The use of Rasch Measurement Theory to address measurement and analysis challenges in social science research

By

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Dedications & Acknowledgements

Dedications

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ABSTRACT

High quality assessment instruments, in conjunction with best practice for data processing, analysis and reporting are essential for the monitoring of academic school achievement. In this thesis, Rasch Measurement Theory (RMT) as the primary method, addressed issues related to the monitoring of academic achievement. Rasch theory makes use of logistic regression models, which calibrate instruments by calculating item and person fit. The main study monitored the academic achievement of 3 697 Grades 8 to 11 learners at seven independent high schools in South Africa over a three- year period. Monitoring was done via specifically designed assessment instruments for Mathematics, Science and English Language. The main research question asked: *How does the application of Rasch models address measurement problems in the processing, analysis and reporting of educational monitoring results?* The thesis comprises three articles (presented as chapters and seen as sub-projects), and investigates challenges arising from the monitoring project. Measurement challenges addressed includes how to impute Missing Not At Random Data (Article 1), how to evaluate anchor items and reframe results (Article 2) and create proficiency bands (Article 3). Recommendations from the articles consist of using Rasch measures as predictors for imputation models, applying the Rasch models for evaluating anchor items and reframing test re-test results and the use of Rasch Item Maps for reporting criterion-referenced results. The thesis concludes by recommending that psychometric theory and application be taught in social science courses for the development of high quality instruments and the strengthening of measurement within the human sciences.

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KEYWORDS

Academic Achievement
Anchor or Common Items
Binary or Dichotomous items
Cognitive Constructs
Competency Bands
Criterion-Referenced Feedback
Education
Human Sciences
Imputation of Missing Data
Measurement
Missing Not at Random (MNAR) Data
Monitoring & Learning Progression
Monitoring Academic Achievement
Multiple Imputation (MI)
Psychometric Theory
Rasch Item Map Method
Rasch Measurement Theory
Rasch Models
Social Science Research
Structural Equation Modelling (SEM) of Missingness Mechanism

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LIST OF ABBREVIATIONS

CAPS	Curriculum and Assessment Policy Statements
CEA	Centre for Evaluation and Assessment
CTT	Classical Test Theory
DBE	Department of Basic Education
FET	Further Education and Training
GET	General Education and Training
IRT	Item Response Theory
MCAR	Missing Completely at Random Data
MI	Multiple Imputation
MNAR	Missing Not At Random
NCS	National Curriculum Statement
NSC	National Senior Certificate (Grade 12)
PCA	Principal Component Analysis
PIRLS	Progress in International Reading Literacy Study
RUMM	Rasch Unidimensional Models for Measurement
RMT	Rasch Measurement Theory
SACMEQ	The Southern & Eastern African Consortium for Monitoring Educational Quality
SASA	South African Schools Act
SEM	Structural Equation Modelling
SPSS	Statistical Package for the Social Science
TIMSS	Trends in Mathematics and Science Study
TST	True Score Theory

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DECLARATION

I declare that this thesis is my own original work. Where secondary material is used, this has been carefully acknowledged and referenced in accordance with university requirements.

I understand what plagiarism is and am aware of university policy and implications in this regard.

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Celeste Combrinck

30 August 2017

ORIGINAL PAPERS

- Combrinck, C., Scherman, V., Maree, D. & Howie, S. (2018). Multiple Imputation for dichotomous MNAR items using a Recursive Structural Equation Model with Rasch Measures as predictors. *Sage Open*, *1* (1-12).
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Chapter 1 - Introduction

A true thing badly expressed becomes a lie.

Fry (2011, p.1)

At the heart of all science is the need to know the subject matter, to truly understand the object of study deeply, constructively and practically. The subject matter of social sciences focuses on humans, who are adaptable and embedded in qualitative experiences that create challenges to objective measurement. In social sciences, measurements are often made of subjects and constructs, which are latent, hidden from view, but inferable from observations or proxy variables (Andrich, 2001; Massof, 2011). The measurement of any phenomenon is the defining of previously unknown quantities in ways that are accessible (Andrich, 2001; Bond & Fox, 2015; Cavanagh & Waugh, 2011; Boone, Staver & Yale, 2014). Theory and observation are required to access latent traits to make the trait manifest for measurement (Bond & Fox, 2015). The operationalisation of social constructs, such as learning, memory, feelings, knowledge, skills and beliefs is the key to making measurement possible (Loubsera, Casteleijn & Bruce, 2015). Practically defining a construct makes it possible to create the ruler with which to measure.

Years ago at a workshop on Item Response Theory at UNISA, the presenter alleged that it is possible to measure anything. An objector in the audience immediately responded saying that this is not true, in that some phenomena, such as 'love', cannot be measured. To which the professor instantly replied: "Madam, you define it and I will measure it". Without measurement, science is not possible (Morris & Langari, 2012; Tal, 2017). Without a way to quantify and classify constructs, the subject remains vague, and cannot be studied scientifically (Granger, 2008). Disciplines that cannot measure constructs within their field become metaphysical relegated to pseudoscience without new insights and growth.

To measure is to understand how objects or people move along a continuum on a theoretical idea (Long, 2015). The construct being measured can be made accessible and explicit, broken down into its parts along the growth line (Hendriks, Fyfe, Styles, Skinner & Merriman, 2012). Deeply embedded in measurement theory is the concept of linearity, that one first learns to

crawl, then to walk and finally to run (Granger, 2008). The degree to which such linearity can be applied in more cognitive and psychosocial constructs varies, but evidence for linearity can be found and documented, even if persons move back and forth on the ruler or skip over certain points on the scale (Engelhard, 1996). In fact, the failure to master a point on the scale when moving along to the next one could indicate malfunctioning at later stages, which means that psychology and education could use these identified gaps on the scale to explain why persons are further along the pathway but are not functioning as expected.

There is a great need for valid and reliable inferences about constructs; however, the inferences should be derived from the use of sound instruments (Moutinho & Hutcheson, 2011). The application of sound measurement principles is not only one of scientific rigour, but also an ethical responsibility of the user of instruments within societal contexts (Engelhard, 1996; Wilson, 2005). The Diagnostic and Statistical Manual of Mental Disorders (DSM-V) is in its fifth edition, and with each new edition, some previously classified disorders are discarded, new ones added and the scientific and general public left wondering: "Do these disorders exist? How can it be that professionals trained to use the criteria in the DSM classify the same patient into different disorders or as having no disorder?" (American Psychiatric Association, 2013). Measurement theory holds some of the answers to these dilemmas, as the answer lies not only in training clinicians but also in the development of instruments from which reliable, valid and invariant inferences can be obtained in the context of the application (Bond & Fox, 2015; Granger, 2008). The same challenges exist in all the social sciences. In education, the most topical question is how to accurately measure latent traits such as ability and knowledge and then to track the development of these constructs over time.

1.1 The main monitoring project

Rasch Measurement is the embodiment of measurement standards; it is the statistical models that represent the requirements of measurement, and assess the degree to which an instrument attains the requirements of true measurement (Boone et al., 2014; Bond & Fox, 2015; Wilson, 2005). By applying Rasch models to assess construct validity, the social sciences are in a position to be able to measure in the same scientifically rigorous ways as is found in the natural sciences.

The research described in this article-based thesis, examined how Rasch measurement models can be applied to solve present measurement challenges. The articles comprising this thesis (accepted in journals both national and international), report on an educational monitoring project involving seven independent high schools in South Africa. The seven schools, funded by an external agency are located in the provinces of Gauteng, Kwa-Zulu Natal, Western Cape and Limpopo. These schools specifically recruit learners from deprived homes and schooling backgrounds and focus on three subjects: Mathematics, Science and English Language. Measures were required to compare the schools, standardise academic performance across schools, in addition to finding mechanisms to improve individual schools through interventions and additional assistance. The schools and funding agency sought a way to monitor learning progress and put accountability measures in place. The funding agency tasked the Centre for Evaluation and Assessment (CEA), based in the Faculty of Education, University of Pretoria, with the design of assessments to monitor academic achievement across the independent schools. In total, more than three thousand (3 697) high school learners from Grades 8 to 11, aged 13 to 18 years old, participated in the monitoring project which ran from 2012 to 2014. Specially designed assessment instruments for the three subjects, Mathematics, Science and English language, were used to assess the learners. Subject specialists developed the assessments which were piloted, refined and updated each year to ensure curriculum alignment. The instruments were analysed using Rasch models to refine items and improve measurement.

The articles report on the practical measurement challenges which arose during the implementation of the project and each article explores one (or more) methodological problem(s). The research methodology chosen was deemed appropriate to address the problem at hand.

1.1.1 Ethical clearance

Ethical clearance was obtained from the Faculty of Education for the study (see Appendix B). The study was conducted according to ethical guidelines as set out by the University. As the articles included in this thesis utilised secondary data from the project, the funding agency consented to the use of the data sets for further research and scientific publications (see Appendix C). Use of data emanating from the assessments for research purposes required learner and parental permission (see Appendix D).

1.1.2 Problem statement and rationale

The South African education system has undergone many changes since the 1994 political transformation (Aron, Kahn & Kingdon, 2009; Fleisch, 2008; Jansen, 1998; Lemmer, Van Wyk & Berkhout, 2010). Several reforms aimed at ensuring quality education for all have taken place (Bloch, 2008; Carter, 2012; Lemmer et al., 2010). The first reform in 1997 involved the introduction of a new national curriculum (Davenport & Saunders, 2000; Valero & Skovsmose, 2002). In 2001, a revision was applied to cement the gaps in the curriculum (Valero & Skovsmose, 2002) and resulted in the Revised National Curriculum Statements Grade R-9 and the National Curriculum Statement Grades 10-12 in 2002. Further reviews and revisions to the curriculum occurred during 2009 and 2011 as content disparities still existed in subject curricula (Bansilal, 2011; Maistry, 2012). The most recent revision resulted in the National Curriculum Statement (NCS) for Grades R to 12 which incorporate the Curriculum and Assessment Policy Statement (CAPS) (DBE, 2012). This last round of curriculum revision was gradually implemented from 2012 onwards (DBE, 2012). The NCS builds on the previous curriculum but also includes updates in order to provide a clearer specification of what should be taught in all approved subjects (DBE, 2012). The NCS includes the National policy pertaining to the programme and promotion requirements of the NCS Grades R-12 and the National Protocol for Assessment Grades R-12. The far-reaching changes in the curriculum have meant that monitoring the impact of various phases has become all the more critical (Davids, 2017; Jansen, 1998), particularly as it has been reported that the newest version of CAPS (2012) may be a congested curriculum, straining teacher time and resources (Care & Kim, 2017).

In a system facing many political and social issues and that is constantly changing, the monitoring of academic achievement becomes all the more crucial. Indeed, monitoring the quality of education should be developed to help achieve the goals of any education system, in order to assess changes, adjust curricula and policy as well to devise interventions (Archer, 2011; Scherman & Smit, 2017). In South Africa, monitoring of academic achievement does take place, in the form of national assessments such as the Grade 12 National Senior Certificate (NSC) and international studies such as the Progress in International Reading Literacy Study (PIRLS) and the Trends in Mathematics and Science Study (TIMSS) (Visser, Juan & Feza, 2015). For some time, Annual National Assessments (ANAs) were also conducted and monitored academic achievement in each grade of the South African school population (Kanjee

& Moloi, 2016). Studies such as TIMSS, PIRLS and the Southern and Eastern African Consortium for Monitoring Educational Quality (SACMEQ) only take place at four, five and six year intervals respectively (Australian Council for Educational Research, 2015; DBE, 2017; Howie et al., 2012; Stephens, Warren & Harner, 2015). The overarching study described in this thesis, developed monitoring instruments due to the unavailability of standardised assessments for monitoring academic achievement in South African schools. The articles comprising Chapters 5 to 7 developed out of measurement challenges experienced during the implementation of the monitoring project.

When data were missing for only one school on the anchor items in the Grade 8 Science assessment, the missing data were classified as Missing Not At Random (MNAR). Due to the nature of the missing data, finding models which could impute the values was challenging. MNAR models have been devised, namely shared parameter models, pattern mixture models and selection models (Enders, 2010; Resseguier, Giorgi & Paoletti, 2011; Yuan & Little, 2009); however, both pattern mixture models and selection models have many restrictions and limitations (Enders, 2010). The possibility of devising a new model was explored, but abandoned in favour of Multiple Imputation (MI) combined with Structural Equation Modelling (SEM). Using existing methods rather than developing a new method was recommended by journal reviewers (when the article was submitted to a journal for review). The combination of MI and SEM with Rasch scores as predictors was chosen due to the strength of this design as the missingness can be modelled by SEM with MI being applied for the imputation (Gottfredson, Sterba & Jackson, 2017). The missing data article (in Chapter 5) addresses the issue of how to deal with MNAR dichotomous data using a combination of methods, an area that currently has limited literature and applications (Zhang & Wang, 2013). The Rasch model played an important role by providing more stable, accurate predictors for the MI model. Exploring hybrid models such as was used in Article 1 (see Chapter 5) is recommended for strengthening methods of handling missing data (Aste, Boninsegna, Freno & Trentin, 2015).

Linked to the importance of monitoring within the South African educational system is the critical issue of monitoring learning progression across years (Mok, McInerney, Zhu &Or, 2015; Scherman et al., 2017). In order to gain a holistic and accurate picture of academic achievement in schools, monitoring and systemic evaluations should link assessments through common items (Howard, 2008; Linacre, 2016; Wang, Kohli & Henn, 2016). Evaluating the

functioning of the common (anchor) items is a key issue related to the accuracy of growth models and monitoring learning progression (Bruin, Dunlosky & Cavalcanti, 2017). In addition, pre-test post-test results have challenges of comparability as the learners are expected to change over time (Wright, 1996, 2003). Article 2 (see Chapter 6) demonstrates a hybrid approach to deal with the challenges found in literature and in the monitoring study by combining Rasch statistics with parametric and non-parametric tests. The multi-disciplinary approach was thus designed to strengthen the methodology (Schnotz, 2016).

The last issue was one of dissemination and impact. Literature reveals that when monitoring results are reported in an interactive and accessible manner, the impact of the findings can be enhanced (Annual Review of Applied Linguistics, 2009; Archer, 2011; Popham, 2014). The challenge faced in the third article (see Chapter 7) was how to report assessment results so that all stakeholders could derive maximum impact, via criterion-referenced feedback (Meyer, Doromal, Wei & Zhu, 2017). The assessments were designed to evaluate curriculum knowledge and benchmark schools based on findings but not designed to be diagnostic, formative or to provide criterion-referenced results (Popham, 2014). Despite the limitation of test design, Rasch item maps and subject specialist inputs were used to derive diagnostic type feedback, which could then be converted into descriptive reports. The problem of multi-purposing assessments was addressed by this article (Lok, McNaught & Young, 2016; Horodezky & Labercane, 2016). Important to note is that monitoring of academic achievement is time consuming and expensive; it therefore becomes both an issue of ethical responsibility and scientific rigour to make use of the results to enhance the system and benefit the most important stakeholder: the learner (Roach & Frank, 2007; Ungerleider, 2003).

1.1.3 Research questions

The development of instruments that yield reliable and valid inferences, identifying cut scores, dealing with missing data as well tracking individuals across years to explore the impact of interventions, are vital issues in psychology as well as education. The project described in Section 1.1 deals with several measurement challenges which formed the basis for the overarching research question as well as the sub-questions addressed in each article.

The main research question of this thesis is:

> *How does the application of Rasch models address measurement problems in the processing, analysis and reporting of educational monitoring results?*

Each article had its own research questions, which provided answers for the main research question. The first article's research questions focused on how to create a hybrid approach to impute missing values. The question asked was: *How can Missing Not At Random (MNAR) data be imputed (MI) by modelling the missingness?* The research questions for the missing data article also included identifying a model for imputation, validating the model and evaluating whether Rasch scores could be used as predictors.

The main research question in the second article was concerned with the evaluation of common items and their accuracy for tracking learning progression. The article's main question asked: *To what extent does each anchor item contribute to tracking/monitoring progression?* Article 2 incorporated a research question about how to apply the Rasch model to reframe results and how this would affect the reporting.

The final article about competency bands posed questions about how to combine quantitative (Rasch item maps) and qualitative (subject specialist evaluations and descriptions) methods to report results in a criterion-referenced framework. The question was stated as: *How can information from Rasch Item Maps and Subject Specialists be combined and applied to establish and define learning progression levels?* This article also included a research question about the alignment of competency bands to the curriculum.

The articles, comprising Chapter 5, Chapter 6 and Chapter 7, answer the sub-research questions and in turn, answer the main research question. Chapter 8 draws the findings together and examines the big picture and offers recommendations emanating from the findings.

1.1.4 Research methodology

The broad study, from which the articles emanated, was underpinned by methodology based on the sound and scientific development of instruments in social science contexts: Rasch Measurement Theory (RMT). Rasch measurement is a philosophy within itself, one of

measurement as an established paradigm on which to base the development and evaluation of instruments. The methodology entailed items being developed according to psychometric principles (Bond & Fox, 2015) so that:

- the constructs were operationalised using the South African school curricula;
- the range of the scale was planned (from easier to more difficult items and topics);
- the dimensions (subject areas) were weighted;
- the item types (multiple choice and constructed response) were weighted according to dimensions and cognitive levels;
- the items were developed by teams of subject specialists, including the development of common items between years;
- the items were reviewed and refined by subject specialists (qualitative evaluation);
- the items were piloted and Rasch statistics used to evaluate overall and item specific functioning; and
- the items were refined based on piloting results and updated yearly, based on curricula requirements and item analysis.

The methodology employed in the individual articles was statistical in nature, with the application of Rasch models, parametric and non-parametric statistics. The articles were based on Rasch analyses of the existing data sets. Article 1's methodology centred on the imputation of missing data. The article applied multiple imputation (MI) and Bayesian methods via Structural Equation (SEM) modelling and the application of the Rasch Dichotomous Model as the methodology for imputing missing values (see Chapter 5).

In Article 2, parametric statistics (paired t-tests), non-parametric statistics (Wilcoxon's Matched Pairs Signed-Rank Test, Gamma associations) and the Rasch Partial Credit Model were applied in a mixture approach. The combinations of the parametric, non-parametric and Rasch statistics were used as the methods to assess item changes over time and to reframe results for tracking learning progression (see Chapter 6).

Article 3 used a mixed methodology by combining quantitative techniques (the Rasch model) and qualitative techniques (descriptions and inputs of subject specialists). Note that Rasch Measurement Theory requires qualitative input by subject specialists. The Rasch Partial Credit

model was used to analyse the data and identify proficiency bands of items in subjects while subject specialists reviewed grouping of items to generate criterion-referenced feedback for stakeholders (see Chapter 7).

1.1.5 Current thesis as meta-science study

Mouton (2001) defined a three-world framework: the first is the real world of everyday problems; the second is the world of science wherein exploration, description and experimentation take place. The last is the world of meta-science in which lies the philosophy of science, paradigms, methodology, ethics and the history of science (Vosloo, 2014). Theoretically, the second world of science should transform the first world through conceptualisation and action. The third world is where scientists reflect on the integration of the first and second world and on how underlying philosophies and methodologies influence the scientific study of the first world.

The world of meta-science, whether examined or ignored, has a pervasive influence on the second world of scientific study. The studies described in this thesis can be classified as being meta-science, belonging to the third world as described in Mouton's framework (Mouton, 2001). Statistical models such as the Rasch Measurement Theory function at the methodological and paradigmatic level. Models of statistical analysis inform the applications of scientific methods at the second world level. While meta-science may seem abstract and far removed from the first world of everyday living and struggles, this thesis makes the argument that where meta-science informs the world of science, this changes the first world, the "real" world. Although the methods and conclusions described in this treatise are classified as meta-science, they influence the real world and the people who need to benefit from science. In Chapter 3, the underlying principles of Rasch Measurement from a meta perspective are described and this chapter also includes the reasons for its practical and real world impact.

1.2 Definition of key terms

Many ideas within this thesis are inter-related and woven together to provide insight into measurement, monitoring of academic achievement and the application of Rasch models. How the definitions apply to various aspects of data processing, analysis and dissemination in the articles is explained in this section by offering definitions from literature in the fields and then relating those definitions to the current thesis.

1.2.1 Measurement in educational contexts

Measurement is known to us intrinsically and like language learnt at a young age, the rules and principles of measurement are deeply imbedded in the subconscious. When more explicit definitions are sought, the definitions tend to be concerned with quantities, concatenation, numbers and intervals. In 1920, Campbell defined measurement as the "process of assigning numbers to represent quantities" (Campbell, 1920, p.4). This lead to a suspicion that measurement was not possible in the social sciences, as the assigning of numbers to latent traits to represent quantities could only be done arbitrarily. The definitions of measurement have since been expanded, and many of the definitions involve the assigning of numerical values to objects in an ordered manner (Wu & Adams, 2007). "A measure is a location on a line", that is to say a point of attainment on a linear line of progression (Wright & Stone, 1979, p.12). The process of creating linear lines and locating objects, constructs or individuals along the line is the process of making measures. Wright and Stone's (1979) definition goes a step further by stipulating that the numbers assigned represent a continuous scale and not just a ranking (Wu & Adams, 2007). This definition also specifies that the numbers are indicative of a continuous variable and that the distances between the numbers are equal. Linear, continuous, meaningful, invariant and equal interval scales are the fundamental aspects of measurement for which the social sciences also strive (Boone, 2016; Cavanagh & Waugh, 2011; Wu & Adams, 2007). In addition, measurement can be defined as a reduction of uncertainty by observing and quantifying that which is observed (Hubbard, 2010). By applying Rasch Measurement Theory, the social sciences are now able to move towards measurement (Bond & Fox, 2015). However, Hubbard (2010) cautions that measurement could fail if the concept of measurement is not well understood, the object of measurement is not well defined and the methods of measurement are not based on scientific principles (that is, concept, object, method). Measurement in this thesis is defined as operationalising a construct, creating units of measurement for a scale, ordering the units equally along the scale and testing if the scale adheres to the principles of measurement. A final step is reflection of the construct, asking: *Do the measures make sense in terms of the construct?*

1.2.2 Assessment, testing and instruments

Assessment is a form of measurement, and in the current context it refers to gathering empirical data about what learners know and can do in subject areas (Archer, 2011; Walford, Tucker & Viswanathan, 2010). Assessments in classrooms and broader contexts should evaluate how far

learners have progressed in the subject, and should be used to inform practice and policy (Black, 1998). There are multiple ways of assessing the content knowledge and skills of learners, but the onus lies on the teacher to use a vast repertoire of assessment tools and strategies, which are aligned to the curriculum and assessment protocols (Hanna & Dettmer, 2004). Both formative and summative assessments provide a more holistic picture of each learner's progress throughout the year in a particular subject (Black, 1998; Kanjee & Sayed, 2013). Assessments should have a clear aim or objective, therefore assessing should not be for the sake of assessing but rather for classroom, school or broader requirements (Black, 1998; Chappuis, 2009; Corrigan, Gunstone & Jones, 2013). The main reasons for assessment include supporting learning, reporting on the progress of the learning and accountability for educational systems (Black, 1998). In the context of this thesis, assessment is defined as tests designed for specific school subjects and utilised for the monitoring of academic achievement.

The terms 'test', 'assessment' and 'instrument' are used interchangeably throughout this thesis. A test is an assessment of a skill or knowledge and tests in school environments are often referred to as assessments. Generally, in social science measurement, the term 'instrument' is used to denote any form of psychological or cognitive assessment, test, task or questionnaire aimed at measuring a construct. The term 'instrument' is used in this thesis to refer to the tests/assessments which were designed for the monitoring study. When measurement is discussed in a general sense in the thesis, instruments refer to tests, assessments or questionnaires.

1.2.3 Monitoring of academic achievement

There is a need for high-quality monitoring of academic achievement in national and international contexts (Scherman, 2007; Smith & Smith, 2004; Tymms, Merrell & Wildy, 2015). In the late 20th century, the focus in education was on access to learning, and this goal has for the most part been reached in many contexts. Now the focus has shifted to the quality of learning and education (Scherman, 2007; UNESCO, 2013). The fact that the quality of learning is lower than is desirable globally is supported by various studies and official reports (Howie, van Staden, Tshele, Dowse & Zimmerman, 2012; Howie, Combrinck, Roux, Palane, Tshele & Mokoena, 2017; UNESCO, 2013). Good quality instruments are the foundation of monitoring academic achievement and assist in gauging the quality of teaching and learning. Thus, feedback into the system can be provided and this contributes to the improvement of

systems (Cotton, 1988; Lokshyna, 2005; Scherman, Bosker & Howie, 2017). Not only do educational monitoring systems have implications for teaching and learning in a broad school and community sense, but also have implications on the individual child. The quality of the measures, the structure and level of the data, the consistency and accuracy of the raters or scorers as well as the analysis techniques used, all play pivotal roles in monitoring systems (Scherman et al., 2017). When monitoring systems are used, the inferences derived should be valid and provide results that can be used to track progression and identify cut points. Results should inform teaching and learning for maximum benefit (Kanjee & Moloi, 2014; The South African Qualification Authority, 2005). The current thesis views monitoring of academic achievement as measurements designed to assess learning progress where the results are used for both benchmarking and the enhancement of teaching and learning within classrooms and schools.

1.2.4 Measurement, assessment and psychometrics

Terms such as measurement, psychometrics and assessment are closely related, having the same general meaning but with different nuances (Andrich, 2001). Used in diverse contexts, the terms could take on various aspects of their meanings. In the current thesis, measuring and assessment are treated as being approximately equivalent, both being the quantification of latent traits through the use of instruments such as tests and questionnaires. Psychometrics has traditionally been defined as the measurement of psychological qualities (Kaplan & Saccuzzo, 2010). Abilities such mathematics and language skills could be seen as cognitive constructs, and could therefore be defined as psychological constructs. Due to the broad nature of psychology, the field of psychometrics could thus be applied to many related disciplines such as education. The current study defines psychometrics as statistical models utilised to inform the design of social science instruments such as questionnaires, tests, assessments and checklists.

1.3 Structure of thesis

The remaining thesis chapters are introduced below with a description of each chapter, as well as an indication of the articles reported on in the three chapters (Chapters 5 - 7).

Chapter 2: The educational landscape and monitoring

Chapter 2 situates the meta-science study within the real world context by examining the educational landscape as well as assessment and monitoring in the South African context. The chapter also investigates and highlights the role of monitoring academic achievement through the utilisation of assessment instruments. The chapter includes sections on school types, what assessment in the South African context entails and the monitoring of education in a multi-cultural environment.

Chapter 3: Methodological and theoretical approaches of thesis

In the third chapter, the ontological point of departure is explained. The chief methodology, Rasch Measurement Theory (RMT), is explained in more detail by examining the principles underlying the method. The application of Rasch models is described via its statistics and interpretation. This chapter includes a section on the Rasch model, explaining its statistical structure for both the Dichotomous Model and the Partial Credit Model. The chapter draws together all the elements of the Rasch models in the conceptual framework, which not only underpins all three studies (articles), but was also the basis for the overarching project.

Chapter 4: The monitoring project's methodology

Chapter 4 describes the monitoring study whose results formed the basis for the analyses reported in the articles. While each article focuses on a different aspect of the monitoring project (different school subjects, year of participation, facet of project), this chapter describes the study as a whole, which ran from 2012 to 2014 and incorporated Grades 8 to 11 for all three years. Descriptions are given of the sample sizes per year and per school, how the assessments were designed and administered as well as how the results were analysed and utilised for the monitoring study as a whole.

Chapter 5: Multiple imputation for dichotomous MNAR items using a recursive structural equation model with Rasch measures as predictors (Article 1)

In Chapter 5, the first article reported on how to deal with missing data, more specifically Missing Not At Random (MNAR) data when combined with Missing Completely at Random Data (MCAR) for dichotomous test items. Common items, which linked the tests from one year to another, were missing for the Grade 8 Science test at one of the seven schools. The common items, or anchor items, were required for tracking learning and equating. A potential solution, Multiple Imputation (MI) was identified for use. However, MI has the assumption of

data being missing at random and in order to correctly impute the missing data, a model had to be built, which took into account the pattern of missingness and had strong predictors. IBM Amos was used to model the missingness with a recursive structural equation model (SEM), and, in addition, Rasch person measures were used as the predictors. SPSS was used for the final imputation as it offers the use of a logistic regression imputation, as the items were dichotomous. Diagnostic checks showed that the differences between the types of missing data (MNAR and MCAR) as well as performance differences between schools had been maintained. This is where the Rasch measures were very useful as they contained the pattern of performance, which could be used to predict the missing data.

Chapter 6: Evaluating anchor items and reframing assessment results through practical application of the Rasch measurement model (Article 2)

The second study, reported on in this chapter, examined the quality of anchor items for tracking learning progression. The Rasch Partial Credit Model and non-parametric statistics were used to evaluate the common items between the English Language Grades 8 and 9 tests. This led to identifying items that did not contribute to monitoring progression over the years. The items were refined, or in the case of two items, removed (see Appendix E). The Rasch model was further used to place the results on the same scale so that progression could be more accurately identified and reported.

Chapter 7: The use of Rasch competency bands for reporting criterion-referenced feedback and curriculum-standards attainment (Article 3)

The final study in Chapter 7 is an exemplar of how the Rasch Person Item Map method can be used to craft criterion-referenced feedback for all the stakeholders. The Grades 8 to 11 monitoring assessments for English Language, Mathematics and Natural Science monitoring assessments were analysed using the Rasch Partial Credit Model (N=1113). Cut-scores were identified on the item maps, and subject specialists evaluated the items in each band. The subject specialists created descriptions of knowledge and skills represented by each level. Reports were set-up so that a child, the teacher and parents could read a description of what skills had been gained in a subject area, as well as the next skill level to be attained. This study shows that the Rasch Person Item Map Method can be used to align assessments and curriculum standards and report learner results regarding criterion-referenced feedback.

Chapter 8: Discussion and conclusions

The last chapter broadly discusses the findings emerging from each of the studies, as well as the conclusions and recommendations which can be drawn from this thesis overall. Reflections on the methodology, research questions and conceptual framework are presented in Chapter 8. The chapter also discusses the limitations and recommendations of the study.

1.4 Conclusion: The article-based thesis as a story

This thesis is article based, but the articles do not stand alone. The articles are contextualised within the South African school milieu and are based on the same main monitoring study. The thesis is a story within a story, smaller stories (articles) in the overarching story of measurement and monitoring of scholastic achievement.

