database that can be used to resolve future learning problems.

In addition to the learning competencies and learning competency potential behaviours discussed above, *Motivation to learn* is an extremely important learning competency potential variable. It plays the energiser, director and maintenance role that helps in creating a positive attitude towards learning. Highly motivated individuals are likely to set aside some time to engage with their work. Several other studies in the field of education have stressed the need to foster student motivation in the classroom as one of the catalysts of learning (Hicks & Klimoski, 1987; Pham, Segers & Gijselaers, 2010). Therefore educators and training development practitioners should come up with intervention programmes to promote student and trainee motivation.

It is vital to promote a *Learning goal orientation* as it promotes learning motivation. Individuals with a learning goal orientation are preoccupied with developing new skills and increasing competence. These individuals promote a challenge-seeking and mastery oriented response in the face of failure regardless of their perceived ability (Elliot & Dweck, 1988). Learning goal oriented individuals believe in the power of effort and hard work in the enhancement of ability and are likely to display higher levels of *Learning motivation* and accept mistakes or setbacks as learning opportunities that is likely to result in further motivation (VandeWalle, Ganesan, Challagalla, & Brown, 2000).

Time cognitively engaged is also an important learning competency. Although *Time cognitively engaged* in the current study is a function of *Motivation to learn and Regulation of cognition,* it is vital and important that students or trainees assign some time to engage with the tasks. Educators and practitioners should come up with some time management interventions to encourage students to devote enough time to touch base with their learning or training tasks.

Openness to experience has emerged in this study as an important learning competency potential variable that is likely to affect *Learning goal orientation*. Unfortunately, *Openness to experience* is a personality characteristic that cannot be changed through interventions. It is a stable and enduring characteristic of an individual. However, educators and training practitioners can assess individuals' openness to experience through standard personality questionnaires or psychometric tests designed to test for it.

The foregoing discussion offers two possible routes to follow with regards to selection into affirmative development programmes. The first would be to enter all the learning competency potential latent variables and all the learning competency measures that were found to play a significant role in the model into a multiple regression model which has the *Learning performance during evaluation* observed variable (a composite of the indicator variables used to operationalise the latent variable) as the criterion. The learning competency measures will have to be obtained with reference to the most recent previous development or training programme or via a simulation. In this approach the prediction model is not assumed to reflect the psychological dynamics underlying *Learning performance during evaluation*.

The ideal would, however, be that the criterion inferences should be derived actuarially from a model that may permissibly be regarded as a valid description of the psychological dynamics underlying *Learning performance during evaluation*. It would be possible to derive latent variable estimates for all the exogenous latent variables in the model via the measurement model equations. An equation (equation 23) to calculate the latent scores from the measurement model parameter estimates are given in Jöreskog (2000, p. 4). These exogenous latent variable estimates can then be propagated through the model via the structural equations derived in this study. The current model would, however, first have to be pruned of its insignificant paths The advantage of this procedure is that it produces latent score estimates of the criterion construct rather than observed score estimates like the regression model.In addition it can theoretically be expected that the model will cross-validate more successfully than the regression model in that it represents a valid representation of the psychological dynamics underpinning *Learning performance during evaluation*. The critical question is how the proportion of variance that the structural model explains in the *Learning performance during evaluation* latent variable (0.127) compares to the proportion of variance that the regression model explains in the *Learning performance during evaluation* latent variable. Most likely the structural model would have to be expanded in the manner indicated above to convincingly outperform the observed score regression model.

The abridged learning potential structural model contains three potentially malleable learning competency potential latent variables that have been shown to exert a significant influenece in the structural model. *Motivation to learn*, *Academic self-efficacy* and *Knowledge of cognition* are person-centred latent variables that can potentially be influenced by interventions aimed at developing these attributes, or in the case of *Learning motivation*, by enginering the organisational conditions under which individuals are admitted onto the development programme. The objective in the latter case would be to affect the parameters of the motivation process (e.g., expectancies, valences, instrumentalities) that regulate the effort that the learner exerts. It can in addition be argued that the learning competency *Academic self-leadership* can be influenced via a leadership development programme. In all cases these interventions will either have to be implemented after individuals have been selected onto the development programme but before the programme officially starts or to run concurrently with the programme.

5.7 CONCLUSION

Significant relationships were found between: *Information processing capacity* and *Learning Performance during evaluation; Self-leadership* and *Motivation to learn;*

Motivation to learn and *Time cognitively engaged; Self efficacy* and *Self-leadership; Knowledge about cognition* and *Regulation of cognition; Regulation of cognition* and *Time-cognitively-engaged*; *Learning goal orientation* and *Motivation to learn; Openness to experience* and *Learning goal orientation.* Support was not found for the relationships between *Conscientiousness* and *Time-cognitively-engaged* as well as between *Time-cognitively-engaged* and *Learning performance*. The moderating effect of Prior learning (indicated by the interaction term ABSPRIO) on the relationship between *Abstract reasoning capacity* and *Learning performance during evaluation* was not supported. The fit of the measurement and structural models can generally be regarded as reasonable fit and both models showed close fit. The statistical power of the model and the discriminant validity of the item parcels were ascertained. The limitations and suggestion for future studies have been highlighted. The results of the present study provide some important insights for educators and training and development specialists on how to identify potential students and talent for affirmative development in organisations in South Africa.

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