Figure 1.1 displays the structure of the thesis visually. Each article is a step in dealing with the data from the main monitoring study/project. Article 1 is concerned with processing the data, whereas Article 2 focuses on analysis of the data. The last article is concerned with how to disseminate the findings in an impactful and content-based manner. The three articles, based on the same study, share important aspects and deal with measurement challenges, applying the Rasch model to meet the measurement challenges, are data focused and fall into the meta-science category. This thesis as a whole presents the main study and its background methodology; it also discusses the context of independent high schools in the complex South African educational system, and finally the thesis draws together the overall findings from the studies and their implications as well as the conclusions and recommendations emerging overall.

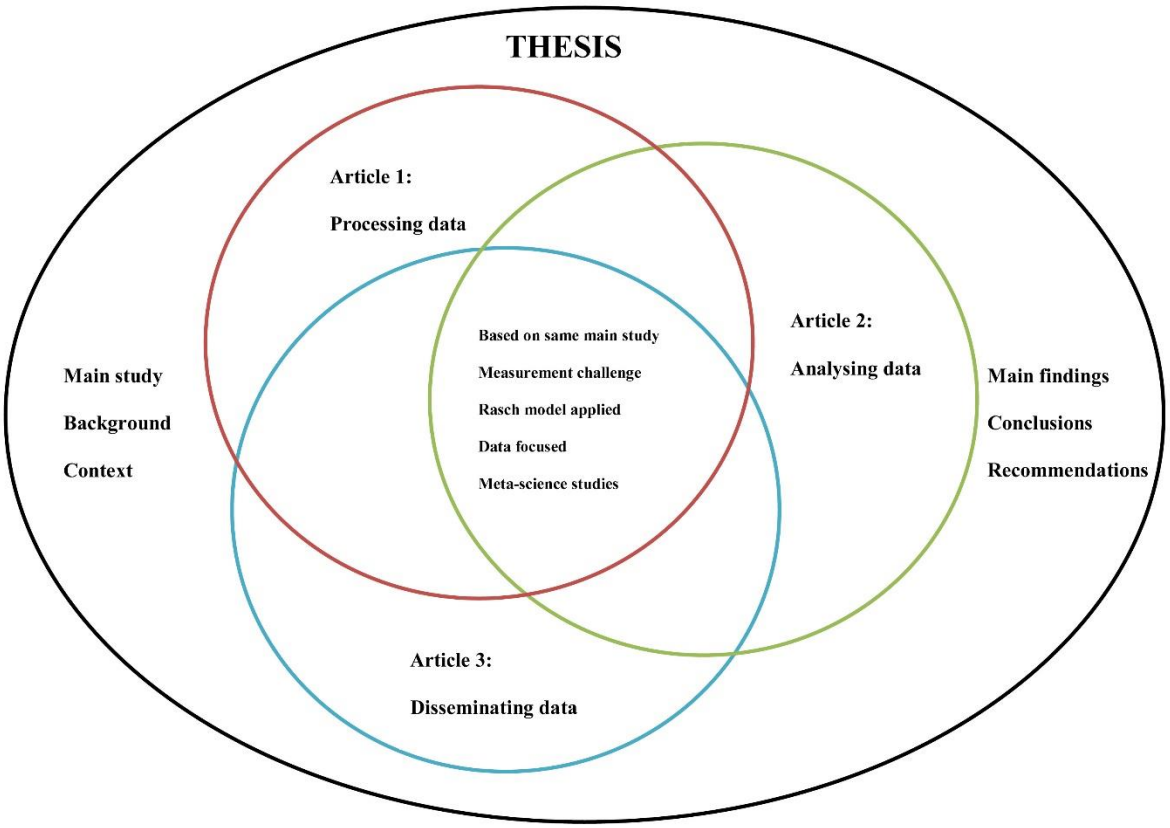

Figure 1.1 The article-based thesis presented visually

The next chapter contextualises the study within the South African educational landscape and explains how the main monitoring study/project and the monitoring of academic achievement fits into the thesis and links to the articles.

Chapter 2 - The Educational Landscape and Monitoring

The function of education is to teach one to think intensively and to think critically. Intelligence plus character - that is the goal of true education (King, 1947).

2.1 Introduction

The importance of education as the producer and enabler of future workers, stable economies and fostering human development is undeniable, making universal access to schooling and improved quality thereof global and national goals, as stipulated in the United Nations' Millennium Development Goals (Gyimah-Brempong 2011; Nworgu & Nworgu, 2013; Tikly & Barrett, 2013; Stijns, 2012). Developing nations face greater challenges in terms of access to education for all as well as quality of educational systems, especially those with children living in severe poverty (Tikly & Barrett, 2013; UNESCO, 2015). Being a developing country and subject to large political fluctuations, South Africa's education system faces immense challenges associated with recent and continuing changes.

The Research on Socio-Economic Policy report (RESEP) on the binding constraints in education emphasises the main reasons the educational system in South Africa maintains its current problems (van der Berg, Spaull, Wills, Gustafsson & Kotzé, 2016). The RESEP report identifies weak institutional functionality, undue union influence, weak teacher content knowledge and pedagogical skills and wasted learning time as the main constraints (van der Berg et al., 2016). The constraints lead to weak educational outcomes and affect academic achievement (van der Berg et al., 2016). The current chapter and thesis makes the argument that unless a system is monitored regularly and accurately, improvements or declines will not be tracked and, as such, addressing binding constraints will be hindered (UNESCO, 2015). Specifically, the significance of assessments and monitoring academic achievement is discussed as a key part of understanding educational development and tracking learning progression over time. The findings of the RESEP report give a broad indication of the challenges faced in South Africa to ensure the quality of our educational system. The quality of an educational system could be defined in many ways, including the well-being of the learners, the physical and pedagogical teaching and resources, the broader community and home environment as well as the structure of the educational system and the curriculum

(UNICEF, 2000; Tikly & Barrett, 2013). The current thesis is principally concerned with the quality of key subjects taught in high schools and how to monitor academic achievement.

2.2 Education in South Africa

The South African school system is governed in general by the Department of Basic Education (DBE). However, each of the nine provinces in South Africa administers its own education department, with the DBE playing an overall governing function (Davies & the Centre for Education Law and Education Policy, 2008). The system is comprised of the General Education and Training (GET) phase which incorporates Grades R-9, and the Further Education and Training (FET) which includes Grades 10-12 (DBE, 2017b). The sample for this study included Grades 8 to 11, which means it was conducted within both the GET and FET phases. The South African education system includes approximately 12 million learners in 30 500 schools (DBE, 2014), in both public (97%) and independent schools (3%). Both the public schools and the independent schools could be fee-paying or non-fee-paying (RSA, 1996).

2.2.1 Public versus independent schools in South Africa

In accordance with the South African Schools Act (SASA) of 1996 (No 84), two types of schools are recognised, namely public (ordinary) and independent schools (RSA, 1996). Public schools receive government funding, whereas independent schools source their own funding, whether this be from school fees or other sources. Independent schools may receive state subsidies, though such subsidies are not guaranteed. The right to establish independent schools is in accordance with the Constitution of South Africa (Section 29), which states that individuals have the right to establish independent educational institutions at their own expense (RSA, 1996). Independent educational institutions must be registered with the educational department, maintain standards comparable to public schools, conform to governmental conditions and may not discriminate on the basis of race or gender. All seven schools participating in the monitoring project were independent schools. The schools in the current study were located in the provinces of Gauteng (3 schools), Limpopo (2 schools), Kwa-Zulu Natal (1 school) and the Western Cape (2 schools). All seven schools were located in impoverished townships areas.

2.2.2 Fee paying schools versus non fee paying

School fees for both public and independent schools are based on a resolution reached with the governing body: parents must agree to pay school fees (RSA, 1996). If the majority of parents adopt the resolution to pay school fees, the governing body can pursue legal action when fees are not paid. More affluent schools source a larger portion of their funds from the community (parents), whereas schools in more impoverished areas should receive larger portions of government funding (Dass & Rinquest, 2017). Schools which are classified as 'non-fee' paying were established to give improvised learners access to education, which is in line with the South African pro-poor model of funding schools (Dass & Rinquest, 2017; Sayed & Motala, 2012). In addition, schools are classified according to quintiles, and schools in the lower quintiles from one to three do not pay school fees. The quintile system classifies schools according to a poverty index, and lower quintile schools are located in improvised areas and the schools have few resources available (Dass & Rinquest, 2017). Independent schools are not classified according to the quintile system; consequently, the schools in the main study in this thesis do not have a quintile allocation of funds. Out of the seven schools in the current study, six were non-fee paying. The seventh school correspond with the traditional model of private schools, where parents pay relatively large fees, but scholarships and funding is also available for a limited number of learners.

2.2.3 Curricula in South African schools

The South African school system uses a series of curricula documents known as the National Curriculum Statement Curriculum and Assessment Policy Statement or CAPS, see Chapter 1 for more details (DBE, 2012). The CAPS documents contain detailed layout of subject areas to be taught in a given year, term, month or even week (DBE, 2012). The independent schools who participated in the main study implemented their own curricula. However, their curricula documents were primarily based on CAPS with some appropriate contextual additions. The CAPS and coalition school documents were used in combination when designing the instruments for monitoring.

2.3 Assessment in the South African context

Assessment in the South African school context has two purposes: to support teaching and learning and to inform the learners, schools, guardians, education departments and society of the progress that learners are making in a given subject (Black, 1997; DBE, 2012; Kanjee &

Sayed, 2013). Formative assessment is designed to support teaching and learning, and could also be termed *assessment for learning* and *as learning* (Bennett, 2010, 2011). Summative assessment is used to inform stakeholders about learner progress, and can be classified as *assessment of learning* (Bennett, 2010, 2011; Sambell, McDowell & Montgomery, 2013). Both types of assessment have an important contribution to make, and can be reported in terms of criterion-referencing and norm-referencing (Kanjee & Sayed, 2013; Mays, Criticos, Gultig, Stielau & South African Institute for Distance Education, 2009). Criterion-referencing is more in line with the philosophy of Rasch theory, which is to define and report developmental pathways and focus on the individual (Long, 2015). Examples of summative assessment include not only tests and examinations but also projects, presentations, demonstrations, performances and practical demonstrations (DBE, 2012).

To illustrate assessment in the South African context, Table 2.1 depicts various types of assessment currently in use (Chappuis, 2009; Kanjee & Sayed, 2013; Long & de Kock, 2014; Palane, 2014; Roux, 2014). Table 2.1 shows that national assessments, such as the National Senior Certificate (NSC) at Grade 12 level, are used to set pass rates and promote learners as well as give access to tertiary education. Similarly, classroom assessments (school examinations which are summative) can also be used as formative assessments. Benchmark or district assessments, designed for formative goals such as designing interventions, also benchmark school, district and provincial performance (Roux, 2014). An example of a benchmark assessment is the Western Cape Systemic Assessments. In the case of international studies, such as the PIRLS, the results are used to monitor academic achievement and compare South African assessment results with other participating countries (Mullis, Martin, Foy & Drucker, 2012).

The assessments used in South African schools serve a multitude of stakeholders, including education departments such as the Department of Basic Education (DBE). Parents or guardians are also stakeholders, and the learners themselves attach assorted meanings to the various types of assessments (which influences motivation). Teachers in turn use the assessment results from national assessments, benchmark assessments and classroom assessments to inform their teaching and to address gaps in learner understanding (Kanjee & Sayed, 2013; Roux, 2014). Principals also pay attention to assessment results as this gives them indications of teacher effectiveness as well as school functioning when compared to other schools, districts and provinces (Reynolds, Livingston & Willson, 2010).

Table 2.1 Types of assessment and accountability

Type of Assessment	Purpose	Stakeholders	Example
National Assessment	Determine pass rate, inform curriculum; qualifications (summative)	Department of Basic Education (DBE), National Departments, Teachers, Learners, Parents, Citizens	Grade 12 National Senior Certificate (NSC)
Benchmark or District Assessment	Devise interventions (formative) School and curriculum effectiveness (summative)	DBE, District offices, National Departments, Teachers, Schools, Society	National: Western Cape Systemic Tests International: PIRLS, TIMSS
Classroom Assessment	Revise teaching practice, Feedback to stakeholders, promotion to next grade (summative)	Teachers, Parents, Learners, Schools, Education Departments	Report cards, Portfolios
	Diagnose possible barriers in the learning process	Teachers, Parents, Learners	Checklists, Observations, Reflections

Assessment in the South African school context is daunting considering the demands of the curriculum and the emphasis on the Grade 12 exit examination (Davids, 2017). Shortages of resources and time may result in 'teaching to the test', where the focus of teaching becomes testwiseness and preparation for examinations (Reeves & McAuliffe, 2012). Assessment should serve teaching and learning, and not vice versa as is the case with teaching to the test, although if a test is well designed it may help to focus good teaching (Davids, 2017). Focusing on exam content may increase achievement results, but will not necessarily increase knowledge and skills as intended by curricula, and as such could be classified as poor instructional practice (Bennett, 2010). An over-emphasis on summative assessment in the school environment may lead to instructional narrowing (Bennett & Gitomer, 2009).

Archer (2011) argues that the monitoring of academic achievement should be used to feed into learning and teaching in the school environment. She contends that the impact of monitoring can be enhanced by increasing data literacy and providing practical information that teachers and schools could and should use for action and decision-making (Archer, 2011). When the monitoring of achievement takes place with the goals of accountability and enhancement of teaching and learning, it serves as a powerful agent of change (Archer, 2011; Scherman, 2007). While an over-emphasis on assessment for the monitoring of academic achievement could have negative effects (teaching to the test), these can be negated by using assessment results to inform stakeholders, and this includes the learners themselves (Lamanauskas, 2012).

2.4 Academic achievement, assessment and monitoring

Globally, more emphasis is being placed on early childhood development, investing in schools and learners, supporting transitions beyond initial education, equality and equity of opportunities and lifelong learning (OECD, 2013). Assessment and monitoring of academic achievement is key to understanding how the goal of enhancing different aspects of learning is being achieved and of finding ways to address disparities (Aron et al., 2008; Fleisch, 2008). In the multi-lingual context of South Africa, monitoring academic achievement in all the eleven official languages is crucial to understanding how well languages are being supported and implemented (Makgamatha, Heugh, Prinsloo & Winnaar, 2013; Moodley, 2014).

Traditionally, classroom assessments such as class tests, school examinations and the national matriculation examinations have been utilised to inform teaching and promote learners to the next levels of education, including tertiary education (Kanjee & Sayed, 2013). However, during informal (assessment for learning) and formal (assessment of learning) assessment, the teacher has the responsibility of clarifying for learners what is expected from them (Roux, 2014). Various types of assessments inform teachers and identify learners requiring additional assistance in mastering a specific topic and/or informing the school to what degree learners are on par with the aims of the national curriculum (Bansilal, 2011; Kanjee & Sayed, 2013). Assessments serve as the method of measurement, the manner in which information is collected, analysed and interpreted in order to track each learner's progress throughout the academic year (Bansilal, 2011). The various types of assessments support and influence distinct aspects of classroom learning, grade-level promotion, end of school promotions, benchmarking, policies and broader educational goals (Kanjee & Sayed, 2013).

The aim of the study reported in this thesis was to set up a system that monitored academic achievement. Monitoring the academic achievement of the schools was designed to serve both as a comparative tool within the system of independent schools, and as feedback for *assessment for learning*. Assessment for learning is aimed at enabling teachers and learners to understand and achieve goals, to provide constructive feedback as well as to encourage learners to take responsibility of their own learning (Bennett, 2010).

Hattie (2009) conducted a meta-analysis is of more than 52637 studies to identify which factors are the best predictors of academic achievement. Hattie (2009) used effect size as the key indicator, with an effect size of 1 indicating that a particular approach to teaching or technique advanced the learning of the pupils in the study by one standard deviation above the mean. Interestingly, such strong effect sizes were only found in less than 75 of the 52637 studies in Hattie's meta-analysis, the variable most likely to enhance learner achievement was feedback. The older the learners were, the more cognitive feedback mattered (Hattie, 2009). There is also a reinforcement component of feedback which helps to shape behaviour, but cognitive feedback should have explicit information, which helps the learner correct errors and refine the performance. Assessment is one of the pivotal ways in which teachers can give constructive feedback in terms of learner progress, as well as areas that require attention and further study. Good quality assessments and feedback based on the results can play a crucial role in the academic development of the learner (Kanyee & Sayed, 2013). In summary, the monitoring of academic achievement informs stakeholders of the progress being made in learning, but can also be used as feedback within the system as was done with the study reported in this thesis.

2.5 Conclusions

Measuring educational and achievement outcomes leads to understanding, interventions and change (Lamanauskas, 2012). Without assessment and monitoring, improvement of the South African educational landscape becomes less likely and less identifiable. Assessment and the monitoring of academic achievement is pivotal to countering the binding constraints faced in the educational system. Strengthening the role and application of assessments, both in the classroom and for broader monitoring of achievement, could enhance the education system. A positive impact on learning for school children, teaching and learning for teachers and principals is a potential outcome of improved assessment. High quality assessment for feeding

into the development of curricula and policy should also be considered. Feedback, through *assessment of* and *assessment for learning* may reinforce learning pathways and development. The monitoring of academic achievement can play the dual role of accountability and the development of a feedback system. Monitoring the changes taking place is key for improving the educational landscape.

The main study/project, described in Chapters 1 and 4, led to the development of sub-projects based on questions which arose during the research. The outcome of the sub-projects led to the publication or acceptance for publication of the articles and were transformed into chapters (5, 6 & 7). The chief methodology employed in the sub-projects, a psychometric theory known as Rasch modelling is discussed in the next chapter. Psychometric theory can play an important role in monitoring academic achievement in the South African educational system. Applying the Rasch Partial Credit and Dichotomous Models presents the opportunity to refine and elevate the quality of monitoring assessments. In any monitoring system, high quality instruments are essential to provide precise feedback and indications of improvements or areas where challenges should be addressed. Connected to the monitoring of the South African education system is the need to improve monitoring assessments. Chapter 3 explores how psychometric theory can be applied to assessments and social science instruments generally.

Chapter 3 - Methodological and Theoretical Approaches

> *Experience is tangible. But it needs ideas to become useful. Raw experience is chaotic. Guidelines are necessary to organize perceptions of reality, to make them recognizable, and to make some sense of them* (Wright & Stone, 2003, p. 912).

3.1 Introduction: Ontological point of departure

The studies described in this thesis are based on the ontology of scientific realism, a view that the world is knowable and that science is the best method for accessing reality (Putnam, 1962). Scientific realism fits well with the statistical models that were used to solve the practical measurement problems: The Rasch family of models. The Rasch models extract the principles of measurement from the natural sciences and hold measurement in the social sciences to the same standards (Bond & Fox, 2015; Boone, Staver & Yale, 2014; Long, 2011). If psychology can be defined as the science of mental and behavioural processes, then the measurement of those processes should be scientific and conform to the principles of measurement (Holmes, 2005). This chapter describes those principles as well as the Rasch models and their interpretation. The articles (reported in Chapters 5 to 7) provide prototypes of practical applications and recommendations for making measurement scientifically and statistically valid in the social sciences.

3.2 The principles of measurement

By examining the principles of measurement, what it means to measure is operationalised. Measures should be equally ordered, additive and meaningful approximations of the construct under consideration (Engelhard, 2013; Massof, 2011; Wilson, 2005). Easy items should be answered correctly by those who correctly answered the more difficult items. Likewise, difficult items would not be answered correctly by those who failed the easier items. Known as the Guttman pattern, the ordering of items and persons in this perfectly structured way is an ideal that is rarely, if ever, found. It is an important structure in Rasch theorising (Cavanagh & Waugh, 2011; Engelhard, 2013). Rasch models are based on the probability of success on an item and assume that the Guttman pattern will not appear and, if it did, it would be an indication of extreme overfit (Linacre, 2013; Wright, 1977). Science views anything that can be observed,

either directly or indirectly, as measurable (Hubbard, 2010). The measurable observations are a crucial way of distinguishing pseudoscience from real science, finding obvious consequences for the construct, phenomenon or claim (Tal, 2017). That which cannot be measured has no claim to scientific reality. If it is real, it can be observed and detected and done so in quantifiable amounts (Hubbard, 2010). Measuring in the social sciences is more challenging as constructs are mostly latent, but it is still possible to do so by applying the principles of measurement described in this section.

3.2.1 Invariance, reliability & validity

Applying a yard stick to different objects should yield the same ordering and intervals, with the same scale being used again and again (Moutinho & Hutcheson, 2011). The ordering also holds for the social sciences: items or questions should measure understanding, memory, beliefs or attitudes in the same ordered way it measured that of another person. The Rasch Model seeks to make invariance more attainable by ordering items and persons on one scale. If the instrument is valid and reliable for a population, it should yield the same ordering of items when another group from the population answers the questions (Andrich, 2011; Golino & Gomes, 2016; Linacre, 2016). However, if groups are heterogeneous in terms of languages, cultures and experiences or any other factors, invariance may be at risk and tests become unfair (ETS, 2014). When a construct as measured by an instrument is invariant in one population, more effort may be required to adapt it to another group, then applying the measurement model to ensure the construct is being measured in the same way becomes all the more paramount (de Bruin, 2011). Invariance means that item order remains constant (Smith & Suh, 2003). A test may be more difficult for Group B than for Group A, but the item order should be the same for both groups (Cavanagh & Waugh, 2011; Randall & Engelhard, 2010).

Invariance is closely linked to reliability and validity of inferences and relates to Thorndike's requirement that items be free from individual opinion (Linacre, 2000; Thorndike, 1904). Reliability is the consistency of the measurement; when repeatedly measuring, the results should be almost identical, barring some small error of measurement (Moutinho & Hutcheson, 2011). Validity is the truthfulness of the instrument for a group, and reveals how appropriate the inferences are for the given population and construct(s) (Moutinho & Hutcheson, 2011). Invariance reflects both these concepts. An instrument should measure with consistency but also yield the same results or concatenation of measures regardless of whom or what is

measured. Invariance is closely aligned to the assumption of local independence, discussed later in this chapter (Andrich, 2001; Curtain, 2007; Smith & Suh, 2003).

3.2.2 Range of scale (targeting)

When the construct assessed is reflected by the measures (items), the measures should also be sensitive to a range within the construct. Like a ruler that measures a certain length, for example, 0 to 30 centimetres, the social construct should be measured by the items with an appropriate and helpful range (Engelhard, 2013). In education, this means having a range of items that measure from least able to most able within a cohort. In psychology, it means having items that measure those less likely to endorse statements to those most likely to do so. When an instrument does not measure those at the lowest or highest end of the scale, floor and ceiling effects emerge, and the range of the measurement scale may not be broad enough to measure these individuals (Wilson, 2005). The sensitivity of a measurement is analogous to using a 30cm ruler to measure a rugby field or the width of a hair; in both cases, the sensitivity of the instrument is not appropriate for the object being measured.

3.2.3 Dimensionality

> *Strictly unidimensional data do not exist in the empirical world. Even straight lines have widths as soon as we draw them. So a central question is: How close to unidimensional is good enough for our purposes?* Linacre, 2008, p.1

Unidimensionality is an assumption of the Rasch Model, but constructs can include composite variables and have more than one dimension or aspect (McCreary, Conrad, Conrad, Scott, Funk & Dennis, 2013; Linacre, 2016; Massof, 2011). The degree of unidimensional measurement depends on the precision of the measures to capture a global image or to zoom in on aspects of the construct (Andrich, 2011; Smith, 2002). An instrument that measures time management may include component constructs such planning, motivation, prioritising and communication skills. Including sub-constructs or component variables in a way that builds a clearer picture of the construct under investigation would lead to a unidimensional construct being measured, for example, that of time management. Messick (1989, 1996) saw construct under-representation as a serious threat to validity. Conversely, if there is too much focus on a component, such as motivation, it may lead to construct-irrelevant variance, and the component may become a competing construct under consideration (ETS, 2014; Messick, 1996; Randall & Engelhard,

2010). While it seems unlikely that a researcher would design an instrument and include irrelevant questions or items, this could happen in subtle ways, for example, if getting the answer correct requires not ability but test-wiseness (Baghaei, 2008).

Unidimensionality is always in degrees, and the extent to which the main construct is represented depends on the focus of the items (Andrich, 2011; Smith, 2002). Too broad an emphasis on related components and unidimensionality is threatened, while a too narrow focus could result in construct under-representation. Dimensionality can be assessed with factor analysis, such as Principal Component Analysis (PCA) (Randall & Engelhard, 2010). Rasch factor analysis is conducted to test whether any sub-constructs compromise the unidimensionality principle (Linacre, 2016). The construct under investigation should be the main explanation for the observed variance.

When various constructs are measured by one instrument and constructs are more independent than dependent from one another, each construct should be analysed on its own using Rasch software. Rasch statistics assist in the identification of construct-irrelevant variance (fit statistics) and construct under-representation (namely the spread of persons to items) (Baghaei, 2008). A lack of invariance, multidimensionality based on groups or populations, can be identified through differential item functioning (DIF) (Bond, 2003). Measurement requires the researcher to think deeply about the construct under investigation, to ask questions such as "What does it mean to have more of this construct? What does it mean to have less?" and "In what detail do I want to measure this construct? Broadly? In greater detail or focus on an aspect of the construct?" To measure is to understand what is being measured and to what degree (Granger, 2008). To measure in the social sciences is to access the construct indirectly, to measure its influence rather than the thing itself (Andrich, 2011; Wright & Linacre, 1989).

3.2.4 Operationalisation of the construct

What does it mean to have more of or less of the construct? To operationalise a construct is to define it in practical ways that make measurement possible (Glass & Stanley, 1970). Rasch statistics also reveal the coherence and coverage of the operationalisation of a construct (Loubserae et al., 2015). Rasch statistics can be used as a way to assess the construct validity of an instrument, with implications for how well the construct was operationalised (Bond & Fox, 2015). Operationalising constructs is a requirement for measurement in the social sciences

as the constructs are often latent traits that cannot be directly observed (Julie, Holtman & Mbekwa, 2011; Peterson, Gischlar & Peterson, 2017; Glass & Stanley, 1970). The definitions of constructs are continuously evolving. Constructs, whose definitions are continuously evolving, should be defined within a context and at a particular point of development (Gómez, Arias, Verdugo, Tassé & Brown, 2015). The operationalisation may also differ for various population groups. Hubbard (2010) recommends asking those who want to measure something intangible to try a thought experiment, to imagine that they have to explain to an alien race what has to measured and why it has to be measured. Lastly, it may be pertinent for social scientists to ask themselves the question: "Do social constructs exist or are we inventing them?" (Bond & Fox, 2015). It may be that constructs exist to the degree to which we can define them. We invent constructs in the same way that we define particular aspects of cognition and behaviour.

3.2.5 Error of measurement and fit

Error when measuring is a natural and expected phenomenon; no measurement is without error (Hubbard, 2010). In Classical Test Theory (CTT), all items were treated as having the same error (Cappelleri, Lundy & Hays, 2014). However, all items are not equal in difficulty; the easiest and most difficult of items are less accurate and prone to more error. Rasch calculates each item's error of measurement independently of other items, the same for persons (Cavanagh & Waugh, 2011). The Rasch reliability estimates for persons and items are calculated on an average of error. Use of the logistic distribution to examine item fit is an advantage of the Rasch models, providing comparable fit indices between items (Törmäkangas, 2011).

3.2.6 Local independence of items

Independence is a key assumption of quantitative research, whether it is the independence of groups, persons or items, the idea remains that they should not influence one another. If persons from the control group influence those in the experimental group, bias and confounding variables are introduced. If persons within either of the groups influence each, the same problem is presented. Likewise, if individuals are answering a questionnaire or test paper and influence each other's answers, the independence of the data is compromised (Field, 2013). The independence of items falls into the same category; the answers on one question should not influence the answers on another question. Each item should independently add to the

conjoint measurement (Boone et al., 2014; Smith & Suh, 2003). Of course, in some cases, this is more difficult to achieve. The answers to questions about a reading passage may influence one another, as the understanding of a passage increases with the progressive answering of the items. In such cases, the items related to the passage could be treated as a "super-item" or testlet, all of the questions forming one large item and can be analysed as such in Rasch software.

3.2.7 Item bias and discrimination

Discrimination is a desirable quality in an instrument; the measure should accurately separate those with less from those with more. Having more or less should be due to a difference on the construct and not due to confusion or interference caused by the structure or phrasing of the item (Wang, 2008). Item bias is a threat to the invariance of the instrument, a distortion of the question which means it functions differently for different groups due to factors other than performance on the construct (Bond & Fox, 2015; Wang, 2008). Rasch provides statistical methods for identifying such as bias, its presence indicating an invalidation of identified items for group comparison. When a confounding variable is responsible for performance on an item, for example, mistranslation caused the bias, the item would have to be removed or restructured (Massof, 2011; Randall & Engelhard, 2010). Conclusions related to individual ability should not be based on biased items.

3.2.8 Categories and scales for ordering

Dichotomous items are the original and most simplistic form of the Rasch models, the person and item parameter being constructed from right or wrong answers, yes or no responses (Hendriks et al., 2012). When scales contain more categories such as 0, 1 and 2, ordering of categories is required (Curtain, 2007). Each category should, in turn, be the next most likely to reach as ability increases. Category 1 should not be harder to attain than Category 2, and there should be gradual movement from one category to the next (Bond & Fox, 2015; Boone et al., 2014). Categories that do not increase gradually and do not discriminate between those of different ability should be investigated (Hendriks et al., 2012). When an investigation of the thresholds and their order is required and items with disordered categories are found, the collapsing of disordered categories should be considered. The question becomes not only "are items ordered and on equal intervals?" but also, "are scores ordered as expected and on equal intervals?"

3.2.9 Models, theories and measuring

When the world changes, creating new demands, this in turn sparks similar responses in various locations and disciplines. As the need for scientific testing has increased, via world wars and greater emphasis on education, so too have models been developed with which to assess the accuracy of assessments and statistical models with which to analyse test functioning. Classical Test Theory (CTT), also known as True Score Theory (TST) or Traditional Test Theory was the most basic of these responses (Cappelleri et al., 2014; Peterson et al., 2017). The assumption of CTT is that a total score accurately represents whatever has been tested plus some error (DeVellis, 2006). However, the limitations of CTT soon became evident, such as the inability of this model to separate items from persons, and as a result, more sophisticated models were needed. In the United States, Fredrick Lord devised Item Response Theory (IRT) and in Denmark Georg Rasch worked on his models (Cappelleri et al., 2014; Lord, 1953; Hambleton et al., 1991).

IRT has similar statistical equations to Rasch models, such as the mathematical modelling of a response based on ability, person ability and item difficulty, invariance and unidimensionality. Rasch models and theory differs from IRT in the key area of how measurement is viewed (Engelhard, 2013). Rasch theory sees measurement principles as the ideal, to which data and real world measurement should conform (Long, 2011). IRT models are not measurement models, but statistical models wherein the model must fit the data. In contrast, Rasch models are measurement models and the data must fit the model (Engelhard, 2013). Table 3.1 shows the theoretical departure point of each of these approaches to psychometrics (Cappelleri et al., 2014; Hambleton, Swaminathan & Rogers, 1991; Lord, 1953; Petrillo, Cano, McLeod& Coon, 2015; Reise & Henson, 2003).

Table 3.1 Comparison of psychometric theories

Psychometric theory	Theoretical point of departure
Classical Test Theory (CTT)	The true score is a function of observed data and error; neither is modelled as they are assumed to be normally distributed and descriptive statistics are used.
Item Response Theory (IRT)	The true score is defined as a latent trait, and the model must fit the data.
Rasch Measurement Theory (RMT)	The true score is a function of person ability and item difficulty, and the data must fit the model

3.2.10 Statistical and construct validity through the creation of an interval scale

Application of the Rasch Model strengthens statistical validity. Statistical tests were developed for normally distributed interval or ratio data (Iramaneerat, Smith & Smith, 2008). Questionnaire and achievement data are not on an interval or ratio level, as items are not necessarily ordered from least to most difficult, nor is the distance between the items or rating scales of equal proportion (Cavanagh & Waugh, 2011; Engelhard, 2013).

Rasch creates the required interval scale by transforming the odds to logits and aligning persons with items (Linacre, 2016). Construct validity is in evidence when an instrument meets the requirements of the Rasch model. Construct validity includes item and person fit, dimensionality, targeting and lack of bias. Interval scales offers possibilities to the researcher, such as the opportunity to use parametric statistical tests to analyse data (Iramaneerat et al., 2008). Figure 3.1 demonstrates the levels of measurement as defined by Stevens (1946). The figure shows where Rasch modelling elevates the scale from interval to ordinal, from categorical to numerical data, from weak to strong data (Glass & Stanley, 1970).

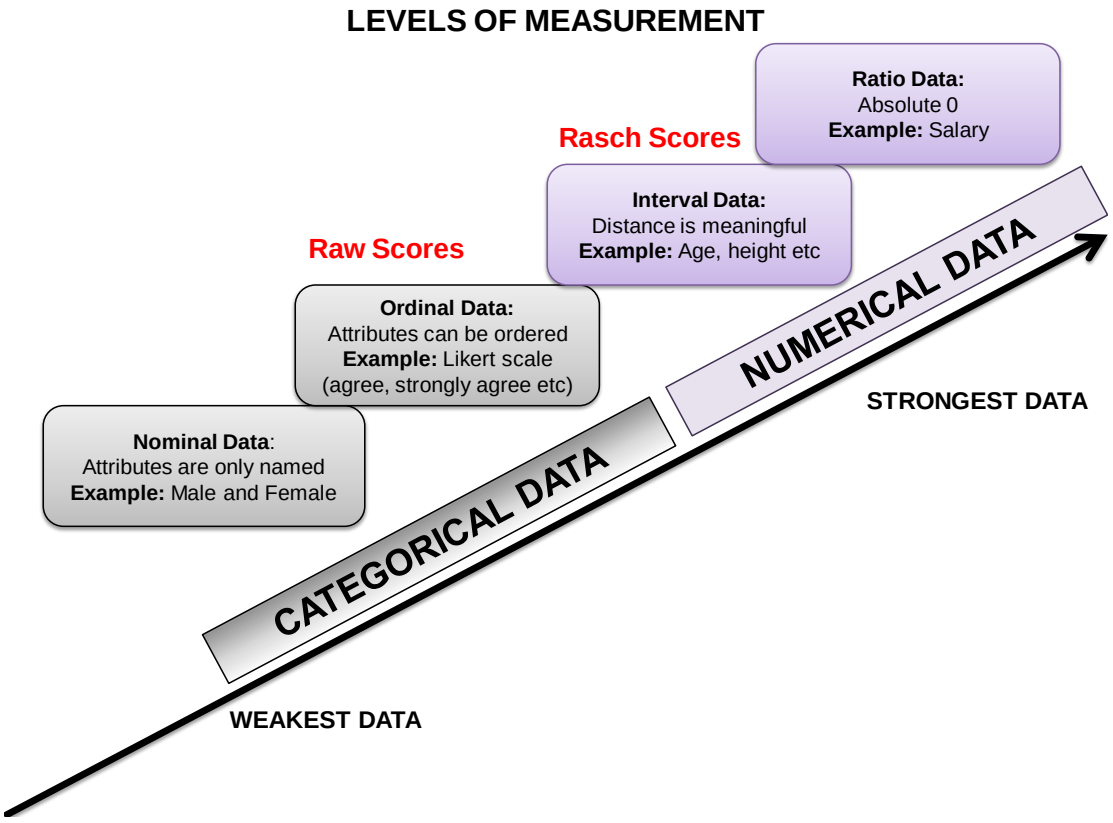

Figure 3.1 The levels of measurement as defined by Stevens (1946)

3.3 The Rasch model

Rasch Measurement Theory (RMT) was first devised by Danish Mathematician Georg Rasch in the 1950s (Bond & Fox, 2015; Cavanagh & Waugh, 2011). During the 1960s, a measurement revolution began as George Rasch, with Ben Wright, promoted Rasch Analysis, and Fredrick Lord and Ronald Hamilton promoted Item Response Theory (Linacre, 2005; Lord, 1953; Hambleton et al., 1991). RMT today is comprised of a family of mathematical models and techniques; however, Georg Rasch originally designed a model for dichotomous test data, also known as the Simple Logistic Model (Cavanagh & Waugh, 2011). Rasch models map persons and items on a linear line from less able or difficult, to more able or difficult and then persons and items are aligned. The central proposition for the dichotomous model is that the response of a person to a binary item is a function of both item difficulty and person ability. The probability of a person achieving success is entirely determined by the difference between the difficulty of the item and the student's ability. Item difficulty is calibrated with a mean of zero. From the mean, the relative difficulty of items is calibrated. This is judged by the number of items answered correctly over the number of items answered incorrectly, i.e. the odds. To

create an interval scale, the log-odds of person ability levels and item difficulties are calculated and used for their communal scale. By calibrating item difficulty and person proficiency, through individual person and item interaction, persons and items are aligned on the same scale. The process involves a number of iterations. Where items do not conform to the model and persons do not conform, misfit is noted. Other RMT models include the Rating Scale Model, the Partial Credit Model, the Facets Model and the Rasch Pair-Wise Comparison Model amongst others (Bond & Fox, 2015).

Measurement always has two aspects, the construct that is being measured and the instrument with which the measurement is done (Iramaneerat et al., 2008). It is measurement in the classical sense that makes quatitative comparisons possible (Andrich, 2011). In addition, it should be noted that while ordinal measurement tells us something, what is more, or less, it does so without the desired property of equal intervals, knowing how much more or less something is (Hubbard, 2010; Glass& Stanley, 1970). It is here that Rasch Theory makes a special contribution by placing persons and items on an equally ordered interval scale (McCreary et al., 2013).

RMT is primarily used to calibrate instruments in the social sciences, by calculating item to person fit so that non-fitting items and persons can be identified and instruments can be refined. The logit scale calibrated by RMT also provides an interval scale so that a summative score derived from an instrument is more precise and gives meaning to distances between persons and items.

Statistical models primarily try to describe data and relationships therein, whereas the Rasch Model is prescriptive and the data must fit the model (Acton, 2003). RMT is a measurement model, and therefore the data should fit the model as is expected for successful measurement (RMT prescribes the criterion for good measurement). It is proposed that using RMT improves the quality and usefulness of instruments and that even though the applications of RMT are extensive they are still being explored and discovered.

3.3.1 The Rasch Dichotomous Model

The dichotomous Rasch model calculates success-to-failure odds for people answering the test or questionnaire, as well as for the items. The odds are then converted to the natural logarithm

of the odds (logits) (Rasch, 1980). The logit scale for items is set to a mean of 0 and a standard deviation of 1, using the 50:50 odds (Wu & Adams, 2007). The 50:50 odds ratio is the point at which a person has an equal probibility of correctly or incorrectly answering a question. The Rasch dichotomous model has only one parameter, that of difficulty (Andrich, 2004; Wu, Tam & Jen, 2016). From a Rasch perspective, the information derived from the item difficulty and the person ability provides a sufficient statistic (Wright, 1989; Wright & Linacre, 1987). The Rasch Dichotomous Model is based on a formula that states the *probability of an event taking place* (getting an item correct, endorsing a statement), is the *log of the person ability* (number of items correctly answered by person), minus *the log of item difficulty* (items correctly answered divided by those who incorrectly answered) (Linacre, 2005). The Rasch Dichotomous Model was applied in the first article (Chapter 5) presented in this thesis.

3.3.2 The Rasch Partial Credit Model

The model that was most frequently used in the articles is the Partial Credit Model. This model allows each item to have a different number of responses so that tests which have items with varying categories can be assessed by the Rasch Model (McCreary et al., 2013; Shaw, 1991; Wright & Masters, 1982). The Partial Credit Model is appropriate for cognitive and educational tests which may include multiple choice items which are scored dichotomously, as well as items on scales of 0 to 1, 0 to 2 and so forth. Some items included in the assessments used for the current studies had items with as many as six categories (0, 1, 2, 3, 4, and 5). The combination of items with a different number of responses allows the research to assess a wider range of skills within sub-dimensions of the constructs. The data was analysed with the use of Winsteps for the grouped response structure. The model is shown below (Linacre, 2016b, p.37):

Logit of (Person probability of getting item correct in a category / Person ability)
= Person ability – Item difficulty at the intersection of equally probable highest and lowest categories – F, the calibration measure of the relative category.

Which can be expressed as:

$$\text{Log}_e\,(P_{nij}/P_{\,ni\,(j-1)}) = P_n - D_{ig} - F_{gj}$$

The Winsteps programme groups items with the same scale, so that an item grouping level is created and items with the same scale are analysed together (Linacre, 2016a).

3.4 Measurement in a South African context

From an African perspective, it may be that too many Western tools are applied without adaptation to the context, and operationalising constructs for African languages and cultures is an urgent measurement challenge (Schutte, Wissing, Ellis, Jose & Vella-Brodrick, 2016). Psychology's responsibility to decolonise is becoming a pressing matter in South Africa's developing context, in all areas of application (Pillay, 2016). To adequately devise measures for the African context, two elements are needed: measures should be developed within the linguistic and cultural context for which it is intended, and the development should be done by applying sophisticated psychometric principles as presented in this chapter.

The necessity of applying scientific principles to measures, whether they are educational, psychological or medical in nature is the same in the South African context as found internationally but is more challenging (Antoninis, Delprato & Benavot, 2016; Bolarinwa, 2015; Dampier, 2014). In a developing context, there may be less awareness of advancements and applications in psychometric theory (Dampier, 2014). Intellectual capital in the form of individuals or organisations with the skills and knowledge to apply sophisticated models is less prominent and fewer in number. The combination of lower demand (due to a lack of awareness) and fewer resources (in the form of persons and institutions with this knowledge) leads to a lower application of the Rasch Model in social measurements. Failing to apply measurement models is to the disadvantage of individuals and society. One example is the National Senior Certificate (NSC), the exit examination written by Grade 12 learners in South Africa. Even though hundreds of thousands of learners write these examinations yearly, the examinations are not linked by anchor or common items from one year to the next, items are not piloted and item statistics are not used to analyse items (DBE, 2015). While qualitative benchmarking and equivalence setting processes are used to compare the assessments to national and international qualifications and tests (Umalusi, 2010), this does not necessarily yield the precision one would expect from such high stakes testing.

Assessment, high-stakes or otherwise, plays an essential role in the South African educational landscape (Dampier, 2014; Davids, 2017; Howie, 2012). When taking into account the large

amount of resources allocated to international, national and provincial assessments and testing, the need to understand and apply the underlying principles of measurement to test design and refinement becomes even more vital and urgent (Bos, Goy, Howie, Kupari & Wendt, 2011; Dampier, 2014). In the developing context, this means teaching assessment and measurement theory explicitly in disciplines where social science instruments are used, such as education, psychology, medical sciences and the humanities in general. Those who design, apply and refine social science instruments such as tests, questionnaires and other assessments in the African context should do so after being equipped to apply the same scientific principles of measurement that are used in the natural sciences (Bos et al., 2011).

3.6 Interpretation of Rasch statistics

Table 3.2 highlights how to interpret Rasch statistics as derived from the Winsteps programme. When analysing an instrument's functioning, the researcher should have the responses for each item captured in a database. After proper cleaning of the data, the data can be imported into Winsteps from either Excel or SPSS (see Bond & Fox, 2015; Linacre 2016). Values used to indicate missing information should be in the control file. Winsteps and other similar software provide large amounts of statistical information about the instrument's function as a whole, as well as individual item functioning.

Firstly, the summary statistics should be investigated, most notably the reliability and separation indexes. Next, examine the item and person fit statistics, as this reveals whether each item and person contributes to the measurement model as a whole. A rule of thumb is that outfit is examined first then infit.

Table 3.2 Rasch Winsteps statistics and their interpretation

Concept	Statistic	Interpretation
Data to model fit statistics (Global fit statistics)	Chi-square	The significant result ($p<0.05$) means the data do not fit the model. Large data sets can result in significance. Not as important as item fit.
Person and item logit scale	Item measures and person measures	A logit scale, generally ranging from -5 to +5. The mean is set at 0 with a Standard Deviation of 1. A logit scale may be difficult for people to interpret, consider rescaling the data to 0 - 100.
Item and Person data fit to model (fit statistics)	Infit Mean Square (MNSQ) – inliers Outfit Mean Square (MNSQ) – outliers Z Standardised ZSTD infit, ZSTD outfit,	MNSQ: 0.5 to 1.5 ideal range <0.5 useful but duplicative 1.5 to 2.0 useful but noisy > 2.0 unexpected responses could be overpowering ZSTD: Ranges from -2 to 2. Values outside the range considered suspicious. Consider MNSQ first, look only at outfit ZSTD if MNSQ indicates problem
Reliability	Person and item separation indexes. Winsteps gives both an index and a reliability estimate (similar to Cronbach alpha)	Low person separation, the index is < 2 & person reliability < 0.8. Low item separation the index < 3 = can separate into 3 ability categories, item reliability < 0.9. Interpret reliability estimates same as Cronbach. More items will increase Cronbach's alpha, having only a few items will decrease it. High item reliability indicates there were enough persons for the items, not test quality.
Targeting	Look at the Wright -map for more information	Look for an even spread of items and persons which align. Is the mean of the items far from the mean of the persons? Also look at outliers on the map. Well targeted tests have item difficulty close to person ability
Dimensionality	Eigen-values and contrasts	Eigenvalues greater than two should be investigated. Two items that could be another dimension. More items are likely to form more clusters. Look at items that may form another cluster, do they have something in common?
Differential item functioning	DIF contrast	DIF Contrast has to be greater than 0.5 to be noticeable with a probability greater than 0.05. If DIF is significant, this indicates that item functions differently for groups.

Table 3.2 Rasch Winsteps statistics and their interpretation

Concept	Statistic	Interpretation
Category functioning	Rasch-Andrich threshold	Rule of thumb is at least ten observations per category to detect DIF properly
Discrimination	In Rasch, this is not a parameter but is indicated by statistics Item characteristic curve (ICC)	Does your test discriminate the sample into enough levels of ability/endorsement for your use? Cronbach's alpha = 0.9 then 3 or 4 0.8 = 2 or 3 levels. 0.5 = 1 or 2 levels. ICC graph: Items are more discriminating where steeper& discriminates less where flatter
Local dependence	Pearson correlation coefficient, *r*. See Table 23.99 in Winsteps	Items should be independent of one another; one item should not lead to an answer on another. When items are linked to a reading passage, consider analysing data as a testlet (treating items as one super-item).
Distracter Analysis	PTMA, the point correlation& ability mean (average measure of persons who responded to category)	The correct option should have the highest PTMA correlation and average measure. The least correct option should have a negative PTMA correlation and the lowest average measure
Directionality of scale	Point-biserial correlation	Negative values indicate that the item's direction is contrary to that of the latent trait. Item should be reverse scored if it is a questionnaire item, and may need to be rephrased or relooked if it is a test item

Outfit statistics give an indication of outliers, items that may be too difficult or too easy. At the extreme ends of the scale, items provide less information about the underlying construct and may not add to the measures but could distort them (see Linacre, 2016b). Infit is more about the overall pattern, whether persons and items conform to the expected model of higher ability means answering more difficult items correctly and lower ability makes this less likely. Infit statistics are less sensitive to outlier effects (Linacre, 2016b). One can examine the global fit statistics, but this is only likely to be significant if the sample size is large. Also important to examine is the directionality of the scale, indicated by the point-biserial correlations.

3.5 Conceptual framework

The conceptual framework applied in this thesis is the theory of Rasch Measurement and is demonstrated in Figure 3.2. Figure 3.2 begins with the most pivotal step in designing an instrument: operationalisation of the construct (A). After the construct has been defined and delineated, frameworks and items should be designed by individuals knowledgeable in the subject area (B). Items should be piloted (C) with data being captured on item level. The refinement should be based on the statistics, which are interpreted by subject specialists (E). When a first "final" version is available (F), it should be administered according to the most appropriate methodology; for example, in an experiment, there would be pre- and post-test administration (dependent on the purpose for which the instrument was designed).

Refinement of an instrument is never truly complete, over time constructs change, item drift may occur and regular updates to the instrument are required, therefore E and F are ongoing processes. Rasch models can also be useful during the processing of the data (G), as anchor items can be calibrated or fixed to established difficulty levels (if for example, the item came from an item bank). Rasch statistics will also indicate possible areas for data cleaning, such as out of range values (RUMM is especially useful for this). During the analysis of the results (H), the Rasch model can be used to produce an equal interval scale, standardised scores and could reframe results for pre-test post-test data. Depending on the type of instrument and its intended purpose, the Rasch model can also be used during reporting to provide competency bands or criterion-referenced feedback (I). That the data should fit the specified model. The model of measurement used in Rasch theory defines measurement as being directional and appropriately unidimensional. Furthermore, the data should follow a logical pattern in that more item difficulty and more person ability should be aligned (the Guttman pattern discussed earlier). The entire process is supported by the underlying theory and philosophy of Rasch models (A0).

When applying the Rasch Models to instrument data and combining the statistical outputs with the qualitative insights of subject specialists, instruments can be developed and refined to yield more reliable and valid inferences from results (Petrillo et al., 2015). The thesis expands this model by demonstrating how the model can also be applied to the processing of the data, the analysis of the results and the reporting of the results as demonstrated in the conceptual framework (Figure 3.2). The Rasch models provide a powerful assessment of item and test

functioning and this, combined with the expertise of those working in the field of the construct(s), results in high quality monitoring assessments and greater accuracy in tracking learning progression, devising interventions and reporting results for impact and improvement (Petrillo et al., 2015; Sondergeld & Johnson, 2014).

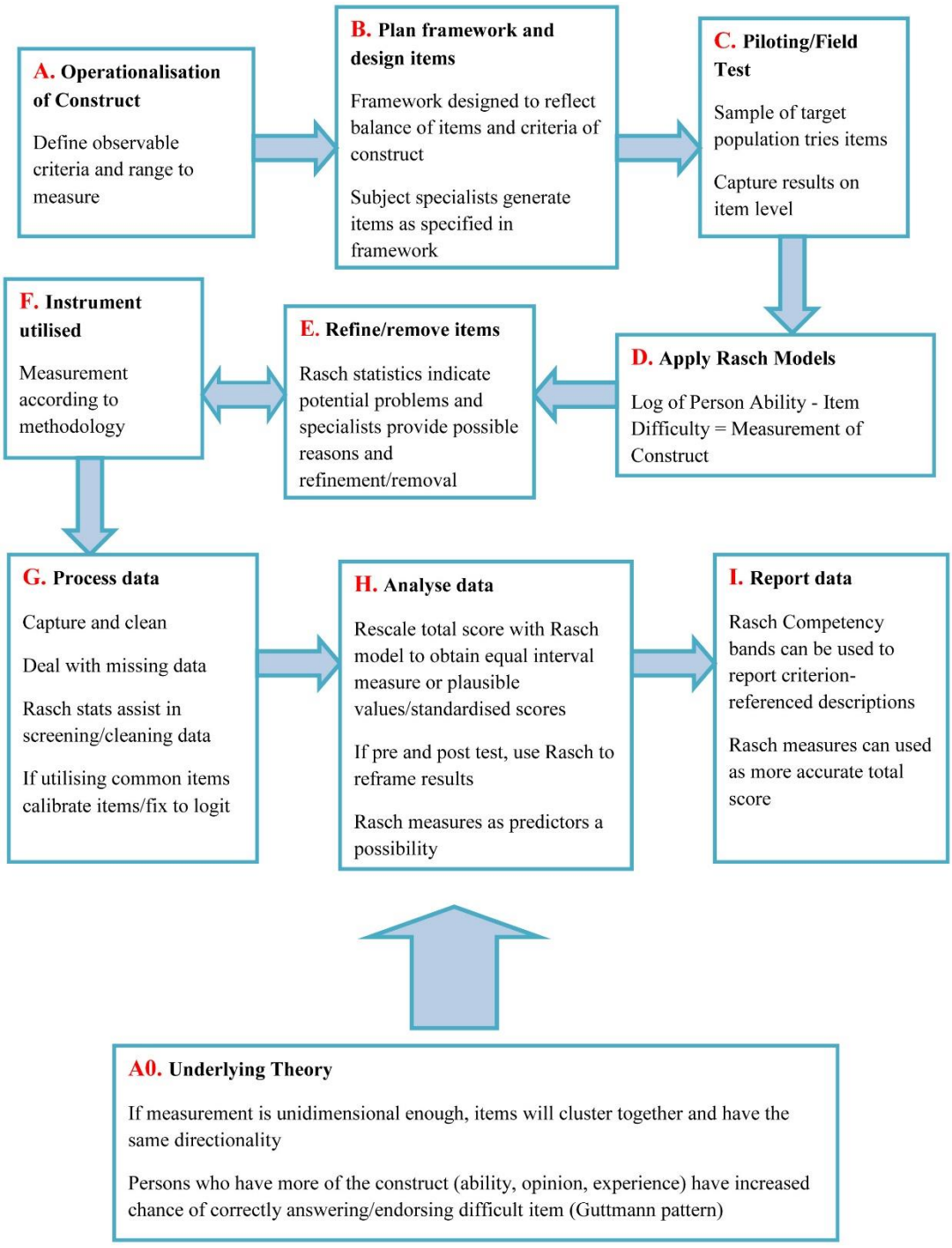

Figure 3.2 Conceptual framework of applying Rasch models for best test design

Figure 3.3 is a visual representation of the principles of measurement such as invariance, reliability, validity, the range of scale and equal intervals discussed in this chapter. Figure 3.3 demonstrates the principles regarding a construct from the natural sciences, as the same principles apply to the social sciences. The Rasch Item Maps arrange items from less to more difficult and show how items representing a different point along the continuum of a construct are ordered in the same way as found in instruments from the natural sciences such as rulers or thermometers.

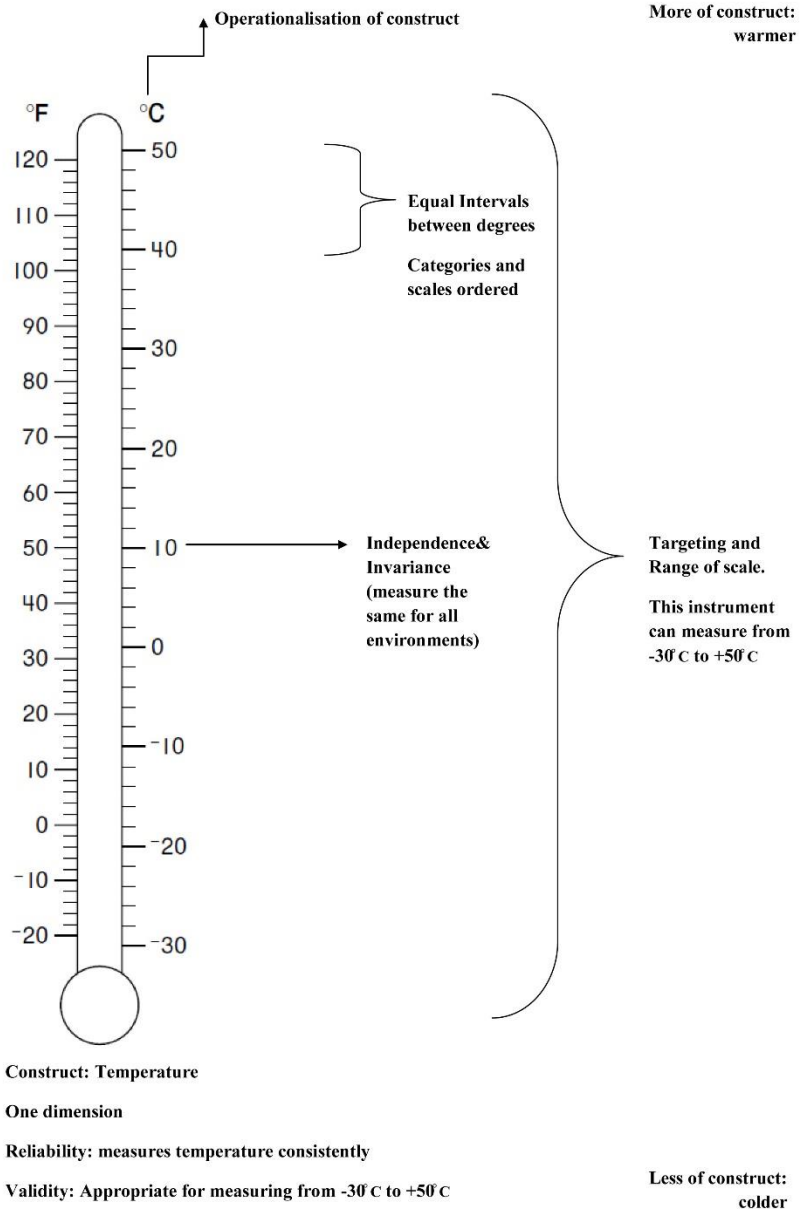

Figure 3.3 The principles of measurement demonstrated with a thermometer

The Rasch model is at its core a very simplistic model: The natural logarithm of the ratio of the probability of success to the probability of failure is equal to a person's ability minus the item difficulty. The basic model is very flexible and has a wide range of applications. Some of these applications are demonstrated in the articles (see Chapters 5 to 7) that follow on from this chapter.

3.6 Conclusion

This chapter provided a broad overview of the methodology used in the subsequent articles. In each of the articles, included as part of the thesis, Rasch models were applied to solve analysis challenges and to strengthen measurements. The principles, statistics and applications discussed in the current chapter are implied and explicitly used in the articles. Each article, based on the same project, described in Chapters 1 and 4, describes the specific methodology used in its analysis, as well the pivotal role played by the Rasch models. To define a construct and create an instrument with which to measure the latent trait in the social sciences is no easy task. We often forget how difficult it has been to create the measurement instruments in the physical sciences, and that those who formulated the models used today in the social sciences also spent considerable time developing what we take for granted (Andrich, 2016).

Explicitly understanding measurement principles gives the social sciences the opportunity to assess with the same precision and thoroughness as found in the natural sciences. Rasch models provide a way to determine what degree measures have been made and to improve the quality of the instrument. At first, the Rasch models may seem complex and confusing, but they are elegant in their simplicity and parsimonious in the application. Modern day technology further simplifies the application by providing programmes such as *Winsteps* (Linacre, 2016a) and the *Rasch Unidimensional Models for Measurement* (RUMM) which produces all the statistics needed to evaluate an instrument and refine and improve measures (Andrich & Sheridan, 2009a; 2009b). Rasch models can be used to improve and enhance measures at every step of the research cycle, from processing data and dealing with missing values, to monitoring progress and change over time and finally, in the reporting of results for maximum impact.

Chapter 4 - The Monitoring Project's Methodology

Aptitude is just a measure of how long it takes to learn something
(Unknown source)

4.1 Introduction

The monitoring of academic achievement study for seven independent high schools was conceptualised by the Centre for Evaluation and Assessment (CEA) at the Faculty of Education, University of Pretoria. A funding agency approached the CEA to design the monitoring system to assess Mathematics, Natural Science and English Language in Grades 8 to 11 across seven schools who shared a common curriculum. The request from the agency was based on recognition of the non-availability of standardised assessments at these grades in the South African context. The project was designed to monitor learning within and across the seven schools, while at the same time using the results to enhance teaching and learning by providing feedback in the form of workshops and reports. From October 2011 to February 2013, assessment instruments were designed and revised to assess the quality of learning broadly in each of the grades and subjects; thereafter, testing took place annually from November 2012 to November 2014.

The innovations that emerged from the project included:

- Designing and administering curriculum-based instruments to assess knowledge gained in a subject area.
- Tracking learning progression from one grade to the next in each subject between grades.
- The assessments were revised and updated yearly to factor in changes in curriculum and to prevent over-exposure.
- Devising feedback for principals, teachers, learners and guardians based on the assessment results so that teaching and learning could be enhanced.
- Providing learner-level feedback that was criterion-referenced.
- Merging an external monitoring system with internal school functioning so that learners and teachers could benefit.

Viewed externally, monitoring and feedback may appear to be exclusive, but this project found ways to merge these processes, gain buy-in from teachers and schools, and make the results practically applicable so that everyone could benefit from the process.

Subject specific sessions were held in the form of interactive workshops for all three subjects. Findings were discussed in detail and teachers and subject specialists engaged in consultations to find ways to enrich teaching and learning. The majority of attendees also indicated that the sessions provided them with relevant information that they can, and do, use to improve teaching and school practices.

4.2 Study population and sampling

The total population of learners is represented in Table 4.1 which displays the count of the learners in each school, per grade and per year (2012, 2013 and 2014) as well as the grand total for all the years. The number of learners in each grade varied by year, based on the number of learners recruited by the schools in a specific year, as well as attrition (learners failing a year and leaving the school).

Each year, new learners also joined in each of the grades. In addition, the schools were still in a development stage, for example Schools 4, 5 and 6 only added Grades 10 and 11 in 2013 and 2014. As a result, there was a 6 to 10% variation in the population. The schools are independent, have their own curriculum and smaller class sizes and longer school days than ordinary public schools. Due to the unique characteristics of the schools, they are seen as a population.

Table 4.1 Count of learners per grade and per school for each year of study

	Grade	School 1	School 2	School 3	School 4	School 5	School 6	School 7	Total
	8	50	69	49	54	50	21	67	**360**
	9	45	48	46	50	30	24	97	**340**
2012	10	43	50	44	45	0	0	71	**253**
	11	44	41	33	0	0	0	78	**196**
	Total	**182**	**208**	**172**	**149**	**80**	**45**	**313**	**1149**
	8	50	68	49	55	50	21	70	**363**
	9	50	71	50	56	50	23	75	**375**
2013	10	45	46	45	50	30	24	141	**381**
	11	46	50	44	44	0	0	78	**262**
	Total	**191**	**235**	**188**	**205**	**130**	**68**	**364**	**1381**
	8	25	25	24	25	25	27	102	**253**
	9	23	47	24	22	23	28	84	**251**
2014	10	49	65	47	43	48	22	71	**345**
	11	39	35	43	50	31	19	101	**318**
	Total	**136**	**172**	**138**	**140**	**127**	**96**	**358**	**1167**
GRAND TOTAL		**509**	**615**	**498**	**494**	**337**	**209**	**1035**	**3697**

Table 4.2 illustrates the gender distribution of the population as well as the average age per grade for all seven schools. The seventh school was an all-girls school, while the other schools comprised two third girls (65% overall).

The ages were generally within expected ranges, for example in November of each year the Grade 8 ages ranged on average between 14.06 and 14.54 years old. The standard deviations for the ages were relatively small, ranging from 0.57 to 1.09 (see Table 4.2). All learners were asked to participate, but were also given the option to withdraw from the study at any point. The full population participated in the study, with less than 2% of the learners being absent on the day of testing in any given year.

Table 4.2 Gender % and average age in each grade per year

	Grade	Male	Female	Average Age (SD)
2012	8	29%	71%	14.54 (0.67)
	9	25%	75%	15.59 (0.96)
	10	23%	77%	17.06 (0.48)
	11	20%	80%	17.21 (0.88)
2013	8	34%	66%	14.22 (1.03)
	9	28%	72%	15.19 (1.05)
	10	22%	78%	16.20 (1.09)
	11	23%	77%	17.19 (0.92)
2014	8	21%	79%	14.06 (0.57)
	9	20%	80%	15.03 (0.61)
	10	27%	73%	16.14 (0.63)
	11	23%	77%	17.27 (0.76)

4.3 Instruments - design and refinement

The value and role of educational assessment was discussed earlier as forming part of the feedback cycle within classrooms, schools, districts, provincial departments and national departments. In this study, assessment was viewed as the process of collecting, synthesising and interpreting information to aid in decision-making (Airasian, 1997). Appropriate and scientific instrument design in the social sciences is time consuming; ideally months or even a couple of years should be factored in as a minimum requirement for all the processes. The design of the instruments for Mathematics, Science and English Language for Grades 8 to 11 began with the recruitment of subject specialists. The specialists were required to have experience and expertise in the subject for high schools teaching, as well as knowledge of setting assessments for classroom use and systemic testing. When the specialists had been recruited, assessment frameworks were designed to provide an overall plan to guide the development of assessments. In defining the framework, factors such as the test length, the proportion of items that would address different aspects of a curriculum, cognitive processing skills and format of the items were all specified (Combrinck & Roux, 2015). The subject

specialists, serving as the reference group, also defined what would be assessed according to the material in the national curriculum and the curriculum of the independent schools.

After the constructs had been defined, the cognitive demand of the items was set to be a balance of item types, item difficulty and to appropriately assess learners from the target population. Field testing was critical to this process so that item difficulty could be statistically calculated. Informed by the design of the assessment frameworks, the reference team constructed items that reflected the constructs to be tested and conform to the framework. The items underwent two review phases, with comments by the external reviewers being made on the final form of the items. The assessments were set to have duration of 60 minutes (Grade 8), 90 minutes (Grade 9) and 120 minutes (Grades 10 and 11). The time constraints for the assessments controlled the extent to which the curriculum content of a subject for a given year could be assessed.

The test designers endeavoured to attain a balance of items and subject areas, to produce assessments that broadly captured knowledge gained in a subject area and subject as a whole over the course of a year. A variety of formats for the items were developed, such as multiple-choice items, closed constructed response items, and open ended short response items. More items than necessary were developed as is best practice in assessment design (Linacre, 2016). This allowed for field testing items that assessed similar concepts and the selection of the best fitting items for the final tests. The test administration time as well as curriculum coverage targets determined the number of items developed. The assessment designers strived to maintain a balance between multiple choice format and constructed response for Science and English Language assessments. In the Mathematics assessments, very few multiple choice items were included, so that learners could demonstrate their ability through calculations. Within each curriculum section, a balance was also sought among easy, moderate and difficult items.

4.4 Assessment administration

The field trial was conducted eight months before the official testing began (at the beginning of 2012), and independent schools similar to the target population were used to trial the items. The field trial provided evidence of question difficulty levels and appropriateness of the items for the specific group of learners. A larger number of items than required for the final tests was

piloted so that less useful items could be eliminated. The tests underwent comprehensive refinement based on the statistical evidence collected during the field trial and items were refinement or removed as decided by subject specialists. In addition, on completion of the assessments, learners were informally asked about their experiences of the items and tests, which aspects they liked and which sections they disliked or struggled with, all of which informed the design process. The yearly test administration took place in November each year and was conducted by the CEA. Standardised assessment procedures were used to ensure that high quality results were collected. Any problems experienced during testing was reported by the administrators and taken into account during scoring and data capturing. Testing times were arranged to fit into the school day and consultations were held with schools to make the programme minimally disruptive to the schools.

4.5 Scoring, capturing and cleaning of data

The scoring (or marking) was done by experienced teachers who were trained by the subject specialists. The specialists also conducted the moderation of the scoring to check for accuracy and consistency. The capturing was done in-house at the CEA and capturing templates were set up in Microsoft Access. The templates did not allow for the capturing of out of range values and capturers were trained to use the correct codes. During capturing 20% of captured data were checked for consistency against paper tests (randomly selected), and the error rate below 1%, was deemed to be acceptable. Cleaning of the data was done by the project coordinator, and clean data was used to report the results to the schools and funding agency.

4.6 Instrument reliability and validity

Cronbach's alpha was calculated for the assessments as a whole (all items), as well as subject areas included in the assessments. All instruments had reliability coefficients above .800 (except one which had an estimate of .702). Several types of validity were investigated for the assessment, the first being content validity. The content validity was examined by subject specialists who compared the instruments to the current curriculum, and assessed the instruments for coverage. This was an ongoing process as the instruments were reviewed every year and minor adjustments made to ensure that the instruments were aligned to the curriculum. Construct validity was considered by applying Rasch analysis and the difficulty of the items aligned well with the ability of the learners. The Rasch results indicated evidence for unidimensionality and consistency. To estimate the predictive validity of the instruments,

correlations of the instruments with the final Matric marks (NSC), were calculated and found to be high (above .700). Concurrent validity was estimated by correlating school marks of learners with total scores on the assessment instruments, and these ranged from moderate to high (.500 to .800).

4.7 Methods of data analysis

During the design and use of the assessment instruments, a variety of statistical techniques was applied to analyse and report the results in school and learner reports. Schools were provided with descriptive statistics in terms of their school's average achievement, as well as that of the other schools for comparative purposes. Mean achievement results per class per grade were also provided to schools. In reports, schools were cautioned to keep in mind factors that could affect achievement on an assessment, such memory effects (learners did not study for the test), fatigue, diverse backgrounds, motivation and that most of the learners are English second language speakers. Results per subject were reported to schools, not only as the average achievement for the subject as a whole but also for different subject areas and cognitive levels. When the second round of assessment took place, progress in learning was also reported based on the common items in the assessment. Throughout the monitoring process, Rasch models were applied to gauge the functioning of the tests and to make adjustments. Rasch item statistics were also reported to teachers to indicate more about the learning taking place. The teachers were taught how to interpret the Rasch statistics for better understanding of learner ability and skills.

The analysis methods were structured to address the aims of the main project:

- To compare schools within the coalition to one another, descriptive statistics (mean achievement) and Rasch scores were shown and discussed in both reports and workshops.
- To identify gaps in the teaching of the curriculum, descriptive statistics were reported for subject areas (each subject per area). When possible, item statistics were discussed during the workshops, which was especially useful for Mathematics.
- To monitor and track learning progression from one year to the next, performance on anchor items were analysed using descriptive statistics as well as applying the Rasch model.

- To give criterion-referenced feedback, learner reports were developed and distributed to schools, teachers, learners and parents.
- To engage teachers in the results, workshops were held. The workshops and feedback stimulated classroom interventions.

The analysis, conducted and reported in the articles (see Chapters 5 - 7), was developed during the life-cycle of the project in response to specific measurement challenges. The first article on missing data fits with all of the aims discussed above as it is linked to preparing the data for reporting descriptive and Rasch statistics. The second article, on evaluating anchor items and reframing results, fits in with the monitoring and tracking goal of the project. The final article, on competency bands, is an account of how the learner reports were developed and fits in with the goal of devising criterion-referenced feedback to enhance teaching and learning within the schools.

4.8 Ethics

Both learners and their guardians signed consent forms before learners participated in the study each year (see Appendix D). Although, the study was designed as an accountability system for the funding agency, for ethical and educational reasons, it was deemed as important that learners, teachers and schools also benefit from the testing programme. Therefore, learner reports were devised to give learners, teachers and parents a clear indication of subject knowledge and skills gained as well the next steps learners would need to master. Teachers and principals received school reports and attended interactive workshops, which in turn ensured that the testing results informed the design of interventions and Saturday classes. The testing programme was set up to benefit all stakeholders and not to interfere with teaching or learning.

4.9 Conclusion

The monitoring of the academic achievement study described in this chapter had many broad aims. The first aim was to compare the academic achievement of high school learners from Grades 8 to 11 across years and among the various independent schools in the coalition. The project also evaluated academic achievement within schools by comparing performance among classes and learners. The project's goal was to serve as both an accountability system for the funding agency and schools, while at the same time disseminating the results to schools, teachers, learners and parents so that gaps in subject areas could be identified and addressed.

This chapter described the main monitoring project in general, whereas the articles (Chapter 5, Chapter 6 and Chapter 7) used data from various cohorts within the main study to investigate ways to resolve measurement challenges. The articles in this thesis had the overall aim to apply Rasch models to explore ways to improve measurement in the social sciences as well as solve measurement challenges within an educational context. The challenges addressed included dealing with missing data, tracking learning progress over time and providing criterion-referenced feedback to stakeholders, all of which is based on the data and study described in this chapter. The study in this thesis falls in the arena of research methods in psychology, more specifically psychometrics. The study investigates statistical validity (Garcia-Perez, 2012) and how to use results in a practical and statistically valid way for real world impact and academic integrity. The main monitoring study provided the data as well as the challenges, and this thesis contains the exemplars of how the measurement challenges in the study were addressed.

Chapter 5 - Multiple Imputation for Dichotomous MNAR Items Using a Recursive Structural Equation Model with Rasch Measures as Predictors

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5.1 Abstract

Missing Not at Random (MNAR) data present challenges for the social sciences, especially when combined with Missing Completely at Random (MCAR) data for dichotomous test items. Missing data on a Grade 8 Science test for one school out of seven could not be excluded as the MNAR data were required for tracking learning progression onto the next grade. Multiple Imputation (MI) was identified as a solution, and the missingness patterns were modelled with IBM Amos applying a Recursive Structural Equation Model (SEM) for 358 cases. Rasch person measures were utilized as predictors. The final imputations were done in SPSS with logistic regression Multiple Imputation. Diagnostic checks of the imputations showed that the structure of the data had been maintained, and that differences between MNAR and non-MNAR missing data had been accounted for in the imputation process.

Keywords: Missing Not at Random (MNAR) data; Multiple Imputation (MI); Rasch person measures; Structural Equation Modelling (SEM); Dichotomous or binary items; Social Science Methods

5.2 Introduction

Perfect data sets do not exist in the real world, and missing data is an authentic challenge facing social science analysts and researchers. Missing values can bias analyses, especially when high percentages are missing or there are patterns in the missingness (Allison, 2002; Osborne, 2013; Wang, Bartlett & Ryan, 2017). The higher the percentage of missing values, the greater the potential problems (Bennet, 2001; Osborne, 2013). Consequently, the handling of missing data has been a topical issue in social sciences and methods dealing with missing values have grown exponentially (Enders, 2010; Little & Rubin, 2002; Peng, Stuart & Allison, 2015; Rubin, 1987;

van Buuren, 2012). Treating missing data as incorrect responses and excluding cases, which is a common practice in large-scale assessments, could lead to significantly biased item parameter estimates (Hohensinn & Kubinger, 2011; Rose, Schiller, von Davier & Xu, 2010). Model-based approaches are recommended for handling missing data that provide the opportunity to consider the likelihood of responding and ability (Peugh & Enders, 2004; Mayer, Muche & Hohl, 2012; Yucel, 2011).

As methods for handling missing data become easier to access, their limitations, including the evaluation of imputations and reporting, should be given more attention (Cox, McIntosh, Reason & Terenzini, 2014; Graham, 2012; Little & Rubin, 2002; van Buuren, 2012). Some forms of missing data, such as Missing Not at Random (MNAR) data, warrant further research, which complicates the use of missing data handling techniques as data missing randomly is an assumption of many imputation methods (Galimard, Chevret, Protopopescu & Resche-Rigon, 2016). In longitudinal research, large-scale assessments, high-stake studies, and research designs which gather sensitive data, missing data are particularly problematic, and could impact statistical validity (Mallinckrodt, Roger, Chuang-stein, Molenberghs, Lane, O'kelly & Thijs, 2013a; Peng et al, 2003). The most popular and recommended methods for handling missing data, such as Multiple Imputation (MI) and Maximum Likelihood Estimation (ML), were originally developed for continuous variables with the assumption of a normal distribution for data Missing at Random (MAR) or data Missing Completely at Random (MCAR). Some studies have found that when missingness mechanisms are investigated, MI can be used for MNAR data (Baraldi & Enders, 2010).

5.3 Current Study

This paper reports on a practical application of Multiple Imputation (MI) using Structural Equation Modelling (SEM) to model the missingness of MNAR dichotomous data using Rasch person measures as predictors. The data contained a combination of MNAR and MCAR dichotomous test anchor items. Data are Missing Not at Random (MNAR) when missingness on a variable is directly related to the outcome variable (for example, Science proficiency) (Enders, 2010; Graham, 2012; Kim & Shao, 2014; van Buuren, 2012). When data are missing due to underlying patterns and variables in the model, the mechanism of missingness is non-ignorable (Wang et al., 2017). The percentage of missing data can be used to guide the selection of methods to handle the missingness: with less than 5% of missing values, listwise or pairwise

deletion is an option as long as MAR data are present (Allison, 2002). Greater percentages of missing data may cause bias in analyses and should be investigated and other options, such as Multiple Imputation should be considered (Mallinckrodt, Lin & Molenberghs, 2013a; McPherson et al., 2015; Roberts, Sullivan & Winchester, 2017).

The study included seven independent high schools in South Africa. The schools are parts of a coalition and are sponsored by a funding agent. The funding agent required a set of year-end assessments to evaluate curriculum knowledge and to ensure that all students in the schools had achieved the same standards. Science assessment instruments were designed for Grades 8 to 11. During the yearly assessment of the 8th Grade students, one school received a copy of the Science test that did not contain the anchor (common) items. This was due to a printing error. The missing data for the anchor items could not be classified as missing randomly as they were completely missing only for that school. The missing data can be classified as Missing Not At Random (MNAR) because their absence from the test was unintended and not part of a planned design. Furthermore, the school with the missing data were different from the other six schools, as it had consistently higher score averages in all subjects. Using data from the other schools in the sample to predict the missing data for the seventh school would have led to the underestimation of achievement.

Treating data which are missing due to a specific variable, in this case one school, as missing at random could have a biased effect on the imputation (Cleophas & Zwinderman, 2012; Fielding, Fayers, McDonald, McPherson & Campbell, 2008). The assumption of missingness has to be carefully investigated and conducting sensitivity analysis to assess the accuracy of the imputations is essential (Fielding et al., 2008; Keene, Roger, Hartley & Kenward, 2014; McPherson, Barbosa-Leiker, Mamey, McDonell, Enders & Roll, 2015). According to Roberts et al. (2017), “Patterns of missingness dictate how data should be analyzed” (p.10). Based on this specific case of missingness (MNAR), the study aimed to investigate and answer three research questions:

1. *How can MNAR missing data be imputed by modelling the missingness?*
2. *Which type of model and variables would best to predict the MNAR data and how would the variables be identified?*
3. *What contribution could be made by Rasch scores in comparison with raw scores to build more accurate MI models for missing item responses*?

5.4 Method

To link the assessments within each subject from one year to the next, common items (anchor items) were included in the assessment design. The 8th grade tests were of particular importance as they served as a baseline assessment of student ability and knowledge. The nine anchor items were present in the tests completed by the other six schools but not the seventh school. This meant crucial items that would be used for anchoring within the cohort were missing for one school. For the school in which the items were not included in the test, the data were Missing Not at Random (MNAR) and were directly related to variables in the data set, namely that of school and science proficiency for tracking (anchoring). It was not possible to exclude the missing data as it was crucial to have responses to the items for anchoring in the subsequent year's assessment. A hybrid approach was explored to handle the missing data. Hybrid approaches are recommended for strengthening methods for handling missing data (Aste, Boninsegna, Freno & Trentin, 2015).

5.4.1 Participants and Ethical Considerations

A total of 358 Grade 8 students from seven independent high schools completed the Science assessment at the end of the academic year. Parents signed consent forms for testing participation, as well as for the results to be used for research purposes. The average age of the Grade 8 students was 15.53 years with a greater number of female participants (71.79%) than males. The sample included a girls-only school, which accounts for the larger proportion of females in the sample. The MNAR school, which received the test copies without the anchor items, accounted for 18.15% of the total sample (65/358).

5.4.2 Instruments and Procedures

The assessments were designed to cover the South African National Curriculum (CAPS) and measure the knowledge gained over the course of a year (Department of Basic Education, 2012). The Science assessments were administered at the seven schools at the end of each academic year and were conducted using standardized procedures, with external evaluators conducting the testing processes at each school. Examination conditions were maintained during the assessments.

4.4.3 Data Analysis

To address the problem of MNAR data for the dichotomous anchor items, this study investigated methods to handle missing data when the mechanism for missingness is known. IBM SPSS version 23 and IBM Amos were used in the analysis and a practical application of modelling the missingness and imputing missing values, based on the model, was demonstrated. Rasch person measures were identified as the most suitable predictors for the missing scores. Rasch theory uses logistic regression models to estimate the likelihood of answering a question correctly and creates an equal interval logit scale for persons and items (Andrich, 2011; Bond & Fox, 2015; Dunne, Long, Craig & Venter, 2012; Linacre, 2016; Uebersax, 1993). The Rasch models are quite resilient to missing data in general (Boone, Staver & Yale, 2014; Bond & Fox, 2015, Linacre, 2016). Winsteps 3.75.0 was used to produce items and person estimates before the imputation (Linacre, 2016). The measures for both persons and items were rescaled from 0 to 100 to make the outputs easier to interpret. The anchor items did not form a scale, and consequently could not be used as predictors; using Rasch person measures addressed this challenge.

The data contained a combination of both MNAR data (one school did not have the anchor items) and MCAR data (the other schools had the items but some students elected not to answer some items). The composition of the two missingness mechanisms is shown in Table 1. Multiple Imputation was chosen as the method to handle the missing data because it uses multiple values to estimate parameters and explicitly accounts for the uncertainty associated with missing data by reflecting the underlying variability (Enders, 2010; Rubin, 1976, 1987; van Buuren, 2012). MI produces continuous imputations for categorical variables if multiple linear regression is used, as opposed to logistic imputation (Cox et al., 2014). Rounding off values so that illogical values fit the original variables' scale has to be done with caution and can be especially problematic for dichotomous items (Finch, 2010, 2011; Horton, Lipsitz & Parzen, 2003). In addition, MI can be used for MNAR data when the missingness is modelled (Dong & Peng, 2013; Horton & Kleinman, 2007; van Buuren, 2012). For ordinal data with a monotone pattern, as was the case discussed in this paper, logistic regression was the preferable method for imputation (Mayer et al., 2012; Schafer, 1999b). Mayer et al. (2012) recommend using IBM Amos when the researcher knows the reason for missingness, in this way the missingness can be modelled explicitly with SEM and the imputations will be based on the model's structure. The model can also be evaluated for fitness and refined so that the MI will

have more accurate imputations which are based on the relationships within the data. It should be noted that both the percentage of missing data and the sample size have an impact on the MI model, and when sample sizes are small, such as N < 50 and missing greater than 20% of values, bias can be introduced into the imputation process and results (Hardt, Herke, Brian & Laubach, 2013).

For the current study, only the nine anchor items in the Grade 8 Science test needed to be imputed. The highest percentage of missing values in this study was 30% for one of the variables and the sample size of 358 was judged to be adequate to estimate the missing data. When utilizing IBM Amos, Bayesian analysis is conducted for ordered-categorical data and the Markov Chain Monte Carlo (MCMC) algorithm is employed to draw random values of the parameters from joint posterior distributions (Arbuckle, 2014b; Grace, 2015; Poleto, Singer & Paulino, 2011). When dichotomous variables are used in an Amos model, additional constraints must be added to identify the model (Arbuckle, 2014a; IBM Corp., 2015; Grace, 2015). As Multiple Imputation uses regression to predict outcomes, SEM is the next natural step and more complex relationships among imputation variables can be specified. All of the anchor items to be imputed were dichotomous, and functioned as endogenous variables in the model. For each item, the residual mean and variance were fixed as 0 and 1, respectively (Arbuckle, 2014b). Dichotomous variables have only one boundary, and to determine the origin and underlying scale required for the variable, parameter constraints must be imposed. The constraints act as priors, restricting the dichotomous variables to a range of 0 to 1. Further priors were not added in this study, as the aim was to analyze the model for use in SPSS, and uninformative priors were recommended for this purpose (Grace, 2009).

Modelling the MI in Amos allowed for the testing of several possible models, as well as refining the model to obtain a model best suited for MI. SPSS was used to conduct the final MI after modelling was completed in Amos, and the most appropriate model was used to specify the imputation in SPSS. The main reason for using SPSS for the final imputations was that SPSS has Logistic Regression Multiple Imputation as an option, which produces categorical variables within the correct ranges. In contrast, Amos Bayesian multiple regression results produce variables on a wider, continuous scale and this requires additional formulae for rescaling and rounding (Graham, 2012). Using Amos to assess the model produced statistics

such as regression weights and the posterior predictive *p* value (Nguyen, Lee & Carlin, 2015). SPSS outputs limited statistics once the MI process has been conducted, making it challenging for users of the MI function to assess the statistical validity of their model and imputations (IBM Corp., 2012). In addition, SPSS does not provide an iteration history for categorical variables (IBM Corp., 2014), which is where Amos proves to be a more advantageous tool. The variables for use in the Multiple Imputation model were identified using Pearson's Correlation Coefficient (*r*) to assess the strength of the relationships. Possible predictors for the MI process were investigated and included auxiliary variables such as gender, school and age, as well as other items in the instrument, the imputation variables and the composite (total test) scores. Only variables with small to large significant correlations found in the imputation variables were used in models for predictive power and improved model functioning.

After the MI process had been performed in SPSS, sensitivity analysis was conducted to compare non-imputed data to the imputations. In this step, the original anchor items were compared to the imputed variables using the McNemar and Kruskal-Wallis tests to determine if the original items differed statistically from the imputed variables when the results were pooled (Schafer 1999a). Using a hybrid approach by combining SEM in Amos with MI in SPSS led to a stronger imputation model, as the advantages of each program were utilized and their limitations were negated.

5.5 Results

Table 5.1 shows the percentage of missing data per item, first showing the percentage of missing values per item for all types of missingness (MCAR and MNAR), and then illustrating the percentage missing only for MCAR. Anchor Item 4 has the largest percentage of missing data at 30% of values missing (valid $N = 250/358$), with 14.68% of that being MCAR data. All anchor items were dichotomous and for MCAR and MNAR data combined, 62.57% of cases and 82.29% of values were complete. For MNAR data only, 76.45% of cases and 93.33% of values were complete. The MCAR data accounted for 6.67% of missing values, whereas the MNAR mechanism explained 11.04% of missing data (overall 17.72% of the values were missing). A monotone pattern of missingness was identified due to data being missing for one school in particular (IBM, 2013; Rezvan, Lee & Simpson, 2015). Little's MCAR test of the data for the schools where the items were completed, confirmed that the missing values were MCAR for the other schools, $\chi^2 = 195.269$, $df = 166$, $p = 0.06$ (within SPSS version 23) (Little,

1988). This established that the data contained a combination of MCAR and MNAR data. A listwise deletion of all missing data would thus result in 37% of cases being excluded.

Table 5.1 Summary of missing data for MCAR and MNAR items

	Missing both MCAR and MNAR		Missing MCAR		Valid N
	N	Percent	N	Percent	
Anchor Item Q1	68	18.99%	3	1.02%	290
Anchor Item Q2	73	20.39%	8	2.73%	285
Anchor Item Q3	106	29.61%	41	13.99%	252
Anchor Item Q4	108	30.17%	43	14.68%	250
Anchor Item Q5	87	24.30%	22	7.51%	271
Anchor Item Q6	99	27.65%	34	11.60%	259
Anchor Item Q7	76	21.23%	11	3.75%	282
Anchor Item Q8	76	21.23%	11	3.75%	282
Anchor Item Q9	68	18.99%	3	1.02%	290

5.5.1 Auxiliary variables

Literature on building missing value models indicates that including auxiliary variables could be very beneficial for imputation (Crameri, von Wyl, Koemeda, Schulthess & Tschuschke, 2015; Manly & Wells, 2015; Nguyen et al., 2015). The advantages of auxiliary variables are dependent on significant correlations (>.40) with the imputation variables, as well as lower percentages of missing values for the auxiliary variables (Dong & Peng, 2013; Enders, 2010). In this study, three auxiliary variables were considered: gender, which did not correlate significantly with any of the imputation variables or predictor variables; then age was considered but it correlated weakly with only one of the imputation variables; and lastly, school membership was assessed with membership in the seventh school, functioning as constant as it was completely missing for the MNAR school. For reasons cited above, none of the demographic variables were included in the model. MI can be robust to application without auxiliary variables when viable alternative imputation variables are utilized (Mustillo & Kwon, 2015).

5.5.2 Predictor and imputation variables in the model

The anchor items had correlations with one another, ranging from non-existent (r = 0.002) to weak (r = -0.273), with a principal component analysis showing that the nine anchor items did not form a factor. Using the anchor items to predict missing values on one another was not recommended, and when a saturated model was attempted, it failed to converge (Poleto., et al., 2011, had similar findings when using a saturated model). The other test items in the assessment were also considered; however, they only correlated well with some of the anchor items to be imputed and thus could not be used as a group. Inclusion of all 79 items in the model may have led to the over complication of the model (Hardt et al., 2013). As a result, two types of composite (total test) scores were considered: raw composite scores and Rasch person measures. The use of item composite scores creates a variable which contains all the information from items without MNAR data, to predict MNAR variables. Correlations among anchor items and raw composite variables showed small to moderate significant correlations to the raw composite scores with five out of the nine anchor items (correlations ranged from r = 0.128 to r = 0.424). The Rasch item measures of all items had small to moderate correlations with six out of the nine anchor items having correlations that ranged from r = 0.133 to r = 0.360. The Rasch item measures variable, based only on anchor items, had small to large correlations with all anchor items (r = 0.173 to r = 0.667).

5.5.3 The SEM model of missingness

The Structural Equation Model (SEM) of missingness, built for this particular study, was specified as a recursive model. The imputation variables were the anchor items, nine items which were all dichotomous, with 18-30% of the values missing in a combination of MCAR and MNAR mechanisms. The predictor variables included the Rasch person measures of the anchor items, as well as the Rasch person measures of all test items (excluding the anchor items). The standardized direct effects (regression weights) indicated good predictive power for each of the imputation variables, see Table 5.2. Both predictor 1 and 2 worked well in the model due to their moderate correlation with each other at r = 0.352 (p = 0.000), as well as small to large significant correlations with the imputation variables. In Amos, five imputations were generated to assess the model and a total of 10 imputations were generated in SPSS (Dong & Peng, 2013; Schafer, 1999a; White, Royston & Wood, 2011).

Table 5.2 Standardised direct effects on imputation items

	Pred1 Mean*	Pred2 Mean**	Max	Min	Lower Bound 50%	Upper Bound 50%	Standard Deviation	Standard Error	Convergent Statistic
Anchor_Q1	0.402	0.099	0.639	0.125	0.355	0.452	0.072	0.001	1.000
Anchor_Q2	0.468	0.051	0.748	0.072	0.414	0.525	0.081	0.001	1.000
Anchor_Q3	0.282	-0.128	0.605	-0.054	0.219	0.346	0.093	0.001	1.000
Anchor_Q4	0.427	0.136	0.688	0.099	0.379	0.480	0.077	0.001	1.000
Anchor_Q5	0.772	0.259	0.890	0.604	0.748	0.799	0.038	0.000	1.000
Anchor_Q6	0.873	0.069	0.941	0.732	0.857	0.891	0.026	0.000	1.000
Anchor_Q7	0.512	0.285	0.736	0.217	0.469	0.558	0.065	0.001	1.000
Anchor_Q8	0.440	-0.083	0.677	0.150	0.394	0.488	0.071	0.001	1.000
Anchor_Q9	0.549	-0.179	0.768	0.175	0.502	0.599	0.074	0.001	1.000

* Rasch Person Measures for anchor items only; ** Rasch Person Measures for all items

Figure 5.1 displays the visual representation of the recursive model which converged after 10 000 observations. Van Buuren (2012) suggests using the most simplistic model for MNAR data, with the result that the model below is both the simplest and most accurate that could be devised with the data.

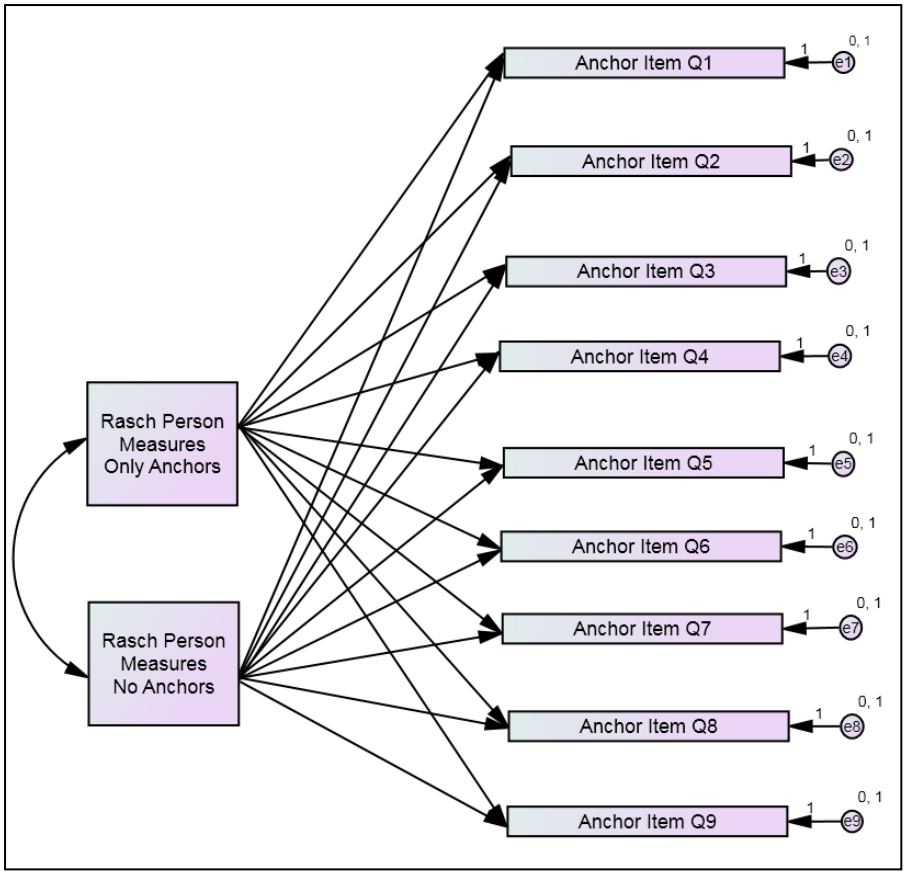

Figure 5.1 IBM Amos recursive model for imputing missing data

The posterior predictive *p* had a value of 0.02, which indicates a lack of good fit between the data and the model, as the ideal value should be closer to 0.5 (IBM Corp., 2014; Nguyen et al., 2015). However, the *p*-value is only one indication of model functioning and is subject to factors such as percentage of missing values and sample size and thus should be treated with caution (Gelman, 2013). Further checks of the model and convergence were done by examining the histograms with first and last distributions. A sample of the histograms, trace plots and auto-correlation plots are displayed in Figure 5.2 to Figure 5.7. The histograms show that the first and last distributions from the analyses are closely aligned and almost equal, an indication that the posterior distributions were successfully identified and modelled.

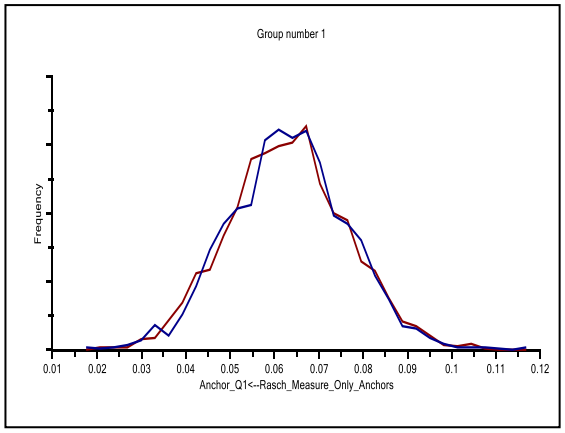

Figure 5.2 Q1 histogram predictor 1

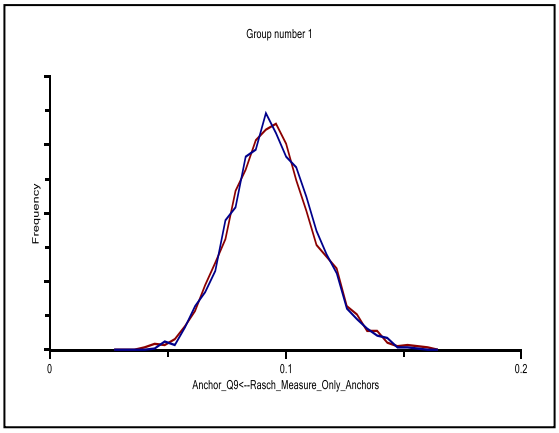

Figure 5.3 Q9 histogram predictor 1

Figure 5.4 and Figure 5.5 illustrate the trace plots or time-series plots and indicate that the MCMC procedures converged quickly. There were no long-term trends or drifts, only minimal fluctuations.

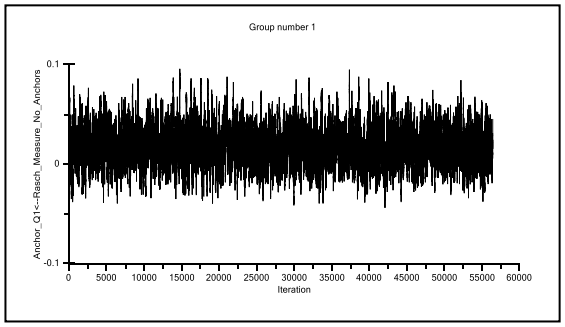

Figure 5.4 Q1 trace plot predictor 1

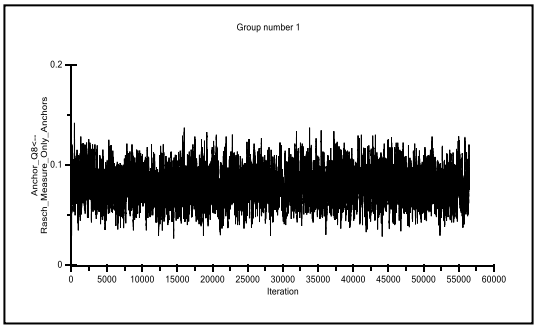

Figure 5.5 Q8 trace plot predictor 1

The auto-correlation plots, depicted in Figure 5.6 and Figure 5.7, show high initial correlation and then small or no correlation by 100 iterations, the point at which the model converged.

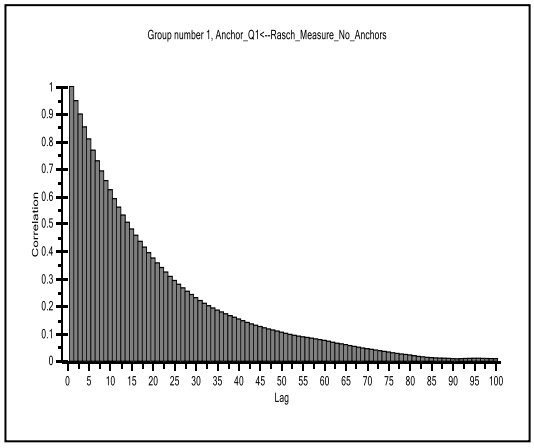

Figure 5.6 Q1 auto-correlation predictor 1

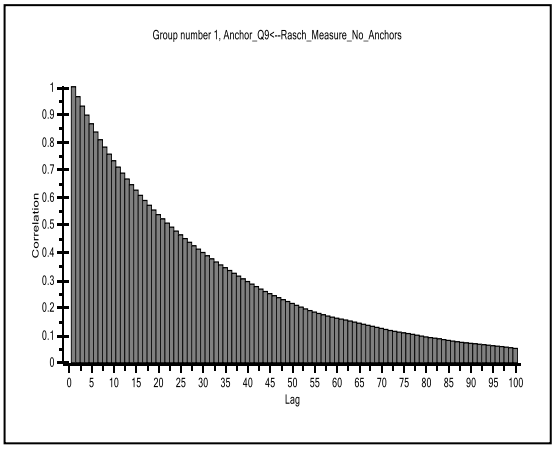

Figure 5.7 Q9 auto-correlation predictor 1

A pseudo R^2 was calculated by using the formula as recommended by Grace (2009) for use in MCMC models in Amos: $R^2 = 1 – (e1/\text{implied variance of predictor variables})$ (see also Grace & Bollen, 2005). This yielded $R^2 = 0.737$ for the SEM model, showing that the overall model accounted for a large percentage of variance.

5.5.4 Diagnostic Checks of the Imputation Model

A comparison of the original data and the pooled data for the 10 imputations is presented in Table 5.3. No imputed item recorded a statistically significant difference between the original item and the pooled item, demonstrating the accuracy of the imputation. As recommended by Schafer (1999b), the McNemar test was used to compare pre-imputation to imputed binary variables. The Kruskal Wallis Test was also reported to use the imputation numbers as grouping variables, so that each imputation was compared to every other imputation in this analysis. Both the McNemar and Kruskal Wallis tests showed that there was no statistically significant difference between the original data and the imputed values, or among the imputations ($p > 0.01$).

Table 5.3 Original data compared to pooled data

	Original N	Original Mean	Original SE	Pooled Mean	Pooled SE	χ^2	Asymp. Sig.*	Exact Sig. (2-tailed)**
Anchor Item Q1	290	0.272	0.026	0.297	0.027	2.828	0.985	1.000
Anchor Item Q2	285	0.179	0.023	0.204	0.028	7.142	0.712	1.000
Anchor Item Q3	252	0.202	0.025	0.215	0.032	9.938	0.446	1.000
Anchor Item Q4	250	0.304	0.029	0.340	0.037	11.377	0.329	1.000
Anchor Item Q5	271	0.472	0.030	0.489	0.030	2.488	0.991	1.000
Anchor Item Q6	259	0.467	0.031	0.473	0.032	3.517	0.967	1.000
Anchor Item Q7	282	0.298	0.027	0.332	0.031	5.493	0.856	1.000
Anchor Item Q8	282	0.294	0.027	0.316	0.030	4.749	0.907	1.000
Anchor Item Q9	290	0.172	0.022	0.207	0.030	9.886	0.451	1.000

*Kruskal Wallis Test, df = 10

**Binomial distribution used for McNemar

When the imputed items were imported into Winsteps, the item measures were found to have remained very stable, with each imputed anchor item correlating above .9 with the original anchor item measures (estimates) (Suarez Enciso, 2016). Each imputation was imported into Winsteps separately and the outputs were produced and compared. The school with data completely missing on the anchor items (MNAR data) tended to have higher performance on the test overall (M = 49.91, SE = 0.48, N = 65) when compared to the other six schools (M = 43.84, SE = 0.36, N = 293). In the MI model, this was accounted for by including the overall Rasch person estimates. The MNAR school had a higher mean for the pooled MI anchor items (M = 46.02, SE = 2.79, N = 65), which was 4.5% higher than that of the other schools (M = 41.45, SE = 0.44, N = 293). Notably, the standard error was much higher for the MI data of the MNAR school than that of the other schools. Figure 5.8 also demonstrates graphically how the mean of Rasch person measures for all items with no imputation compares to the multiply imputed anchor items' person mean.

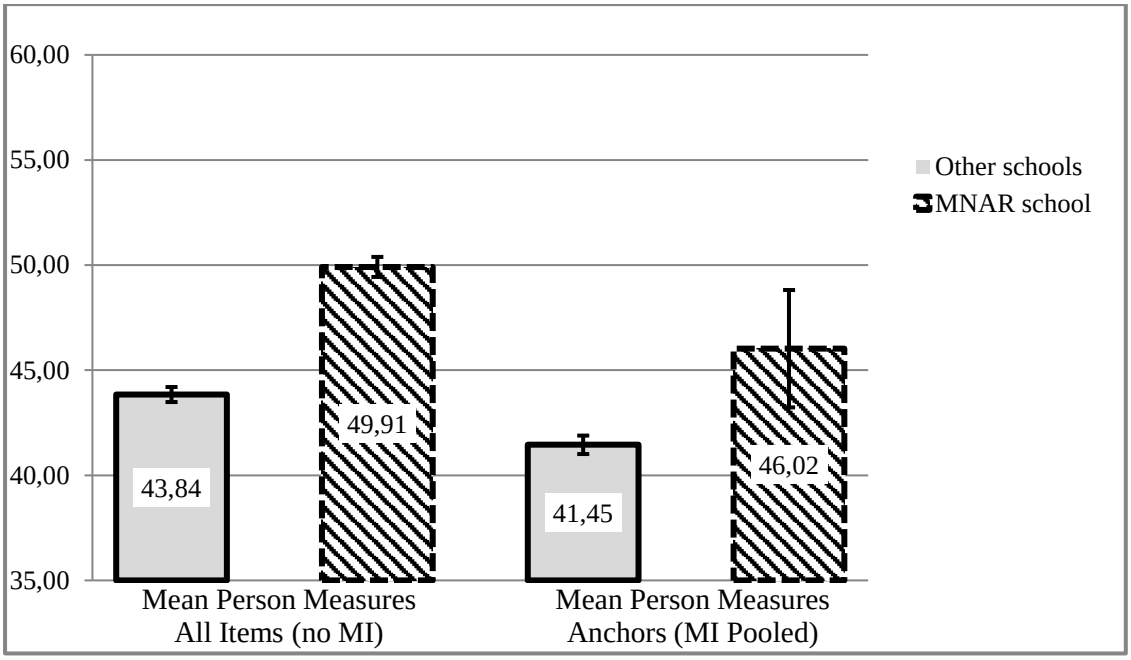

Figure 5.8 Mean person measures for all items (no MI) versus MI pooled

5.6 Discussion

The quality of analyses and findings improves when researchers acknowledge missing data, investigate the reasons thereof and actively find ways to deal with the missing values (Carpenter, Bartlett & Kenward, 2010; Manly & Wells, 2015; Peng, Harwell, Liou & Ehman, 2003). By building SEM models with Bayesian analysis to find the best model and assess the convergence, an MI model could be structured for imputations in SPSS using logistic regression. Using IBM Amos, a recursive model was built with Rasch person measures as predictors, and had one predictor based on all items and the other on the anchor items only. The result was that the Rasch person measures were better predictors compared with using composite scores of the raw values, and as a result, the recursive model worked best. Other models were attempted, such as a saturated model and possible path models with either both or one of the Rasch person measures or with the raw composite scores, but these models either failed to converge or had poor model fit. Poor fit for the other models is attributed to the fact that the imputation variables did not form a scale. Finding good predictors for MI models should be done by identifying variables that correlate moderately to highly with the imputation variables. For this reason, imputation items alone could not be utilized in the model. This is where the Rasch scores were useful, since they created an estimate of persons which was on an equal interval scale, thus providing a more accurate measure. The Rasch measures also provided significant correlations with the imputation variables while maintaining the pattern of performance between the MNAR school and the other schools with MCAR missing data.

IBM Amos provided a way to model the missingness and check model functioning. In addition, Amos produced continuous imputation variables for MI. Considering the problems caused by rounding off variables and the importance of using the correct MI method for the type of variables imputed, the model constructed in Amos was used as the guideline for imputation in SPSS (hybrid approach). Checks of the multiply imputed variables from SPSS showed that they maintained the structure of the original variables with similar means, standard deviations and standard errors. The imputed variables were not statistically different from the original variables (p = 1.000). The MNAR school had a higher mean for all items in comparison with the other schools in the test. This pattern was maintained by the MI model, with the multiply imputed anchor items of the MNAR school having a 4.5% higher mean than that of the other schools after imputation. This is similar to the original pattern of the other items in the assessment, which had on average 6.0% higher means for the MNAR school items (see Figure

8). The impact of the MI on the measurement model was also investigated and it was found that the item and person parameters remained stable and highly correlated with the original estimates. However, for the MNAR school, it should be noted that the imputations increased the standard error.

5.7 Conclusion

MI is mainly conducted by assuming data are MAR or MCAR and the imputation variables are used as both predictors and imputed variables. Imputations are often conducted without checking the accuracy of the predictors (Kim & Shao, 2014; Osbourne, 2013). Factors such as the missingness mechanism, the strength of the predictors in the MI model, variable types for imputation (such as dichotomous items) and ways to improve the MI model should be considered and the statistical validity should be strengthened. MNAR data are especially challenging to handle and this paper is one demonstration of how to take important factors into consideration and to use MI for dichotomous MNAR items. Other applications have been carried out with different types of MNAR data and in various disciplines using a variety of approaches (see for example Galimard et al., 2016; Poleto et al., 2011; Wang et al., 2017). The study described in this paper adds value due to its realistic set up, and demonstrates a single application of MI using SEM to model the missingness and Rasch scores as predictors. If missingness can be modelled, then the best identified model can be used to specify the imputation process. The usefulness of Rasch scores as predictors was also explored, as well as the impact of MI values on the measurement model. The following steps were used and could be considered for similar studies:

(1) The missingness mechanism was known, and correlations of demographic and other variables with the missing values were calculated to find potential predictor variables.
(2) The MNAR data were modelled with Structural Equation Models (SEMs) to find the model that best predicted the missingness mechanism.
(3) Predictors were identified by calculating the correlations among imputation variables, as well as composite scores (outcome variables) and demographic variables. Only predictors that had significant correlations with the imputation variables were used in the model. Rasch scores were used as they had higher correlations with the anchor items than raw total test scores (imputation variables).
(4) Logistic Regression Multiple Imputation was utilized for the dichotomous anchor items.

(5) The imputation model was checked statistically by comparing the imputed variables with the original. For the Structural Equation Model, the convergence statistics, goodness of fit and other indicators, such as graphs and plots were checked for evidence of convergence and goodness of fit. A pseudo R^2 was calculated for the model.
(6) The measurement model was assessed by comparing how the imputations affected the item and person parameters.

Multiple Imputation has become less complicated to apply, particularly with the availability of statistical programs. Thus, the onus rests on the researcher to investigate the underlying assumptions before applying MI and finding the most accurate models with which to predict the missing data (Fielding et al., 2008). It also highlights the importance of strong predictors in MI models and checking the imputation model after imputations have been completed.

This study was conducted on a relatively small sample (N = 358) and it is suggested that larger studies with more dichotomously scaled items or ordered categorical variables could expand knowledge in this area. Several methods are available to deal with MNAR data, including many different software packages (Mayer et al., 2012). It is recommended that researchers learn how to handle missing data with software they are familiar with and that they should examine the advantages and disadvantages of their software for imputing missing data. Researchers should take into consideration assumptions of imputation models, limitations and sensitivity analyses when handling missing data. More research is needed in educational and psychological disciplines so that guidelines can be established for imputing data for special cases, especially where anchor items are concerned, as well as for MNAR dichotomous test items.

Chapter 6 - Evaluating Anchor Items and Reframing Assessment Results through a Practical Application of the Rasch Measurement Model

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6.1 Abstract

The monitoring of learning over time is critical for determining progression within and across cohorts of learners. This research investigated the use of the Rasch Measurement Model to determine the functioning of anchor items as well as an application of the model to convert the results to the same metric. A group of 321 Grade 8 learners and the same in the following school year wrote English Additional Language Comprehension Tests aimed at monitoring learning progression over years. The two tests were linked with 15 anchor items. This study examined the results of the anchor items from Years 1 and 2, applying non-parametric statistical tests as well as the Rasch Partial Credit Model to identify items which did not contribute to monitoring learning progression; these items were removed or refined based on the results and reviews by subject specialists. Learner results from Grades 8 and 9 were placed in the same frame of reference by applying the Rasch Partial Credit Model in order to establish a more accurate representation of the magnitude of learning progression. The first finding illustrated that applying non-parametric statistics and Rasch Measurement Theory identifies potentially problematic anchor items, and that when items are improved or removed, the overall results tend to be more stable and precise. Second, it was found that when applying Rasch item and threshold calibrations to assessment results, a more accurate indication of learning progression is obtained which can be used to communicate results to stakeholders and more importantly, inform teaching and learning.

Keywords

Anchor items, item and threshold calibration, monitoring learning progression, Rasch Measurement Model, Rasch Partial Credit Model, stacking

6.2 Introduction

The accurate monitoring of learning progression is a key issue in psychological and educational assessment design. Designing anchor items, finding methods to analyse such items for tracking learning progression, and reporting these findings in useful ways is crucial if monitoring systems are to serve their purpose and have a positive influence on educational settings (Wilson, 2009).

Monitoring change in learner understanding over time is a complex task and fraught with difficulties. This might well be the reason for a shift in thinking regarding interventions to focus on the issue of teacher training and measuring change in teacher understanding of the content topic over time (Cunningham & Bradley, 2010). One of the major challenges of monitoring learner progression is controlling for extraneous variables, especially where the cognitive development of learners is concerned. This article examines ways in which to determine the usefulness of anchor items as well as the application of the Rasch Measurement Model (Rasch Measurement Theory [RMT]) to more accurately report on learning progression.

Monitoring progress is significant for a variety of reasons, which include providing accountability and information for citizens on the quality of an educational system. Measuring change over time is challenging, with some studies finding less predictive validity for interim measurements throughout the year (Petscher, Cummings, Biancarosa & Fien, 2013) while others show the value of interim monitoring for predicting future performance (Safer & Fleischman, 2005; Scherman, 2007). Identifying ways to monitor performance is of utmost importance, and finding ways in which to do so accurately even more so (Bercher, 2012; Scherman, 2007). Proponents of external assessments, as well as critics of such systems, have, for decades, argued about the value of monitoring (Popham, 1987). This raises a key question about the value attached to the monitoring system, as learners, teachers, schools, or external agents may perceive its significance in various ways (Williams & Ryan, 2000). The impact of the assessments will, however, be determined by the nature of the feedback and the manner in which the results are used to inform the schooling system (Lyon, Gettman, Roberts & Shaw, 2015; Stecker & Fuchs, 2000; Van Acker, 2002). A balanced and fair perspective is needed of the role that monitoring assessments play in the schooling system and the value attached to them.

For this study, an association of independent high schools, with an external funding agency, requested the development of a monitoring system to determine the level of teaching and learning across a group of schools. The testing system was intended to serve as an accountability system but had an added advantage in that it was specifically designed to give feedback on performance to schools, teachers, and learners. The English Additional Language, Mathematics and Natural Science assessment instruments were designed, piloted, and refined, to be administered at the end of each year to all learners in Grades 8–11. Upon further discussion, it was determined that tracking learner progression should be an additional aim of the monitoring system. Anchor items were designed for the three subjects to link the grades (8–11) and monitor learning progression. The schools recruit from low resourced communities and low functioning schools, focusing on learners who have the potential to perform better if placed in a resource-rich environment. The medium of instruction at the schools is English but as learners are not English Home Language speakers, English as an additional language is offered for learners to acquire and develop the English language skills necessary for learning. This context has made it crucial to track learner progression, to ascertain whether the schools have made a difference beyond that of expected development, and the level of development that could have been expected if learners had remained in their previous educational environments.

During the progression of the study, the researchers became critically aware of the challenges of monitoring learning progression, especially in the case of language development as a medium for learning in second language speakers. The design of the tests presented both measurement and conceptual challenges. One of these challenges was tracking learning progression in a subject such as English Additional Language, when the processes of language development are so integrated, complex, and varied. Another difficulty was measuring learners in the same frame from year to year, so that measurement is done consistently despite the fact that learners have changed within that year (developed into new versions of themselves). Learners constantly develop and change, and therefore one cannot assume that using the same items would result in measuring the same persons in the same way. This study examined and compared anchor items in the Grade 8 and Grade 9 English language comprehension assessments, both the total scores of the anchor items and the scores of the individual anchor items. Parametric and non-parametric statistical tests, as well as the Rasch Partial Credit Model, were applied to address the following research questions: (1) To what extent does each anchor

item contribute to tracking/monitoring progression? (2) How can the Rasch Measurement Model be used to more accurately monitor learning progression and report results?

6.3 Method

6.3.1 Participants

Schools in the association are found in rural Limpopo, near Durban in Kwa-Zulu Natal, two schools near Cape Town and three schools in Gauteng located in or near informal settlements. All seven schools were included in the study which meant that all learners participated; therefore, the full population was assessed. As the schools follow a unique implementation of the curriculum, and is structured differently in terms of smaller class size, providing Saturday and holiday classes resulting in a more intensive focus on academic achievement, the learners are considered to be a specific population with unique characteristics.

A total of 321 learners wrote the English Additional Language comprehension test at the end of Grade 8 in November 2012, and then wrote a different English Additional Language comprehension test at the end of Grade 9 in November 2013; however, both tests had an anchor passage with 15 shared items based on that passage. In November 2012, the learner mean age was 14.1, and in November 2013 the mean age was 15.1, resulting in an age range of 5.78 and a standard deviation (*SD*) of .653. A total of 96% of the sample ranged between the ages of 13 and 15 years for Grade 8 and between 14 and 16 years for Grade 9, a range that is within the grade appropriate range. More girls (78%) than boys (22%) constituted the sample which included a girls-only school as well as other co-educational schools. However, these tended to have more girls (65% on average) than boys as schools reported that it was easier to recruit girls than boys. As previously mentioned, learners were English additional language speakers but received instruction through the medium of English language.

6.3.2 Instruments

The assessment instruments were two English Additional Language Comprehension tests, one designed for Grade 8 and the other for Grade 9 learners. Both instruments had 15 common items based on the same anchor passage. The tests were designed by subject specialists, piloted, refined, and continuously updated so that they were aligned with the South African national curriculum (Curriculum Assessment Policy Statements [CAPS]). The two language tests

showed high reliability, with the Grade 8 test having a person reliability index of .83, and an item reliability at .98 (Real root mean square error [RMSE]). The Grade 9 test had a person reliability index of .81 and an item reliability of .98 (Real RMSE). (Additional information on Rasch reliability indices is provided in the 'data analysis' section).

6.3.3 Procedure

The data collection took place in November of each year, and all learners in Grades 8–11 in the seven schools wrote the English Additional Language, Mathematics, and Natural Science assessments over 2 days. The assessments were administered by the monitoring agent and administration procedures were standardised. Learners were instructed to answer the assessments to the best of their ability, and were assured that feedback on their performance would be given and that the results would inform classroom practice. The tests were scored by specialist teachers and then moderated, after which all data were captured on item level and analysed. The results were reported to the teachers, principals, and the funding agent, all of which was facilitated through interactive workshops.

6.3.4 Ethical considerations

Ethical clearance was obtained from the Faculty of Education at the University of Pretoria. The names of the learners, their parents, school personnel, and names of the schools were strictly confidential. All steps were taken to ensure the conduct of an ethical research project, which included obtaining informed assent from learners older than 16, full disclosure of how results would be used, and consultation with stakeholders. Learners younger than 16 years old obtained signed consent from their parents, whereas learners 16 years or older submitted both a signed parental consent form as well as an assent form. The results were fed back into the school system via interactive workshops with teachers to enhance both teaching and learning and thus benefit all stakeholders. Learner motivation can be challenging when administering external monitoring assessments. To encourage learners to participate fully, learners were given content-level feedback with detailed descriptions of the skills and knowledge gained in curriculum areas as well as new areas on which to focus. These reports were also sent to teachers and parents. The possibility of including assessment results as a small percentage of the final school mark was considered, but schools felt that this may disadvantage learners as these assessments do not require prior study. However, learner results for English Additional Language correlated highly with their school marks ($r = .756$, $p < .01$), providing concurrent

validity that learners were performing at expected levels and were motivated to complete the assessments as fully as possible. When learners were queried on their motivation to complete the assessment, 10% responded *not very*, 48% *moderately*, and 42% responded being *highly motivated*.

6.4 Data analysis

Rasch person and item reliabilities were used to assess the functioning of the instruments. Reliabilities are calculated slightly differently in RMT than in Classical Test Theory (CTT). CTT would calculate reliability on an overall standard error of the mean, whereas Rasch theory calculates the standard error for each item or person. CTT uses Cronbach's alpha as an indication of reliability as it is hypothesised that all items should correlate highly in one construct (Gliem & Gliem, 2003). RMT deviates from this model because in RMT, there is an assumption that items differ from one another because they should measure different difficulties (points) along the continuum (Clauser & Linacre, 1999; Linacre, 1997). RMT refers to reliability values as separation indices and Linacre (2011) sets a minimum value of 2 as an acceptable value for the person index, and for the item index, a minimum value of 1.5 is required to measure individuals. Therefore, the reliability index is an indication of overall error of measurement in the data, which is the reason Rasch theory uses the measures' standard errors to calculate the indexes for persons and items. Person reliability is equivalent to the traditional Cronbach's alpha, with reliabilities above .80 indicating 2–3 groups of ability being identified in the sample. Item reliability has no traditional equivalent, but indicates whether a sample is big enough to locate persons on the latent trait (Boone, Staver & Yale, 2014).

> *Measurement of change presents a nasty challenge. We expect persons (patients, learners, experimental subjects) to change from Time 1 to Time 2. But the functioning of test items and rating scales may also change, even when identical data collection protocols are used. (Wright, 1996, p. 478)*

According to Linacre (2011), a rule of thumb is that a minimum of 10 common items is needed to prevent distortion of the measurement by problematic items. After problematic items are removed, 10 items should remain. To examine the functioning of the 15 anchor items, items were examined using several methods. First, the raw total percentages for the anchor items from Year 1 (Grade 8) were compared with Year 2 (Grade 9) using paired samples *t*-tests to

obtain a global view of whether all items, as a total score, indicated change from Grade 8 to Grade 9. Next, the mean raw scores per item were examined and Wilcoxon's Matched Pairs Signed-Rank Test was applied to assess whether these raw scores indicated statistically significant change. Effect sizes were calculated to determine the magnitude of the differences found when applying *t*-tests and the Wilcoxon (Field, 2013). Effect sizes were calculated using Pearson's Correlation coefficient, *r*, as a standardised measure of effect size (Tabachnick & Fidell, 2007). After conducting statistical tests on the raw scores, the Rasch Partial Credit Model was applied independently to each year, then to stacked data and finally, calibrations were applied to the Grade 9 anchor items. The Partial Credit Model was utilised as some items were dichotomous and others were polytomous. The processes are described in more detail below. The total sample size was 321, with the schools being considered a population.

6.5 Results

The raw total score percentages for Grades 8 and 9 were compared using the paired samples *t*-test to ascertain whether the results from the items indicated change from Years 1 to 2. Grade 9 learners achieved discernibly higher mean score percentages (M = 46.631, SD = 16.558) than in Grade 8 (M = 35.826, SD = 14.245). Pearson's correlation coefficient was used as an effect size and Cohen's criteria for interpreting effect sizes applied (Cohen, 1988; Field, 2013). The results were significant, $t(320) = 13.102$ ($p < .0001$) as can be seen in Table 6.1. A large effect size, $r = .591$, was found for the differences between the Grade 8 and 9 results.

To investigate the usefulness of each item, the raw scores were examined. The items were dichotomous with the exception of Item 8 (maximum score 3), and Items 11 and 15 (maximum score 2). The dichotomous items were multiple-choice, whereas the other items were constructed-response. In Winsteps, the guessing parameter can be estimated. Note that this is still the one parameter model being applied, and the parameters for guessing are estimated but do not form part of the calculation for the measures, either persons or items. With the Rasch Measurement Model, guessing and carelessness would be classified as misfit, which is why it is not parameterised when the data are fit to the model. When examining the output for an estimation of the guessing parameter, Linacre's guideline for a lower asymptote of .10 or greater, was used. However, none of the problematic items had asymptotes greater than .10, and therefore, guessing does not appear to be a reason for the possible problematic nature of the items.

Most items followed the expected pattern: learners performed better in Grade 9 than in Grade 8 and this fits the expectation of the measurement model, with progression indicated by the anchor items. However, Items 5, 11, and 15 produced means which were very close in both Grades 8 and 9. Items 5, 11, and 14 show a reversal of the expected pattern, with learners performing better in Grade 8 on these items than in Grade 9. However, further investigation showed that for Items 5 and 11 this reversal was not statistically significant (see Table 6.1).

Table 6.1 Paired t-tests between Grade 8 mean score and Grade 9 mean score

	Paired differences					*t*	*df*	Sig. (two-tailed)
	M	*SD*	Std error mean	95% confidence interval of the difference				
				Lower	Upper			
Grade 9 mean score – Grade 8 mean score	10.805	14.776	.825	9.183	12.428	13.102	320	.000

Table 6.2 shows the means for each individual item for Grades 8 and 9 as well as the mean difference between the years.

Table 6.2 Item means based on raw scores and mean difference

Item	Max score	Mean Gr.8 Nov 2012	Mean Gr.9 Nov 2013	Mean difference
Q1	1	.20	.30	.10
Q2	1	.37	.63	.26
Q3	1	.52	.75	.23
Q4	1	.50	.63	.13
Q5	1	.96	.95	–.01
Q6	1	.64	.78	.14
Q7	1	.39	.60	.21
Q8	3	.20	.71	.52
Q9	1	.41	.54	.13
Q10	1	.39	.55	.16
Q11	2	.61	.59	–.02
Q12	1	.41	.66	.25
Q13	1	.58	.86	.28
Q14	1	.94	.74	–.20
Q15	2	.11	.20	.09

N = 321.

The Wilcoxon Signed-Rank Test compared items from Grade 8 to Grade 9 (missing values excluded listwise, $N = 205$) (see Table 6.2). A significant difference in the scores for most of the item pairs from Grade 8 to Grade 9 was discerned, with the exception of four pairs, Items 4 ($p = .088$), 5 ($p = .491$), 11 ($p = .298$), and 13 ($p = .166$) which were not statistically significant when the 2 years were compared (see Table 6.3). This result suggests that these particular item pairs do not monitor English Additional Language comprehension development as intended by the designers.

All items in Table 6.3 were based on positive ranks, indicating a positive increase from Years 1 to 2 (increase in mean from Grades 8 to 9 which was the aim). The only exceptions were Item pairs 11 and 15, which were based on negative ranks (decrease from Years 1 to 2) and also identified as being potentially problematic in the descriptive examination.

Table 6.3 Wilcoxon signed-rank test of anchor items from years 1 to 2

	N	*Z*	Asymp. sig. (two-tailed)	Gamma[a]	*r*
Pair 1 – Q1	205	–3.151[b]	.002	.538	–.220
Pair 2 – Q2	205	–5.315[b]	.000	.445	–.371
Pair 3 – Q3	205	–4.696[b]	.000	.444	–.328
Pair 4 – Q4	205	–1.706[b]	.088	.310	–.119
Pair 5 – Q5	205	–□.688[b]	.491	–.075	–.048
Pair 6 – Q6	205	–4.032[b]	.000	.496	–.282
Pair 7 – Q7	205	–6.333[b]	.000	.630	–.442
Pair 8 – Q8	205	–5.340[b]	.000	.470	–.373
Pair 9 – Q9	205	–2.251[b]	.024	.381	–.157
Pair 10 – Q10	205	–3.022[b]	.003	.491	–.211
Pair 11 – Q11	205	–1.041[c]	.298	.178	–.073
Pair 12 – Q12	205	–5.126[b]	.000	.226	–.358
Pair 13 – Q13	205	–1.387[b]	.166	.257	–.097
Pair 14 – Q14	205	–5.969[b]	.000	.433	–.417
Pair 15 – Q15	205	–3.072[c]	.002	.023	–.215

$N = 206$, missing data excluded listwise.
[a]Measure of association for ordinal variables.
[b]Based on positive ranks.
[c]Based on negative ranks.

Item Pair 11 was not statistically significant in its change, but in the case of Item Pair 15, further investigation was recommended. The gamma statistic shows the association between the pairs of items. Item 5 ($\gamma = –.75$), Item 11 ($\gamma = .178$), and Item 15 ($\gamma = .023$) resulted in very low

associations. Most of the items, which were not statistically different from Years 1 to 2, also produced low or no effect sizes, as can be seen for Item 5 ($r = –.048$), Item 11 ($r = –.073$), and Item 13 ($r = –.097$).

The descriptive statistics identify many of the same items as being problematic, as identified by the Wilcoxon Signed-Rank Test, such as Items 5, 11, 15 (mean differences marginal) and Items 5, 11, 14 (reversal of expected pattern). The descriptive statistics gave an indication of potential problems with items. The non-parametric statistical tests assessed whether what was observed via descriptives, was statistically significant and gauged the magnitude of differences (effect sizes and association). The non-parametric statistics, used to analyse the items, also identified additional problematic items, such as Item 13 which was not, however, significantly different from Years 1 to 2 ($p = .166$). These findings highlight the need for examining the descriptive results and also conducting statistical testing to confirm results and identify additional problems. As a result of the findings, subject specialists examined the items identified as potentially not adequately assessing change, and consequently rephrased Items 11, 13, and 14.

The subsequent step was to apply the Rasch Measurement Model to the data, using Winsteps 3.75.0 (Linacre, 2016) to confirm the findings of the raw score analysis, to ascertain whether the items identified as potentially problematic should be removed, and in addition, to estimate the proficiencies of the persons in relation to the item difficulties on the same scale.

6.5.1 Independent Rasch analysis

The anchor items and all other items from the Grade 8 test, were entered into Winsteps for analysis, with the same being done for the all Grade 9 test items. The item difficulties, with the measures from the independent analysis rescaled from 0 to 100, were exported for both sets of items. The independent Rasch analysis revealed that the anchor items were very stable, with item difficulties from Time 1 and Time 2 having a correlation of $r = .882$, $p < .01$ (see Figure 6.1). Item 5 was identified as more difficult in Time 2 ($M = 29.47$) than in Time 1 ($M = 27.06$) showing that the item is less stable and has disordered thresholds. The same is true of Item 15 (Mean $T1 = 48.81$, Mean $T2 = 57.80$). Figure 6.1 depicts the item-measures from Time 1 and Time 2 plotted with 95% confidence interval lines in Winsteps using Pearson's correlation coefficient, with Item 15 lying well outside the 95% confidence interval. The empirical slope

was 1.023, satisfactorily close to 1. From the independent Rasch analysis, Items 5 and 15 are indicated as less stable items for measurement.

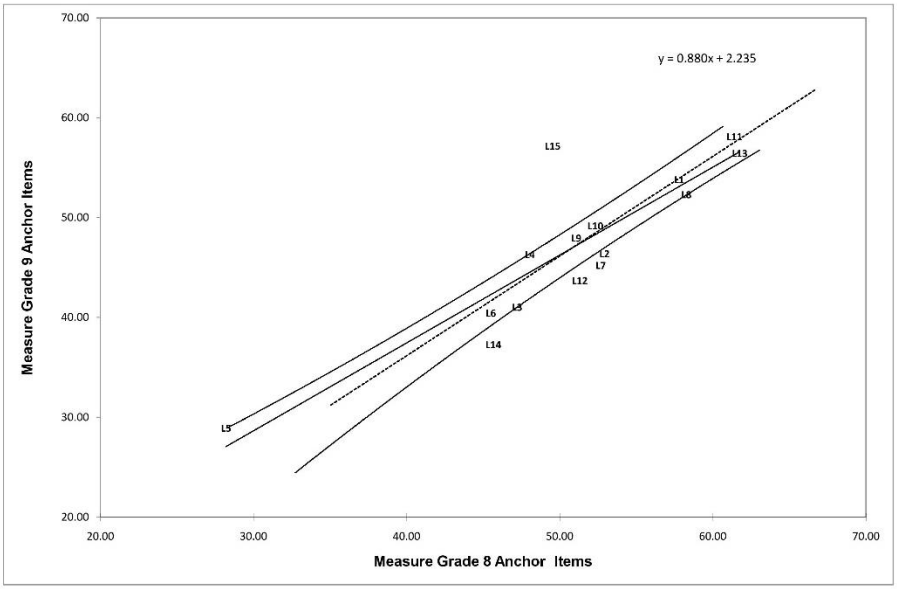

Figure 6.1 Item-measures based on independent Rasch analysis

The person and item indices were also examined as these are related to the interpretations of the independent analysis and the precision of the assessment (see Table 6.3 for a summary of the indices). The person separation indices were above the acceptable cut-off point of 2, and the reliabilities were also within a suitable range with values above .70 (Wright & Stone, 2004). The item separation indices fell well above 2 and the item reliability coefficients were found to be satisfactory, all falling within the prescribed criteria (Bond & Fox, 2007; Boone et al., 2014; Fisher, 1992).

The infit and outfit mean square statistics (MNSQ) showed that no items were misfitting for either the Grade 8 or Grade 9 data sets (no items had values above 1.5) and there were no negative point measure correlations (Wright & Linacre, 1994). A total of 2 out of 321 persons had high outfit statistics in the Grade 8 group with none occurring in the Grade 9 group. The high fit statistics were below 2, indicating that the persons were neither adding to the measurement nor detracting from it (Linacre, 2016).

The threshold functioning of items with polytomous scales was also examined, and only Item 8 was found to have disordered thresholds (outfit MNSQ above 2.00 for one category, number 2). Item 8 had four categories (0, 1, 2, and 3) and based on RMT results, Categories 1 and 2 were collapsed. After collapsing these two categories, Item 8 no longer displayed disordered thresholds. Further analysis was conducted with collapsed categories for Item 8. When examining the raw means of each item, Items 5, 11, 14, and 15 had potential problems (means close or reversal of the expected pattern).

Table 6.4 Person and item statistics for independent analysis (all items)

	Person		Item	
	Separation	Reliability	Separation	Reliability
Independent Gr.8 Assessment	2.22	.83	8.07	.98
Independent Gr.9 Assessment	2.09	.81	7.57	.98

The Wilcoxon Signed-Rank test showed that Items 4, 5, 11, and 15 may be problematic (low associations and not statistically significant). The Rasch analysis showed that Items 5 and 15 were less stable for measurement. Based on the fact that Items 5 and 15 were indicated by all the methods as potentially problematic items, these were examined by English language specialists. Based on a qualitative analysis by the language specialists, these two items were removed from the analyses and the instruments. In Table 6.4 the indices are shown for the independent analysis.

6.5.2 Stacking of data for second Rasch analysis

Stacking was done to measure persons in a more similar frame of reference, thus stacking persons from Time 1 and Time 2 in one data set. After the stacking of the data, the person-measures from Time 1 and Time 2 had a stronger relationship, Pearson Correlation coefficient, $r = .697$ ($p > .01$; $N = 642$). The measurement of persons could now be done in a more comparable framework, though they were not as yet in the exact same framework (Wright, 1996, 2003). However, the stacked analysis did not result in any persons showing high infit or outfit MNSQ values. Local dependence of items was also investigated and no test items were correlated above .41, which was well below the recommended number of .70 indicating that

items were independent (Linacre, 2016). All items from both tests were included in the analysis.

The total variance explained by a principal component analysis (PCA) conducted in Winsteps was 46.9%. The unexplained variance in contrast 1–3 was above the 2.0 threshold, with residual variance being between 1.9% and 2.5% and variance explained being between 1.1% and 1.5%. The PCA residual variance statistics indicated that the stacked data may contain more than one dimension, possibly due to the presence of data from two different years.

Figure 6.2 shows a visual representation of the relationship between the Grade 8 and Grade 9 person-measures (stacked), rescaled from 0 to 100.

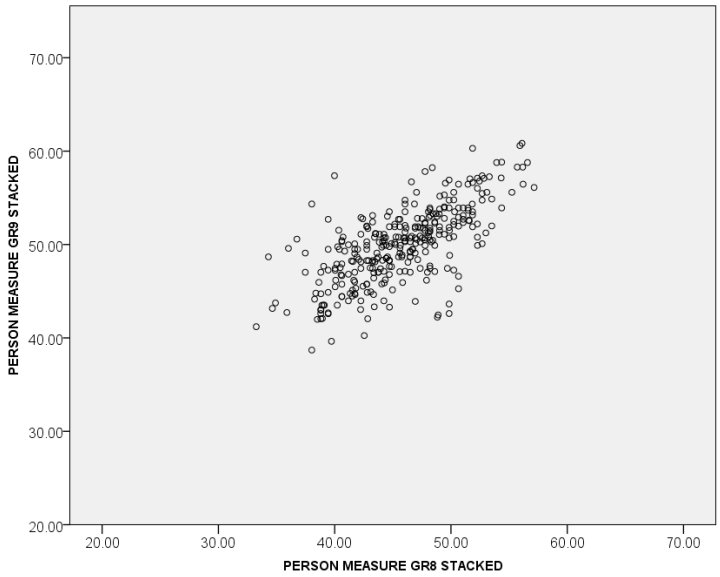

Figure 6.2 Person measures based on stacked Rasch analysis

Table 6.5 contains a summary of the indices for the stacked analysis. The person separation index was above the cut-off point of 2, and the reliability for the persons was acceptable, above .80 (Boone et al., 2014).

Table 6.5 Person and item statistics for stacked analysis of anchor items

	Person		Item	
	Separation	Reliability	Separation	Reliability
Stacked	2.41	.85	7.85	.98

The item separation indices were again well above the satisfactory levels and also recorded an increase. The reliability estimates, calculated in Winsteps, were mainly based on sample ability and item difficulty variance, length of the instrument and rating scale length, number of categories, sample to item targeting, and sample size (Linacre, 2016).

The wider the range of ability and item difficulty, the higher the reliability estimate. The same holds for the length of the instrument, as more items could result in higher reliabilities and if items are well targeted, reliability estimates are also likely to increase (see Tables 6.4 and 6.5).

Table 6.6 Grade 8 and Grade 9 independent measures calibrated descriptives

	M	*N*	*SD*	Std error mean
Grade 8 measure	46.946	321	4.607	.257
Grade 9 measure (calibrated)	52.031	321	4.133	.231

Pre-test standardised residuals were correlated with post-test standardised residuals, resulting in correlations ranging between –.02 and .20, an indication that dependency was not a problem in this analysis.

Table 6.7 Paired samples t-tests between Grade 8 independent and Grade 9

	M	*SD*	*Std error*	*Lower*	*Upper*	*T*	*DF*	*Sig*
Grade 8 measure – Grade 9 measure (calibrated)	5.085	3.478	.194	4.703	5.467	26.191	320	.000

6.5.3 Item calibrations applied to time 2

In this step, the benchmark item and threshold calibrations from Time 1 were applied to Time 2 so that Time 2 could be measured with the same metric. The results indicate significant growth in English Additional Language comprehension from Years 1 to 2. To assess the significance of the growth, a paired sample *t*-test comparison of the Grade 8 and Grade 9 person-measures was done (see Table 6.6 for Grade 8 independent and Grade 9 measures calibrated descriptives and Table 6.7 for paired samples *t*-tests between Grade 8 independent and Grade 9 measures calibrated results).The results indicate growth from one year to the next,

with Grade 9 (M = 52.031, SD = 4.133) having a substantially higher mean than Grade 8 (M = 46.946, SD = 4.607). A paired samples t-test yielded $t(320) = 26.191$, $p < .0001$. This result is statistically significant and the effect size indicates a very large difference from Years 1 to 2, r = .826 (Smith & Stone, 2009).

6.6 Discussion

Rasch modelling allows for the interval ordering of both persons and items. Stacking creates the possibility of comparing different time periods so that persons assessed at different times can be measured with the same metric. This article illustrates measurement of change with Rasch models, using stacking methods. Raw score analysis revealed that the anchor items overall and total score showed learning growth and progression. However, further investigation identified some individual items which might not measure change as these items showed little or no difference from one year to the next and potentially could reveal a reversal of the expected pattern. Applying the Rasch Measurement Model in an independent analysis, with the 2 years being entered separately for analysis, showed that the items functioned well overall but two items were found to be less stable for measurement (Items 5 and 15). These two problematic items were therefore examined by subject specialists and after discussions, the items were removed for future analysis. One polytomous item also had disordered thresholds and to address this, the two problematic categories were collapsed.

In the stacking of data, persons were entered twice as though they were two different people, to measure persons in a similar framework and to determine how well person-measures correlate. This illustrated that person-measures correlated moderately well and that the calibrations should be applied for a more precise comparison. The final step, using the Rasch Measurement Model, was to apply the item and threshold calibrations from the independent analysis of the baseline, that is, Grade 8 results from Time 1 to the Grade 9 results from Time 2. When persons were measured in the same frame, a more accurate indication of growth was available and paired sample t-tests were done to compare the development from Grade 8 to Grade 9, which resulted in a large effect size. A visual representation of the processes followed is given below (see Figure 6.3); these processes determined whether each item contributed to measurement and then finally measured the persons in the same frame of reference.

The advantages of using the Partial Credit Rasch Model included more accurate measurement of the longitudinal results. Both the raw score analysis and the Rasch modified results showed large effect sizes (r = .591 and r = .826). However, the mean score differences between Grade 8 and Grade 9 for the final analysis was smaller than that of the raw score analysis, with mean difference for raw score = 10.805 versus mean difference for calibrated results = 5.085. These differences are attributed to the refinements made to the anchor items, such as collapsing categories for Item 8 and removing Items 5 and 15 (see 10.5 Appendix E: Evaluating anchor items study - removed items). Also important was the application of the threshold calibrations, which were applied in the revision of the assessment instruments. All of these changes have resulted in more precise indications of change from Time 1 to Time 2.

The sample was well placed for measuring improvement using anchor items as the learners in the sample came from impoverished backgrounds, and had previously attended low-resourced schools. The anchor items assisted in identifying a significant difference in English Additional Language performance from the time the learners entered the schools (end of Grade 8) to having had a year of schooling in these changed circumstances (end of Grade 9). It is important to note that at the time, the coalition schools began at Grade 9 level and as such, had no Grade 8 track; therefore, learners were tested prior to or just after entering the new school system. This study illustrated that the use of the Rasch Measurement Model assists in refining the anchor items and enhances reporting the final results in the most accurate frame of reference. These results were then fed back into the school system so that teachers and learners could benefit from the monitoring system which would thus inform teaching and learning.

6.7 Conclusion

This article found that the usefulness of anchor items for monitoring learning progression can be gauged by conducting non-parametric tests and applying the Rasch Measurement Model through independent analysis and stacking analysis. Improvement of anchor items is important for gaining a clear picture of the progression made by learners, especially for an external monitoring agent that also feeds back into the school system. Earlier it was noted that one of the problems associated with monitoring learner progression is that learners develop and essentially become different persons. The Rasch Measurement Model controls for this shift by applying item and threshold calibrations so that persons are measured in the same way from Time 1 to Time 2. This also gives clearer results of the change that took place and whether this change is beyond mere development.

Figure 6.3 Processes followed for refining anchor items & reframing results

Chapter 7 - The Use of Rasch Competency Bands for Reporting Criterion-Referenced Feedback and Curriculum-Standards Attainment

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7.1 Abstract

This study describes how criterion-referenced feedback was produced from English Language, Mathematics and Natural Sciences monitoring assessments. The assessments were designed for grades 8 to 11 to give an overall indication of curriculum-standards attained in a given subject over the course of a year (N=1113). The Rasch Item Map method was used to set cut-scores for the Rasch competency bands, after which subject specialists examined the items in each band. Based on the content and difficulty of the items, descriptions for the proficiency levels were generated. Learner reports described each individual's current proficiency level in a subject area as well as the subsequent level to be attained. This article shows how the Rasch Item Map method can be used to align assessments and curriculum-standards, which facilitates reporting learner performance in terms of criterion-referenced feedback and empowers learners, teachers and parents to focus on subject content and competencies.

Keywords: Rasch competency bands, proficiency levels, criterion-referenced feedback, Rasch Item Map method, curriculum-standards, reporting learner performance

7.2 Context

There is a growing realisation worldwide of the importance of learner content-focused feedback as opposed to only providing norm-referenced feedback (Bennett, Tognolini & Pickering, 2012). Norm-referenced feedback is based on numbers, means achieved as well as a comparison of a learner or groups of learners to others in the cohort(s). But with standards-referenced feedback, also known as criterion-referenced feedback, the spotlight is on informing learners about what they know and how they can increase their knowledge and skills (Bennett et al., 2012, Long, Dunne & Mokoena, 2014). Standards-referenced feedback is crucial for meeting curriculum requirements as the criteria are based on learning standards set in curriculum documents (Great Schools Partnership, 2014). The alignment of assessments to curriculum-standards is linked to this type of feedback. Therefore, assessments would be designed to provide diagnostic information and feedback in order to inform teaching and learning.

This article specifically investigates methods using external and internal monitoring assessments for deriving standards-referenced feedback, which serves the purpose of developing accountability and a measure for comparability as well as presenting a method for deriving criterion-referenced feedback. The argument is made that by offering feedback that is content specific and linked to curriculum-standards, monitoring assessments, which comprise systemic evaluations, large scale studies and standardised tests in the schooling system, can serve the additional purpose of enhancing teaching and learning. Content-specific feedback is empowering to teachers and learners and when monitoring assessments are utilised, all stakeholders, including the participants, should benefit from the testing system (Long et al., 2014).

7.2.1 Large scale assessments for norm and criterion-referenced feedback

Systemic and standardised tests are generally not utilised for diagnostic purposes, though such applications could contribute to an impact on the system they evaluate (Khosa, 2013). The main goal of most systemic testing systems is to serve as indicators of performance levels, mainly for norm-referenced comparison and for quality assurance in education (Jiao et al., 2011; Osman et al., 2008). Designing criterion-referenced tests can be time- and resource-intensive but has advantages that benefit those being tested and the systems in the long-term (Stone, Beltyukova & Fox, 2008). Such advantages include monitoring a system but also improving

its functioning by identifying attained curriculum standards and pinpointing the next achievable levels. This approach taps into the notion of competency as moving along a continuum (Griffin, Gillis & Calvitto, 2007).

Criterion-referenced results give feedback in terms of what skills and knowledge a person has gained, whereas norm-referenced feedback focuses on comparing a person to others in terms of achievement. The study described in this article has utilised criterion-referenced and norm-referenced feedback approaches, using the monitoring assessments to provide learners, teachers, parents, principals and funders with criterion-referenced and norm-referenced feedback. Norm-referenced feedback gave schools learner-level insight into where their school's achievement was located in relation to other schools. Criterion-referenced feedback gave insights into school-level proficiency levels and curriculum standards achieved by learners, in addition to offering subsequent target levels for teachers. During interactive workshops, teachers and subject specialists discussed ways in which the results could be used in developing/initiating interventions and thus enhancing classroom practice.

7.2.2 Learner-level feedback as an ethical application of large scale assessment

Large-scale assessments, such as standardised testing and systemic evaluations, are time consuming and expensive (Khosa, 2013; Popham, 1987). Time is taken from teaching and learning while results are generally used to broadly inform policy and not necessarily to give feedback to learners, teachers and parents. Providing learner-level feedback by using methods such as the Rasch Item Mapping method, is one way of assessing in a more ethical manner as participants can benefit more directly by receiving feedback which is explicit and useful due to its content-based nature (Long et al., 2014). By providing criterion-referenced feedback, teachers can also benefit from the assessments as they become aware of specifically attained curriculum standards and how to structure their teaching to target standards which have not been fully achieved. Giving criterion-referenced feedback could also contribute to learner motivation (Boone, Staver & Yale, 2014). If learners realise that the testing does not influence their academic performance, they could be less motivated to write such assessments. In contrast, if learners understand that they will receive usable feedback, which will also be disseminated to their parents and teachers, they could be more motivated to participate fully.

7.2.3 Identifying competency levels

The idea of using the Rasch Measurement Theory (RMT) to align assessments to curriculum standards is not a new idea. Ingebo (1989) discussed the use of RMT for alignment to curriculum-standards because the Rasch Model creates an equal interval scale of curriculum tasks (items in tests) which can be used for a comparison to curriculum-standards.

> *As dichotomous items that are actually curriculum tasks are lined up and given values with respect to each other, these calibrations (values) are on an equal interval scale generated by the confluence of knowledge and position in the curriculum (Ingebo, 1989: 43).*

The use of the Rasch Model to set standards and identify proficiency levels has been demonstrated by several studies (Boone et al., 2014; Grosse & Wright, 1986; Long et al., 2014; Shen, 2001; Stone, 2000). In fact, aligning item banks to curricula with equal intervals for every item was one of the main achievements of Benjamin Wright (Ingebo, 1987). Over the course of the last 30 years, much research on the use of RMT has been conducted in the United States, Australia, Great Britain, European countries and Southern Africa (Bond & Fox, 2015; Boone et al., 2014; Wright & Grosse, 1993; Stelmack et al., 2004; Wissing, 2013). Some of the recent literature on the use of RMT for setting standards and proficiency levels are discussed next.

Holster and Lake (2015) showed how items could be scaled with the use of the Wright map for diagnostic vocabulary tests and these results can be used to identify learners needing remedial intervention. Their study also demonstrated how identifying competency levels with the Rasch Model are applicable for classroom use, curriculum planning and the refinement of vocabulary tests for placement purposes (Holster & Lake, 2015). In addition, Jiao *et al.* (2011) used the Mixed Rasch Model (multi-dimensional) to classify student performance in a simulation into proficiency levels by analysing item response patterns and the achievement represented on the latent trait by achievement. This resulted in high student classification accuracy and had the added advantage of assisting with the classification of borderline case or minimally competent students. This accurate classification was achieved by fitting the data to the Rasch Model and using the intersecting points between adjacent distributions to distinguish varying proficiency levels. Similar studies, such as that of Jiao *et al.* (2011), are needed as the findings can be strengthened by using real data as opposed to simulated data. The study presented in this article is based on empirical data and addresses the limitation of using only simulated data to illustrate the usefulness of certain approaches.

Studies utilising the Rasch Model to create competency bands are based on the theory that the item difficulty and person ability alignment reflects the complexity of the content and levels of proficiency in the content areas (Shen, 2001). Shen's study (2001) on medical licensing data compared the Angoff method, the Hofstee and the Rasch Item Map method. This study found that the Angoff method identified test subjects with expertise, whereas the Rasch Item Map method was more likely to identify those with fundamental knowledge. The Rasch and Hostee methods gave equivalent results. In the case of Shen's study, using the Rasch Item Map method made more sense, as fundamental knowledge was required to practise medicine and was more significant than specialist knowledge for those entering the field of medicine. The Rasch method also provided more criterion-referenced results whereas the other methods were more likely to yield norm-referenced results. The Rasch Item Map method was also more time efficient, as reviewing maps versus reviewing individual items takes less time. Other methods may also lack content explanations of what a standard means, a crucial aspect of reporting learner and student performance levels (Shen, 2001).

Other studies of a similar nature have been conducted with equivalent results, showing the potential advantages of using the Rasch Item Map method over that of traditional methods (Wang, 2003). Stone *et al.* (2008) demonstrated how the multifaceted Rasch Model could be used to firstly identify minimal competence and then incorporate it into the model of standard setting, especially for criterion-referenced standards when assessments are scored with rubrics. They note that the rating scale used, the unique context of their study and their sample size all influenced the outcome, suggesting that more studies of this nature are required to evaluate the applicability of modelling minimal competence in other settings. Herrmann-Abell and DeBoer (2015) used RMT to map science items onto curriculum materials to compare, with precision, how ideas are taught and how learner understanding of these ideas progress. By aligning items to curriculum standards and progression of understanding, they were able to identify areas for improving teaching and learning in the subject areas. It should be noted that Rasch methods could be combined with other methods, as Bennett et al. (2012) did; the multi-stage Angoff procedure was used in conjunction with the Rasch theory to establish performance standards in curriculum-based exams.

The research and findings discussed in this article contribute to the body of knowledge by demonstrating how monitoring assessments can also be used for standards-referenced feedback. This article explains how to establish and define progression levels, how to structure

feedback and why this is advantageous to learners and other stakeholders. The purpose of the study described here was to find ways to give teachers and learners useful feedback, more than just comparative information derived from external monitoring assessments. The aims included locating each learner on the subject area developmental continuum, defining what has been gained at each level as well as making explicit the subsequent level of development and curriculum-standard required.

7.3 Methods

7.3.1 The study

Seven independent high schools form part of an association that strives to give disadvantaged learners the opportunity to grow academically and socially. These seven schools have longer school days, smaller classes and Saturday classes to offer learners additional support. The schools have outside funding to maintain their intervention model of schooling. In order to monitor the progress of learners across schools, set an accountability system in place and to give feedback into the development of the schools academically, an educational research agency was approached to design and develop monitoring assessments. The findings discussed in this article are a component of that monitoring process.

7.3.2 Study group

One thousand one hundred and thirteen learners participated in the assessment study and the cohort for each grade differed in size (see Table 7.1).

Table 7.1 Descriptive statistics of sample (percentage by column for grades)

Grade	**Gender**					
	Male		**Female**		**Total**	
Grade 8	52	20.4%	198	23.1%	250	22.5%
Grade 9	50	19.6%	201	23.4%	251	22.6%
Grade 10	87	34.1%	232	27.0%	319	28.7%
Grade 11	66	25.9%	227	26.5%	293	26.3%
Total	255	100.0%	858	100.0%	1113	100.0%

There were 250 grade 8 learners, 251 grade 9 learners, 319 grade 10 learners and 293 grade 11 learners. More girls (77%) than boys (23%) participated in the study due to a girls-only school being included in the sample, in addition to the other schools having more female than male learners (a 60% girl: 40% boy composition). The sample sizes, overall and per grade, were judged to provide adequate power, based on the fact that the whole group participated, with the independent schools being considered a population on their own due to their unique intervention model of schooling.

7.3.3 Assessment instruments

The curriculum standards for school subjects are contained in the National Curriculum and Assessment Policy Statement Grades R-12, also known as CAPS (Department of Basic Education, 2011, 2012). The CAPS documents aim to set "minimum standards of knowledge and skills to be achieved at each grade" and this includes high, achievable curriculum standards (Department of Basic Education, 2016: 1). The documents also endeavour to show progression in content and context of each subject with development from the basic to the more complex skills and knowledge. In line with the curriculum standards as set by CAPS, subject specialists designed the assessment instruments for English Language, Mathematics and Natural Sciences for grades 8 to 11. The assessments were designed to cover the national curriculum topics that would be taught within a school year. The results provided an indication of knowledge and skills gained for a subject within a year and per curriculum area. Multiple-choice items (approximately 60% of a test) and constructed-response items were included in all the assessments. The average scores per school, per class and per learner were fed back into the system via school reports, workshops and data sets containing learner achievement. To give criterion-referenced feedback, a more qualitative approach was also sought to communicate the results, which led to the creation of content descriptive reports discussed in this article.

To determine the overall functioning of the monitoring assessments, the Rasch Partial Credit Model was applied. Rasch Measurement Theory (RMT) holds up the ideal of measurement and aims to compare real item and person responses to this ideal. Where reality diverges from the ideal is where there is an indication for potential improvement (Herrmann-Abell & DeBoer, 2015; Linacre, 2016). The Winsteps 3.75.0 programme provides in-fit and outfit mean-square statistics (MNSQ) which reveal where items and persons fit and where there is misfit (Linacre, 2012). All statistics are reported in terms of log odds units and have a range of -5.00 to +5.00

with a mean set at 0.00 and a standard deviation of 1.00 (Bond & Fox, 2015; Boone et al., 2014).

Table 7.2 shows the ranges for the Rasch item fit statistics for the three school subjects and for all four grades. Rasch mean square statistics have been found to remain relatively stable for polytomous item type data and such statistics are relatively independent of sample size (Smith et al., 2008). In-fit and outfit mean square statistics (MNSQ) should have an expected value of 1.0 and values which are above 2.0 are considered potentially problematic and noisy, while values above 3.0 degrade the measurement (three standard deviations above the mean).

Table 7.2 Range of Rasch item fit statistics for instruments from Gr. 8-Gr. 11

	English Language		**Mathematics**		**Natural Science**	
	In-fit MNSQ	**Outfit MNSQ**	**In-fit MNSQ**	**Outfit MNSQ**	**In-fit MNSQ**	**Outfit MNSQ**
Mean	1.01 - 1.00	1.01 - 0.99	1.00 - 1.01	0.98 - 1.04	1.00 - 1.01	1.00 - 1.01
Standard Deviation	0.08 - 0.22	0.13 - 0.15	0.09 - 0.14	0.23 - 0.35	0.06 - 0.09	0.18 - 0.22
Maximum	1.16 - 1.27	1.25 - 1.67	1.26 - 1.47	1.69 -2.76	1.15 - 1.46	1.53 - 1.92
Minimum	0.80 - 0.86	0.59 - 0.73	0.77 - 0.84	0.45 - 0.68	0.53 - 0.72	0.04 - 0.64
Item separation index (reliability)	6.08 (.97) - 7.49 (.98)		7.19 (.98) -8.04 (.98)		5.36 (.97) - 8.01 (.98)	
Item S.E. of mean	0.12 – 0.14		0.16 – 0.20		0.11 – 0.13	
Person separation index (reliability)	2.03 (.81) - 2.41 (.85)		2.33 (.85) - 2.81 (.89)		1.88 (.78) - 2.63 (.87)	
Person S.E. of mean	0.03 – 0.05		0.04 – 0.05		0.03 – 0.04	

The mean ranges per subject were well within acceptable limits for the in-fit and outfit MNSQ statistics, with ranges between 0.98 and 1.01 across the three subjects. Maximum values of MNSQ values show that the Mathematics Grade 8 and Grade 9 tests have outlying items with values above 2.00. The standard deviations are small and within expected limits. The standard error of the item mean lies well within the expected range of ± 0.33 logits, ranging from 0.11 to 0.20. The person separation index ranges were above 2.00, with the exception of one science test, which may require more items to separate low and high performers. For all other instruments, the values above 2.00 indicate that there was an appropriate spread of item difficulties. The item separation index ranges were above 3.00, demonstrating that there were

enough learners answering the items to confirm the item difficulty hierarchy (Fisher, 2007; Linacre, 2016). Item reliability was also high, with most tests having reliabilities of .98. Overall, the assessment instruments functioned well and were deemed appropriate. As the assessment information is expansive, the Grade 9 assessments are used for illustrative purposes and shown in Table 7.3.

Table 7.3 Number of items, mean %, comments for grade 9 assessments

Grade 9 Assessment topics	Number of items	Mean %	Comments
Mathematics			
Data handling & measurement	17	22.21	The *data handling and measurement* section contained the most difficult items, with the other sections being relatively easier. Overall the assessment was challenging for the learners, but item difficulty was set to curriculum standards and workshops were held with teachers to address gaps in learning.
Number, operations and relationships	11	35.65	
Patterns, functions and relationships	33	45.15	
Space and shape (geometry)	14	31.36	
Grand total	**75**		
English			
Reading for meaning (A)	24	61.42	*Poetry* was the most challenging section for learners with these items being considerably more difficult than items in other sections. The other sections had an even spread of difficulty from easier to more difficult items. Teachers said in workshops that poetry is more difficult for second language speakers due to the subtle nature of meaning in poetry.
Poetry	15	37.16	
Non-fiction text	16	54.23	
Visual literacy	8	57.27	
Reading for meaning (B)	16	64.17	
Grand total	**79**		
Natural science			
Earth and beyond	12	54.90	The topics were spread evenly in terms of difficulty. The *life and living* section had more difficult items than the other sections, followed by *matter and materials*. Teachers confirmed that these were sections which learners found more challenging in general and strategies for dealing with this was discussed in workshops.
Energy and change	14	54.43	
Life and living	30	33.72	
Matter and materials	31	44.41	
Grand total	**87**		

7.3.4 Procedure

The assessments were administered in November 2014, using standardised procedures and examination conditions. The educational research centre trained assessment administrators who implemented the testing process. Informed consent was obtained from parents for learners in all grades and in addition, assent was obtained from learners older than 16 years. After administration of the assessments, specifically recruited and trained teachers conducted the scoring and moderation. Thereafter, the assessments were captured on item level and data cleaning, processing and analysis was conducted. The competency bands were set using procedures described in the next sections and thereafter subject specialists crafted the descriptions. Once descriptions were available, a report structure was created and reports generated using mail merge. The reports and data files were then sent to the schools to utilise.

7.4 Data analysis

7.4.1 Proficiency levels

The assessments used in this study included items based on a variety of rating scales, from dichotomous items, which had only right or wrong answers to items of five scores, with each increasing score denoting higher ability. Considering this, the Rasch Partial Credit Model was used to analyse the results so that each item could be treated as an individual rating scale. Rasch-Thurstone thresholds set the 50% probability level (Linacre, 1998). These thresholds identify rating scaling positions on the latent variable at the precise point where observing each category is at the 50% probability level (Linacre, 2003, 2009).

This dichotomises rating scales of items, so that that an item with, for example three scores (0, 1, 2), are dichotomised at the 0 and 1 as well as the 1 and 2 intersections (Linacre, 2003, 2009). This process simplifies the analysis and gives more precise locations as movement from one category to the next is compared per pair of ratings per item. Based on the 50% probability levels, the medians were calculated and used to create the number of levels that were decided upon *a priori*.

For example, if five levels of grouped ability were hypothesised to exist in the assessment, the 50% probability levels were divided into five sections after sorting ascendingly and the median of each grouping was calculated which gave the logit points at which to group the person

measures, from lower levels of proficiency to higher levels. Thereafter item maps, with the bands indicated, were generated and subject specialists were able to utilise the maps and align them with items to create descriptions per band or level. Figure 7.1 illustrates the Rasch Item Map method applied to the English Language Grade 8 results. Subject specialists agreed on three proficiency levels and cut-scores were set using the Rasch-Thurstone thresholds.

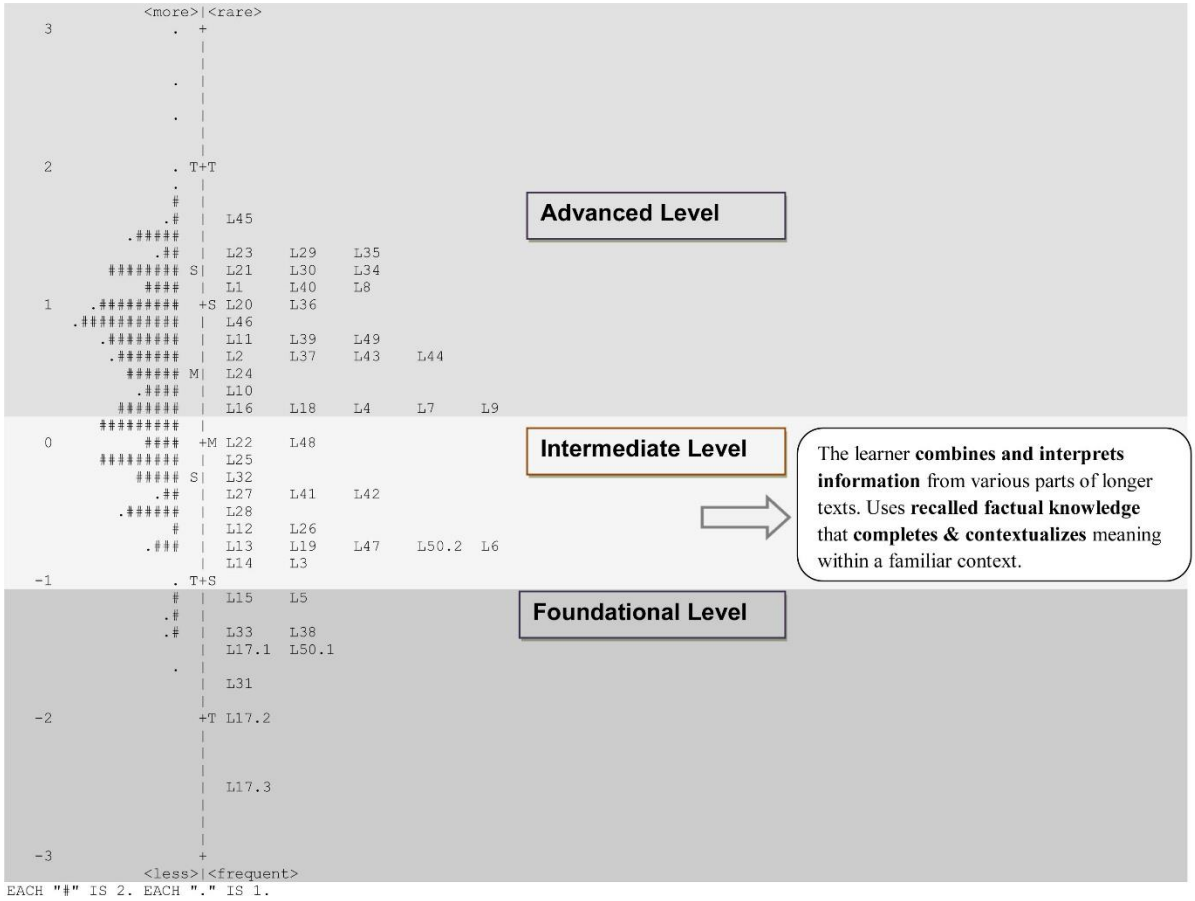

Figure 7.1 Item map – Example of Gr.8 English Language descriptions

7.4.2 Descriptions of different levels

Subject specialists for each subject were required to define the content areas of each band as indicated on the item maps after determining the points at which to cut the scores (see Figure 7.1 as example). While it was decided beforehand to set five proficiency levels, examining the item maps showed that this was neither practical nor suitable for each subject. For English language specifically, the specialists determined that there were three proficiency levels when classifying the types of items and abilities associated with the items. Based on their recommendations, the levels were recalculated and item maps regenerated. Table 7.4 shows

the total number of levels per subject as well as examples of descriptions. Note that sections of the descriptions are shown as an example to illustrate the method used.

Table 7.4 Levels per subject and examples of level descriptions

Subject	Levels	Example
English language	**Three levels:** • Foundational • Intermediate • Advanced	**Taken from the grade 8 intermediate description*:** The learner combines and interprets information from various parts of longer texts using his/her recalled factual knowledge that completes and contextualises meaning within a familiar context.
Mathematics	**Five levels:** • Elementary • Intermediate • Adequate • Proficient • Advanced	**Taken from the grade 9 proficient description*:** Learners are able to write numbers in scientific notation and work with large numbers. A learner at this level can reason about decimal numbers and about rational and irrational numbers. The learner can use the operations on fractions in a context and work with the simple and compound interest formulae.
Natural science	**Four levels:** • Intermediate • Adequate • Proficient • Advanced	**Taken from the grade 10 adequate description*:** Learners at the adequate level are able to describe the mole as the SI unit for amount of substance. They can do basic stoichiometry calculations. They have some knowledge of ionisation energy. The learners are able to draw Lewis Dot Diagrams of elements. These learners can plot a heating curve for water.

*A section of the description for illustration purposes, descriptions per level were more extensive than illustrated here.

The subject specialist re-examined the items and content in each level and after reviewing the items in each band, a description was generated per level. Other specialists reviewed and discussed the descriptions and once consensus was reached among the subject specialists, the descriptions were accepted and used for feedback.

7.4.3 Report design

This project served as an external monitoring system but in addition, results were also used to improve the teaching and learning within the schools. Teachers and principals attended

interactive workshops in which the results were discussed. To give learners criterion-referenced feedback, a learner report format was devised in which the proficiency level with its description was shown as well as the subsequent level for which the learner should aim. Each learner received the criterion-referenced report to share with his/her parents. Teachers were provided with the learner reports, school reports as well as data sets containing the performance and proficiency levels of each learner per subject and per curriculum area. These results were used by schools to facilitate their intervention plan and to inform extra classes and Saturday classes so that learners could be assisted in content areas where developing proficiency was required.

Table 7.5 below shows an excerpt from a learner report for Grade 8 Science. The table in the report first shows the level, in this case *adequate* and then offers a description of the curriculum-standard attained in the proficiency band. In the last column, the subsequent areas to attain are shown.

Table 7.5 Section of the learner report from a grade 8 Natural Science section

Level	What you have learned	What comes next
3 Adequate	*You have gained knowledge about **matter, mixtures of elements** and **compounds**.* *You can recognise the **forces between particles** and discuss the **contraction of materials**.*	*You should focus on learning to **analyse chemical reactions** and **bonds** as well as identifying **which chemical test to use** in experiments.* *Learn how to apply your understanding of **density** in an investigation.*

7.5 Results and discussion

7.5.1 Proficiency levels across different cohorts

Figure 7.2 displays the three English Language proficiency levels that could have been attained per grade based on the results. In grade 8, 41% of the learners were at the foundational level, 43% at the intermediate level and 16% had reached the advanced level. Considering the disadvantaged background of the learners and that they had only been attending school for a year, these results were to be expected. However, with each advancing year, fewer learners

should fall in the foundational category with more learners moving to either the intermediate or advanced level. By grade 11, 36% of the learners could be classified as advanced, an improvement on the 16% at grade 8 level. Even though these are different cohorts, the selection criteria results in homogenous samples are selected yearly and some indication of improvement can be glimpsed from these results. The results indicate that English language proficiency increases with each advancing grade, possibly due to the increased exposure to English and the intervention model followed by the schools. Furthermore, as anchor items are included it is possible to make extrapolations across cohorts.

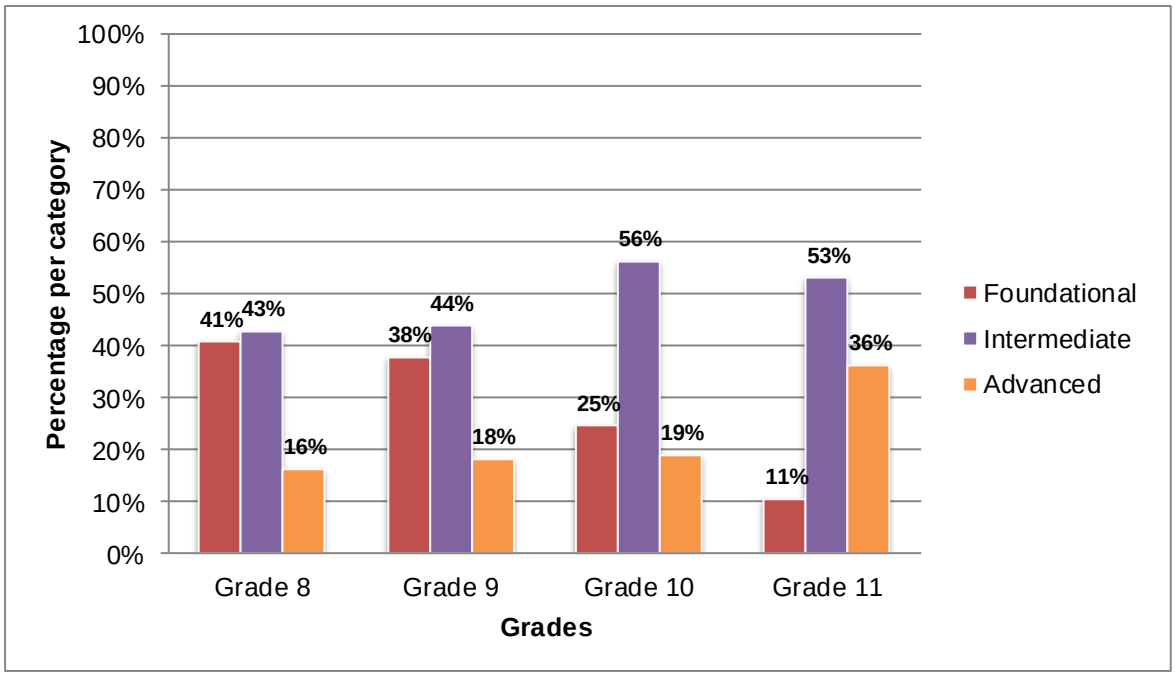

Figure 7.2 English language proficiency % of learner in levels per grade

In Figure 7.3, the results for the mathematics levels are presented. The results across the different grades remained mostly stable for Grade 8, 9 and 10 with the majority of learners falling into the adequate level. In Grade 11, a movement towards the higher levels can be seen and more learners, 45% in total, are at the proficient level. It may take more years for the intervention school model to improve the Mathematics ability of learners. Improved English Language proficiency may also assist in improving performance in mathematics and science by improving the ability to read, comprehend and problem solve.

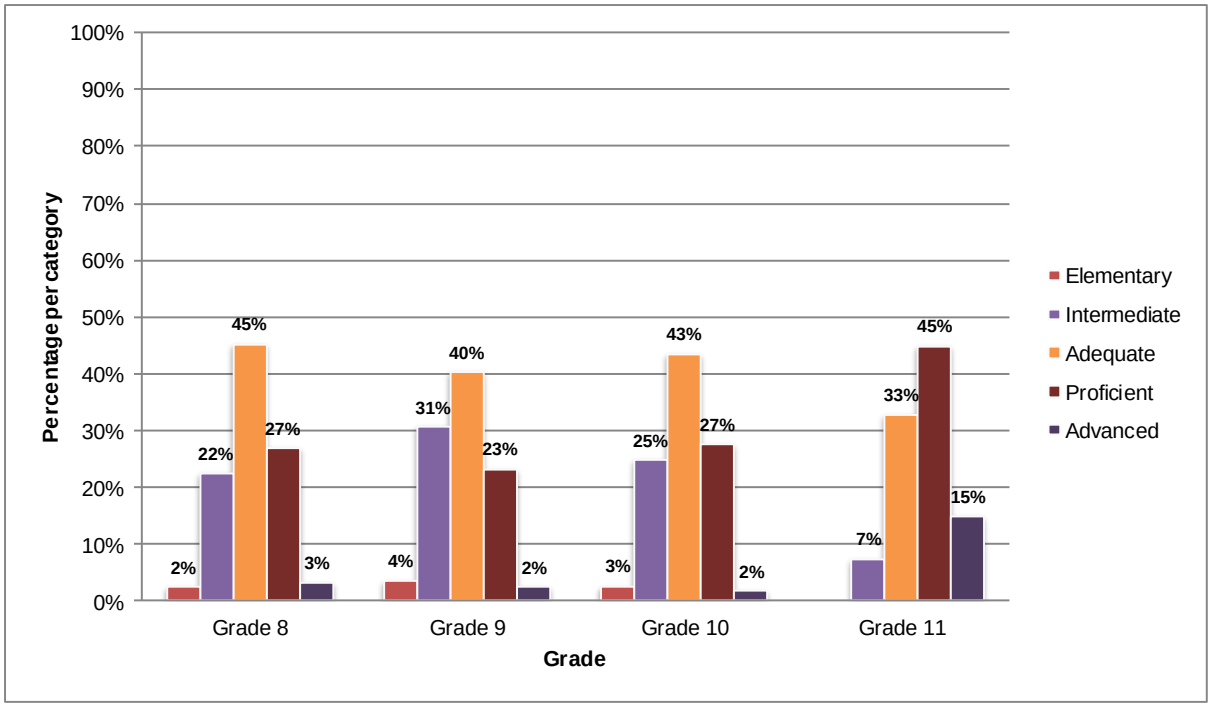

Figure 7.3 Mathematics proficiency – percentage of learner in levels per grade

Figure 7.4 illustrates the proficiency percentage levels of learners attained in the natural sciences assessments. Here a reversal of the pattern is observed, with more learners falling into the intermediate level (the least proficient level) with each advancing grade. Fewer learners seem to reach the more proficient levels in the higher grades, which may reflect the increasingly complex nature of the content and the challenges of attaining proficiency as difficulty in these content areas increases.

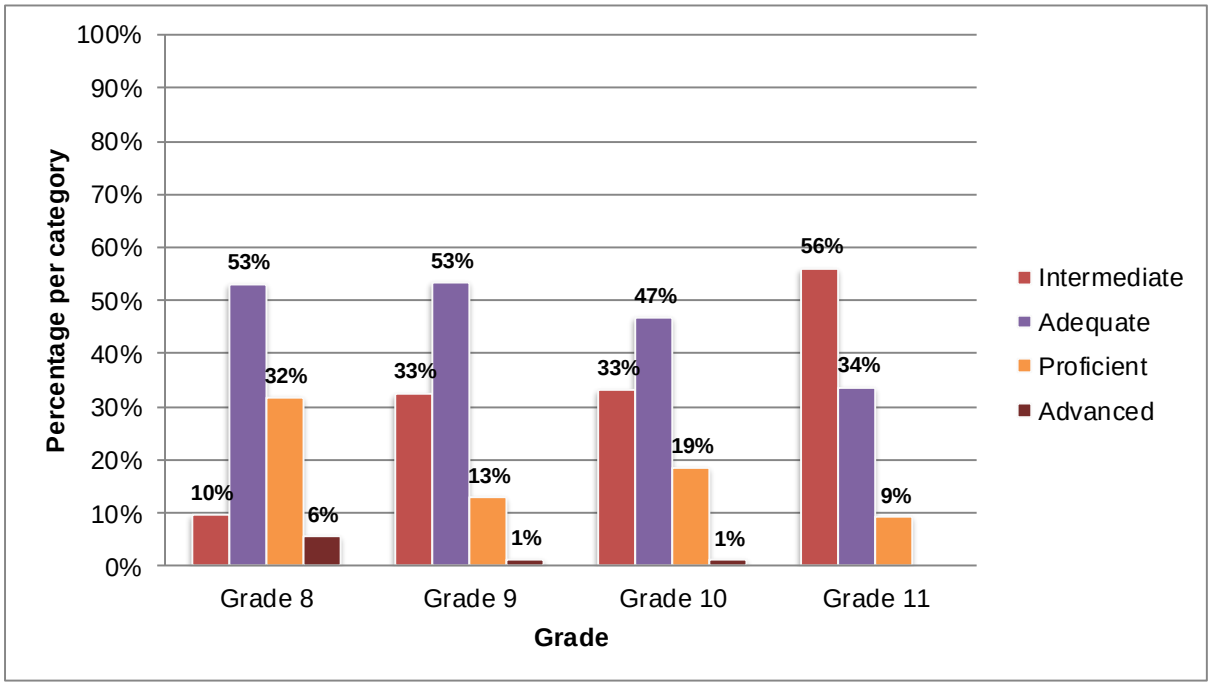

Figure 7.4 Science proficiency – percentage of learner in levels per grade

Teachers (n = 25) were asked how useful they found the reports to be. Eight per cent commented that they were *somewhat useful*, 56% reported that they were *very useful* and 36% verified that they were *entirely useful*. Comments sent by two of the schools are quoted below for illustration purposes.

School 1:

> *I love these, and will make sure that we communicate to teachers how to train parents how to read them. We are actively looking at how teachers can get a more accurate picture of every student for intervention.*

School 2:

> *Thank you for these comprehensive reports. They will be very helpful in driving our teaching.*

Figure 7.5 illustrates the processes followed to design the learner feedback reports. The first step was to determine the cut-scores using the Rasch-Thurstone thresholds to calculate where the bands are located. Next, the subject specialists examined the items in each band and determined the skills and knowledge represented by each level. Subject specialists also influenced the setting of cut-scores when they found that the assessment bands were too broad or did not accurately reflect the proficiency levels. In such cases, subject specialist feedback facilitated recalculation of the bands. In the last stage, other subject specialists examined the descriptions and items and discussions assisted in reaching consensus on the descriptions, which resulted in the report format.

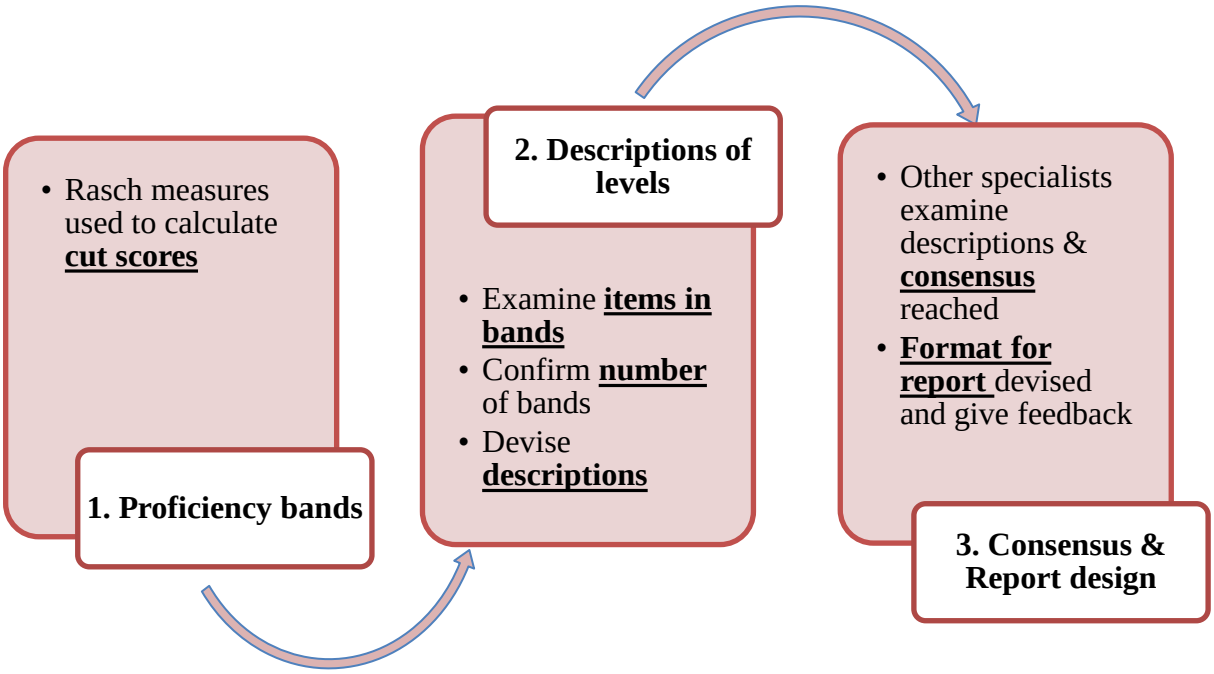

Figure 7.5 Process of creating criterion-referenced feedback

7.6 Implications for practice

The reporting of learner results should be moving past the "numbers only" era (de Vos & Belluigi, 2011; Green, 2002; Ottevanger, van den Akker & de Feiter; 2007; Popham, 1978). Increasingly there is a realisation that criterion-referenced results, based on curriculum-standards, are more aligned to the goals of educational assessment, which aims at mapping progression and outlining the subsequent developmental path. In addition, the equal interval measures provided by RMT also provide the opportunity to compare growth and development in subject areas (Ingebo, 1989).

This study has demonstrated the combination of using Rasch-Thurstone thresholds to set cut-scores for the proficiency levels and the value of subject specialists examining the items in the bands to create descriptions of the curriculum-standards represented by each band. The fact that not all subjects lend themselves to the same number of proficiency levels points to the fact that the quantitative numbers, the Rasch logits and the qualitative interpretations, by subject specialists, need to interact to inform the most appropriate definitions and explanations of what proficiency in a subject area means. Giving learners criterion-referenced feedback removes the focus from only aiming to attain a symbol and refocuses it on becoming more proficient in a learning area. This type of feedback is valuable in assisting teachers focus on specific subject

areas in the curriculum, particularly where there are gaps in understanding so that learners can move more smoothly along the continuum of developing proficiency in a subject area. When teachers refocus their teaching, they are also likely to align their classroom assessments to the changes.

There are of course, limitations of implementation. Not all assessments have been designed to give criterion-referenced feedback. The process of setting cut-scores, creating descriptions for proficiency levels and validating the process requires expertise and resources to which teachers may not always have access. It should also be noted that in contexts where there are a greater number of learners in a class, it might also be more challenging to give each child such detailed feedback. Where external assessments such as systemic and standardised tests are concerned, the focus may be on norm-referenced results for comparative purposes. This article suggests that even when benchmarking and comparing learners, schools or systems is the aim of the assessment, criterion-referenced reporting should be included as it can positively influence the learners and teachers and is specifically linked to curriculum-standards attainment. Large-scale assessments and systemic testing can be costly to implement and time-consuming for learners while disrupting teaching and school functioning. As a matter of social responsibility, the findings from such studies and assessments should be used to directly benefit the learners and criterion-referenced reporting is one way this can be accomplished.

While there are still challenges for reporting criterion-referenced results, the findings in this article suggests that progressively more emphasis should be placed on this type of feedback and less on norm-referenced feedback. The Rasch theory can effectively be used to set cut-scores to create proficiency bands and subject specialists should provide descriptions of each level and curriculum-standards represented in levels. The Rasch Item Map method can be used to align assessments and curriculum-standards by linking content to results. This results in diagnostic type feedback, which can be used by learners, parents and teachers to enhance teaching and learning.

7.7 Future research

It is suggested that continued research could expand the findings by having larger samples and conducting cross-validation studies using subsets of learners or test items (Jiao *et al.*, 2011). This would allow for examining the reproducibility of the competency levels in various sample sizes of learners and items across time. More stable parameters for classifying learners into competency bands could be identified, increasing the correct classification of persons. Ways in which to introduce criterion-referenced reporting in the school system should also be explored. Possibilities include assessments or items on a platform for teacher use which comprise proficiency bands for reporting purposes.

Chapter 8 - Discussion and Conclusions

I was taught that the way of progress was neither swift nor easy.
(Currie, 1923, p.168)

8.1 Introduction

The studies and chapters included in this thesis have all centred on measurement challenges in the social sciences and how Rasch models and theory can be used to solve problems and improve results. The studies reported on in Chapter 5, Chapter 6, and Chapter 7 all rest on the premise that measurement plays an essential role in the discipline of monitoring learning progress and academic achievement. Accurate measurement is presented as the method through which education and psychology are established as scientific fields of study. In the South African educational landscape, monitoring academic achievement can play a pivotal role in releasing the binding constraints which inhibit the system. Rasch models are the mechanisms through which the scientific principles of measurement can be applied and the validity of inferences derived from instruments. Through the application of psychometric theory, instruments utilised to monitor academic achievement are strengthened and evidence of construct validity can be collected.

Education and cognitive psychology stand at a pivotal point in history and societies, as education can give individuals the opportunities for personal and financial improvement and wellness, escalating their quality of life (Antoninis et al., 2016; Fontannaz, 2012; UNESCO, 2015). The enhancement of education can take place if there is accurate monitoring and tracking of learning progression (Dampier, 2014). The argument was made throughout this thesis that monitoring academic achievement should take place via the use of high-quality assessments to enhance teaching and learning and fill gaps in knowledge and skills (Archer, 2011; Scherman et al., 2017). An emphasis on content-driven feedback is recommended so that competing with others is less imperative and building the individual's skills and knowledge becomes the focus point. The Rasch models offer ways by modelling the developmental pathways taken in learning a skill (Long, 2015). Internationally, there is a shift to making measures in the social sciences as explicit and dependable as possible (Panayides, Robinson & Tymms, 2010). South Africa is also participating in this change, but faces the challenge of

having fewer resources with which to make the change from old test theories to new ones and to set up instruments with more rigorous methods. The studies presented in the current thesis serve as both examples of how to apply the Rasch models and also demonstrate why it is so crucial that measurement in the social sciences be held to the highest and most appropriate standards. An overview of the challenges examined and addressed in this thesis, with the use of Rasch models, is presented visually in Figure 8.1.

Figure 8.1 shows three focal points that were addressed in each article, as well as an overarching goal, that of impact.

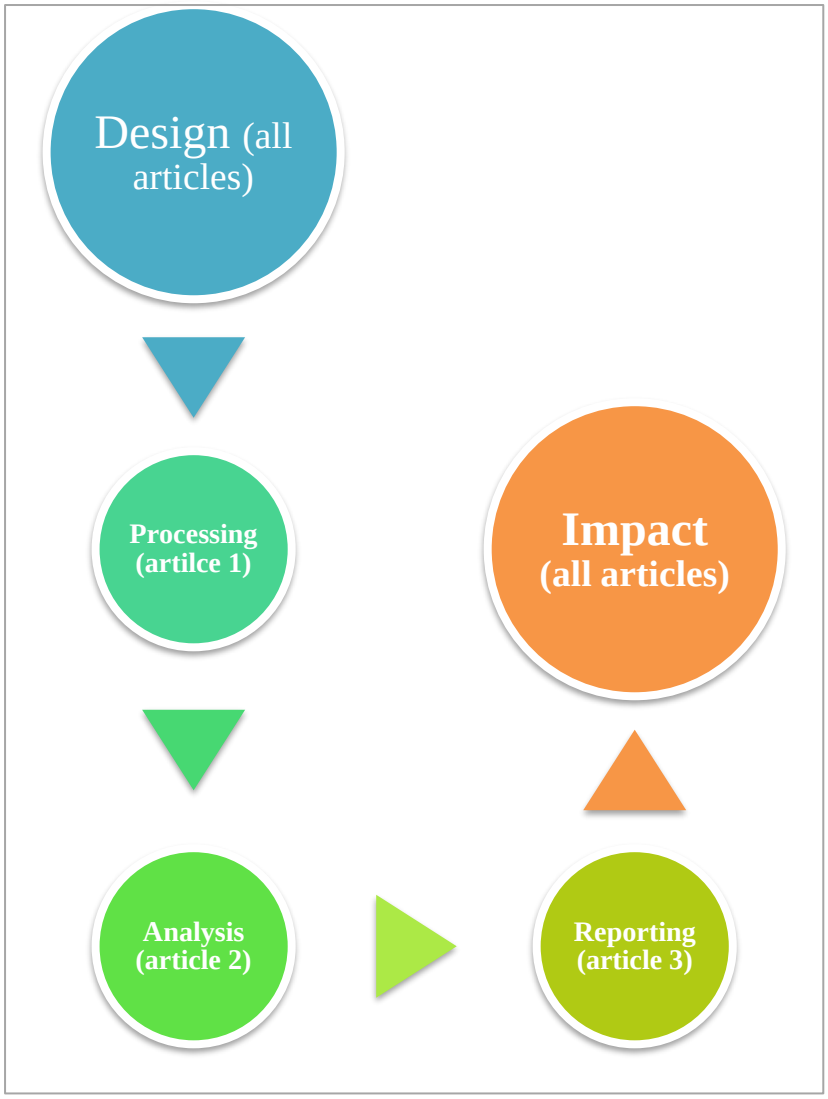

Figure 8.1 The main processes presented by the articles and ultimate goal

Underlying all three articles and the study as a whole, is the scientific design of the instruments through the application of Rasch models. The first article (see Chapter 5) focussed on dealing with missing data and processing data. The second article (Chapter 6) dealt with anchor items and reframing results. The last article in Chapter 7 examined the contribution of Rasch theory to the reporting of results that are criterion-referenced. While Rasch theory is often referenced as imperative to the design of an instrument, the articles included here have shown how useful the models can be at every step of the instrument's application.

8.2 Summary of methodology

Each phase of instrument design and use can present the researcher with different challenges. In this thesis, the challenges were: dealing with missing data (processing), tracking learning progression through common items and reframing results (analysis), and reporting of results with criterion-referenced bands (dissemination).

Article 1, reported on in Chapter 5, dealt with non-ignorable missing data. The values could not be dropped or excluded; they were crucial to monitoring learning progression over time. In this study, multiple imputation (MI) was used to predict missing values with Rasch Person Measures as predictors after applying Structural Equation Modelling (SEM). Checks of the accuracy of the imputations showed this to be a suitable solution. Missing values and more specifically Missing Not At Random (MNAR) data presented a threat to the validity of the analysis. An innovative and apt method for handling the missing data was sought and found. Here Rasch models played an important role by providing reliable predicators for the SEM and consequently, improved the imputations and statistical validity of the results.

The second study, discussed in Chapter 6, examined methods for establishing the usefulness of anchor items to track learning progression and reframe test results so that pre and post-test results can be compared more accurately. The problem of evaluating anchor items for accuracy of tracking learning from one year to the next was resolved by applying non-parametric statistics and the Rasch Model to identify items that did not contribute to monitoring learning over time. Placing the results from Time 1 and Time 2 in the same measurement frame was another aspect of testing and research explored. Applying Rasch models reframed results for more accurate tracking and monitoring of learning progression and resolved the problem that

learners changed over time. The growth from pre-test to post-test could be quantified more accurately by applying the Rasch Partial Credit Model and calibrating items.

The third study, presented in Chapter 7, explored how to report results for greater and more positive influence. The aim was to report test results in a developmental framework so that the focus would be on content and competencies. Rasch statistics were used to set cut-scores, and subject specialists examined the Rasch Item Maps and created an explanation of skills and knowledge represented by items in each band. The results were presented to learners, teachers and parents as current competencies as well as next steps in the learning continuum.

Table 8.1 contains a summary of the methodology used in each article.

Table 8.1 Summary of methodology for each article in thesis

Article	Sample	Instrument(s)	Data Analysis
Study 1 on data processing: MI for MNAR dichotomous data	358 Grade 8 learners	• Natural Science Grade 8 assessment	• Rasch Dichotomous Model • Structural Equation Modelling (SEM) • Multiple Imputation (MI)
Study 2 on data analysis: Evaluating anchor items and reframing assessment results	321 Grade 8 learners(2012) 321 Grade 9 learners (2013)	• English Language Comprehension Grade 8 assessment • English Language Comprehension Grade 9 assessment	• Rasch Partial Credit Model • Wilcoxon's Matched Pairs Signed-Rank Test • Pearson's Correlation Coefficient, *r* • Gamma Statistic
Study 3 on data reporting: criterion-referenced results	2014 cohorts: 250 Grade 8 learners, 251 Grade 9 learners, 319 Grade 10 learners 293 Grade 11 learners Total: 1113 learners	• Mathematics Grades 8-11 assessments • Science Grades 8-11 assessments • English Language Grades 8 – 11 assessments	• Rasch Partial Credit Model • Rasch Item Maps • Subject Specialist Qualitative Analysis

The articles all drew their samples from the same over-arching study, the monitoring of achievement study described in Chapters 1, 2 and 4. The measurement challenges presented themselves for different grades and different years of the study. The first article was concerned with Grade 8 learners and the Science Assessment designed for the end of Grade 8. The second

article used the data from the English Language assessments for Grades 8 and 9. The last article utilised information from all four grades in the 2014 year of the study.

Rasch models provide the researcher with support for processing data from tests, checklists and questionnaires. The models can be used to produce a true interval scale, ordering items and persons according to difficulty and ability, and then aligning them (Boone et al., 2014). Rasch item and person estimates can be used as variables which are on an interval scale, normally distributed (if spread of items to persons is well distributed) and more precisely representative of the construct. Using an interval scale in turn offers more statistical options, such as using parametric tests and can therefore improve the statistical validity of a study. Finding ways to deal with missing data is also crucial, and here the Rasch models have two strengths: they are robust to relatively large quantities of missing data (up to 50%) and can also be used in the imputation process because of the probabilistic nature of the mathematical model and the individual person item calibrations. Rasch models also have other advantages during the data processing stage, such as identifying problematic items which do not add to the measures or distort the measures. Problematic items can be removed prior to analysis or improved if the instrument is in a pilot stage. Other processing additives include identifying whether categories function adequately and collapsing categories where needed. Aspects such as bias in items can also be examined. In the multi-cultural and multi-lingual context of South Africa, this is especially important.

The models themselves provide an analysis of the instrument's functioning. Rasch models can contribute to data analysis in other ways, as demonstrated in the second article. The most common goal of research is to measure change, from pre-test to post-test or measure growth at different points in time. Rasch models can be used to anchor instruments when common items are built into the framework. Or if the same instrument is used in the pre-test and post-test design, Rasch modelling can be used to reframe the results so that the change over time is measured more precisely. In both scenarios, Rasch models have the potential to make significant contributions to the analysis of the data and to enhancing the accuracy of the results and reporting. With an emphasis on developmental pathways and monitoring progression, Rasch models give researchers the opportunity to place more focus on how an individual is growing or progressing on a given construct. This is in contrast to only comparing persons or groups. Both norm-referencing and criterion-referencing are vital to understanding a construct and formulating interventions. But when offering feedback to the individual stakeholders, it

may be more beneficial to present evidence of what has been gained and how to progress further along the line.

8.3 Summary of results for research questions

Each article presented in this thesis offered pioneering solutions for challenges such as missing data, monitoring progression and reporting results. Table 8.2 displays each research question for the respective studies as well as the results. For the first article, the research questions were answered by identifying which variables could be used to model the missingness with Structural Equation Modelling (SEM). To answer the question of how to best identify a model which would be appropriate for imputing the missing values, several models were fitted and a recursive model was found to be the best fit. Applying Rasch theory strengthened the modelling by providing variables which correlated more highly with the items than raw total scores.

The second article's research questions were answered by using a combination of Rasch items, non-parametric and parametric statistics. The result was that items for improvement were identified and two items were removed from the instrument after consultation with subject specialists. The second article also examined how the Rasch model could be applied to reframe measures from different times. The result was that after the application of the model, more accurate and precise indications of growth was obtained.

The third article looked at the contribution of Rasch models to report criterion-referenced feedback. Rasch item maps were generated and subject specialists examined the spread of the items, commented on the utility of the number of the bands and defined the skills within each band. The result was paragraphed descriptions of what learners can do in each subject area as well as an explanation of the next set of skills they need to learn. The descriptions were included in reports which learners, parents and teachers received and used.

Table 8.2 Research questions and results

Study (article)	Research questions	Result
Study 1 on data processing: MI for MNAR dichotomous data	1. How can MNAR missing data be multiply imputed to model the missingness? 2. Which type of model and variables would best predict the MNAR data and how would these be identified? 3. What contribution could be made by Rasch scores versus raw scores to build more accurate MI models for missing item responses?	1. Identified the variables linked to missingness, modelled the missingness mechanism via SEM 2. An iterative process was used of model building that identified the most appropriate model, in this case, a recursive model 3. The Rasch scores correlated more highly with all of the items and utilising Rasch scores led to improved MI
Study 2 on data analysis: Evaluating anchor items and reframing assessment results	1. To what extent does each anchor item contribute to tracking/monitoring progression? 2. How can the Rasch Measurement Model be used to more accurately monitor learning progression and report results?	1. The combination of Rasch statistics and non-parametric tests led to identifying items for improvement and the removal of two items 2. Through calibration and stacking of data and deriving a total score from the Rasch model, the results from Time 2 were reframed to that of Time 1. The result was a more accurate indication of growth
Study 3 on data reporting: criterion-referenced results	1. How can Rasch Item Maps and Subject Specialists work interactively and applied to establish and define learning progression levels? 2. How can the competency bands established in an assessment be linked to the curriculum? 3. In which format should results be reported so that the emphasis for stakeholders is on learning progression?	1. Rasch statistics were used to set cut-scores on the item maps, creating competency bands which subject specialists reviewed 2. Subject specialist reviewed the items within a band, described the competencies represented as well as where the competencies are linked to curriculum content 3. The descriptions of competencies mastered and next steps were outlined in a report. Links were made to curriculum content as well as clear specifications of focus areas

8.4 Reflection on methodology

The blind peer reviewers from the journals, the thesis supervisors and other colleagues suggested ways to strengthen or change the methodology, analysis and conclusions. This reflection section contains a consideration of the ways the methodology was improved as well as the implication of the iterations. During the analysis and write up of the first article (missing data), an attempt was made to devise a new model to impute the missing data based on the Rasch model. Reviewers advised that tried and tested methods should be used instead, such as Multiple Imputation (MI). Existing missing data methods were better options as those methods were established and refined for the purpose of imputing missing data. Due to the recommendations, the first article was completely rewritten, with a new methodology and data analysed afresh. A new methodology was devised, combining existing methods (Multiple Imputation) with Rasch measures as predictors. The usefulness of modelling the data with Structural Equation Modelling was explored, where after the imputations were done in SPSS.

The second article went through a similar process, but this time major changes to the methodology were recommended by Professor Tim Dunne (emeritus professor of statistics at the University of Cape Town). Originally the second article used only parametric statistics to analyse the items. But Professor Dunne (statistician) highlighted the fact that dichotomous items are not on a continuous scale, and therefore not suitable for parametric statistics. Instead the statistician recommended using the Gamma statistic as well as other non-parametric tests (Kruskal-Wallis). Based on his recommendations, the methodology was recreated and analysis for the second article was redone. The main benefit was correct comparisons and more accurate results.

The third article (bands) had several options for its methodology. Methods for setting cut-scores and devising competency descriptions were considered for the article, including: Angoff's method, Ebel, Nedelsky method, adjusted Angoff's method and Bookmark methods. Each method has advantages and disadvantages; for example, the Angoff's methods has the potential disadvantage that judges find it difficult to estimate item response probabilities for minimally competent candidates (Ricker, 2006). Methods such as Angoff's and the Bookmark method

may require not only a panel of experts, but also that such experts receive training to reduce their propensity to give biased ratings (Arce & Wang, 2012). When Rasch models are applied and present evidence for construct validity, it becomes possible to use person measures as a method for setting standards as opposed to relying on raters or judges. According to Khatimin et al., (2013), using Rasch Objective Standard Setting mitigates some of the problems with using panellists to set cut scores and standards. The Rasch item map method was applied in the third article as it presented a viable alternative to panel methods and has built in validation checks as the bands are determined by performance on the items and not subjective opinion alone. The Rasch item map method combines the elements of quantitative (performance on items) with qualitative evaluation of what that performance means. After the major revisions discussed above were implemented, changes were made to the methodology and this is explained in more detail in the section below.

Article 1: Missing Data. The blind reviewers advised that details of the methods used in the study should be explained more clearly, whereas as before only explanations of the software were provided. Both the introduction and the methods section were too long, which made the reading of the article tiresome. Writing in a way that is both succinct and yet adequate, is a challenge for any writer, indeed for any format of communication. The reviewers advised that the discussion section should be revised to clearly explain the rationale for each finding and then to discuss how the results could be used as the population selected limits generalisability. The methodology required clearer justifications for why the data were classified as MNAR, and why the recursive SEM model was used. The reviewers also recommended providing a pseudo R^2 for the model, an explanation as to why correlations of -.179 and .285 were considered to be moderate in size. Due to the fact that a Bayesian analysis with MCMC algorithm had been conducted, one reviewer recommended providing the properties of the prior distribution and to explain how the model would differ from a conventional path analysis such as using weighted least squares. The recommendations emanating from the study were judged to be too firm, considering the limits of the sample used. Instead, it was recommended that the steps be listed rather than providing pointed recommendations. The official supervisors also added to this paper by correcting errors; for example, that item and person measures were not calculated conjointly in the Rasch model, but separately and then aligned.

Article 2: Anchor item evaluation. The methods in the second article were significantly reworked based on the suggested use of the gamma statistic, as well as the use of the Wilcoxon's Matched Pairs Signed-Rank Test due to the ordinal nature of item level data. The advice proved to be invaluable, and the analysis and interpretation were considerably revised based on his suggestions. The changes results in more accurate comparisons of the anchor items from one year to the next, especially the identification of items that did not show improvement. The blind reviewers from the journal added suggestions, these included that the literature section be rewritten more concisely, that the difference between home language and additional language learners be explained more clearly as well as why the sample had considerably more girls than boys. The reviewers also advised that items from the test should be shown, and this was added as an appendix (see Appendix E). A section on learner motivation was also included in the paper based on recommendations from the blind reviewers, and this strengthened the argument as it is important to take into account learner motivation for external assessments. The sample description was expanded based on suggestions from the official supervisors, and mean age and gender was added to the methodology section. The blind reviewers asked for a more detailed description of the Rasch model used as well as justification, and this was added to strengthen the argument of the paper. The blind reviewers wanted an explanation as to why Pearson's Correlation coefficient, *r*, was used as the effect size indicator when other formulae are available. Justifications for this method use were also added to the paper (see Chapter 6).

Article 3: Competency Bands. This article was presented at a conference, and later published. Both the audience at the conference, as well as the blind reviewers from the journal provided useful insights. The blind reviewers asked for more details on the assessment instruments, such as how they were developed and how the assessment frameworks were set up. The section on the methodology was expanded to include a more detailed description of the instruments. The audience and blind reviewers asked for better explanations of how the different cohorts could be compared, and the author added a section explaining the use of the anchor items that linked instruments across years. A member of the audience at the conference challenged the multi-purpose use of the assessment instruments. The assessments were used for both monitoring of academic achievement and for feedback into the schooling system. The issue of using assessment results for multiple purposes as opposed to designing and using results for only one is debatable. Both sides of the argument can be defended, and the inputs from the audience

member contributed to the article by prompting an argument for the multi-purposed use of the assessment results.

The methods of each article contributed to fields of social science by presenting innovative ways to deal with measurement challenges faced in the processing, analysis and reporting of social science data. The overarching methodology of the thesis was the application of Rasch Measurement Theory (RMT). The usefulness of RMT in contributing to the processing, analysis and reporting of academic achievement results was presented in each article respectively. Overall, RMT provides a strong framework for social sciences to approximate true measurement as found in the natural sciences. Further evidence for the use of RMT as a guiding methodology was presented in Chapter 3, in terms of making valid inferences from the assessment instruments. RMT supported the construct validity of the instruments in the development and refinement of the instruments. Evidence for the content, concurrent and predictive validity was also collected and was found to be adequate for all the assessment instruments, further supporting the positive impact that using RMT as methodology had on the assessment design and development.

8.5 Reflection on conceptual framework

A psychometric model of instrument development and analysis served as the conceptual framework (see Figure 3.2 in Chapter 3). The model was based on best practice in psychometric theory as well as guidelines embodied by the Rasch models (Boone, Townsend & Staver, 2011; Osborne, 2008; Wright, 1977; Wright & Stone, 1979). The conceptual model is suitable for the type of research reported in this thesis, namely that of meta-science (see Chapter 1). The conceptual framework represented each phase of instrument development, whereas the studies described focused on the processing, analysis and reporting phases of the framework (D to I). The other phases were implied and had been implemented when the instruments were developed and updated (see Figure 8.1).

The conceptual framework shows the full life cycle of the instrument, from conceptualisation to application, as well as analysis and reporting of results. The philosophy and theory underlying the best test design used in this thesis is also shown on the framework, that of Rasch

theory (A0). Within the context of this thesis, each step (A to I) was crucial and contributed to the studies represented here. The instruments (school subject assessments) were developed prior to the articles being written in a project described in more detail in Chapter 4. The processes of operationalisation (A), framework and item design (B), piloting (C), application of the Rasch models (D), instrument refinement (E) and instrument administration (F) all took place before the secondary analysis but remain crucial stepping stones.

The first article in this thesis dealt with missing data, which fits with the data processing step (G) in the conceptual model. Article 1 demonstrated how Rasch models can make a useful contribution to the imputation of missing data as well as using Rasch measures as possible predictors in SEM models (linked to step H of data analysis). The second article was also based in part on the processing step (G), as items were anchored and fixed to difficulties. The second article went to the next step, that of analysing the data (H) where Rasch models were used to reframe results for more precise measurement of change taking place over time. The third article dealt with the final step, the dissemination of findings from the instrument administration (I). Here the value of Rasch theory for reporting criterion-referenced feedback was explored and demonstrated by creating competency bands to report the results. The conceptual model served both as guidance for the development of the instruments prior to the studies (A to F), as well as indications of further uses for the Rasch model when applied in the studies (G to I).

8.6 Limitations of the study

Like all studies, the applications and results are limited to some extent to the sample population: South African high school learners as well as the sample sizes and the constructs. The assessments were designed to assess Grades 8 to 11 in Science, Mathematics and English Language and findings may be more relevant for the subjects. The fact that the independent schools in the study are seen as a separate population, also means that the generalisability of the findings are limited. The methods in the current studies could be applied to larger samples, to constructs other than cognitive abilities and to a wider variety of populations. An important limitation of Rasch models should also be noted here: they cannot negate the effects of inadequate instrument design.

Valid inferences from assessments may be limited when:

- the construct was not well-defined;
- the range was not considered;
- the items were not designed with inputs from subject specialists;
- the context of the population not taken into consideration; and
- refinement of items based on pilot results did not take place.

As all steps were followed, as shown in the conceptual framework, the following limitation is not applicable to the current studies but should be mentioned as a general limitation of the models. Applying Rasch models after the design of an ill-planned instrument cannot undo or redo what has not been done. In such cases, Rasch models could show which items lack fit, as well as the overall functioning of the instrument but the onus lies with the designers to address the underlying issues of construct validity. The processing, analysis and reporting of data derived from an instrument which lacks the basis of good design would also be questionable. The studies rested on the assumptions that the first phases of the conceptual framework were firmly in place and had been adequately applied.

8.7 Recommendations

Each article has its own results and recommendations (see Table 8.2). The main recommendation emanating from the thesis as a whole is that Rasch Measurement Theory be taught in social science courses as well as in statistics, qualitative and quantitative research courses. This will equip future researchers with the skills and knowledge to develop high quality and appropriate instruments within their field. This in turn would strengthen any given field and have a positive impact on the individuals, groups and societies they study and serve. The conceptual framework (see Figure 3.2) can be used as a basic guide for developing an instrument and utilising its data for dissemination.

The five main recommendations emanating from this thesis are:

1) For practice, use the best available models and processes as demonstrated in the conceptual framework and throughout this thesis. When instruments are designed according to the principles of measurement as presented by RMT, more evidence for valid inferences can be assembled and instruments can conform to higher standards.
2) Future research for the monitoring of academic achievement can be enhanced by the application of Rasch models at each stage of instrument design, refinement, use and reporting of results. Future research can investigate the application of Rasch models to evaluate anchor items and reframe test re-test results. Other areas for investigation include the examination of Rasch measures in MI and SEM, and how the models can be used to report results as content feedback.
3) The Rasch models are exemplars of how measurement principles can be applied in the social sciences. To strengthen disciplines such as psychology and education, it is recommended that the models be taught as a part of statistical courses at fourth year level.
4) Monitoring systems such as the one upon which the studies in thesis are based, can also be used to inform teaching and learning practices. The external monitoring of academic achievement, such as is found in this study and other systemic evaluations, should benefit all the stakeholders. This was demonstrated in the final article on the creation of competency bands for criterion-referenced feedback.
5) The use of sophisticated psychometric methods such as RMT in developing contexts may be more limited than is desirable due to socio-economic constraints and lack of knowledge. To promote the application of statistical models such as Rasch models, various forms of marketing should be done by proponents of the models. This includes workshops, conferences, presentations and publications for government and non-government stakeholders. Rasch could be applied to a variety of disciplines, including education and psychology.

Investing in sound measurement is the best way forward and will lead to quality instruments being designed. In turn reliable and valid inferences can be drawn from educational monitoring programmes. Sound measurement produces fair comparisons, the identification of areas for

enhancement and identifies if system-wide improvements are taking place. Sound measurement is both a scientific and social justice issue for future research.

8.8 Conclusion

Rasch measurement theory makes an especially vital contribution to the construction of instruments in the social sciences, by converting the principles of measurement into models and producing statistics which indicate to what extent an instrument conforms to the principles. Following the principles of measurement allows for approaching true measures, moving towards accessing of latent constructs in the softer sciences and elevates fields such as education and psychology. Progress can be assessed with greater precision and improvement more accurately tracked over time. Considering that constructs in the soft sciences are latent and socially constructed, it is all the more important to find evidence of their existence and to measure with some degree of certainty. It is here that Rasch modelling offers social scientists a golden opportunity: the scientific development and application of instruments. Throughout the chapters and articles included here, various aspects of the Rasch theory have been examined and applied. More importantly, the contribution of the models to three pivotal phases of the research process was examined: data processing, analysis and reporting. In each of the three research processes, the Rasch models were applied to serve as innovative and useful solutions to problems or challenges. The applications of the Rasch models continue to be explored in various fields, including the natural sciences. More uses for Rasch Theory continue to be found, and this thesis contributes to that body of knowledge and to the strengthening of measurement.

9. References

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10. Appendices

10.1 Appendix A: Permission letter from the Centre for Evaluation and Assessment, Faculty of Education

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA
Faculty of Education

Centre for Evaluation & Assessment

12 October 2015

Humanities Ethics Committee
University of Pretoria

RE: Permission to use MSDF CEA data for Scientific Publications

The Centre for Evaluation and Assessment (CEA), gives permission to Ms Celeste Combrinck to use the Michael and Susan Dell Foundation (MSDF) data generated by the project: *A Developmental Approach to Information Driven Teaching: Tracking Progression, towards Improving Teaching and Learning in Coalition Schools* for further analysis and scientific publications provided the stipulations mentioned in this letter are adhered to.

The stipulations are that the names of learners and schools are kept confidential and anonymous and that no article should refer to the grant holder by name. Only disaggregated results should be reported. Also, at least one article should have Prof Sarah Howie as a co-author.

Sincerely yours,

Professor Sarah Jane Howie
Director of Centre for Evaluation and Assessment
Tel: +27 12 420 4175 (PA)
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10.2 Appendix B: Permission letter form the Research Ethics Committee, Faculty of Humanities

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Faculty of Humanities
Research Ethics Committee

1 October 2015

Dear Prof Maree

Project:	**The use of Rasch Measurement Theory to address measurement and analysis challenges in social science research**
Researcher:	**C Combrinck**
Supervisor:	**Prof D Maree**
Department:	**Psychology**
Reference Number:	**27313192 (GW20150912HS)**

Thank you for the application that was submitted for ethical consideration.

The application was ***conditionally*** **approved** by the **Research Ethics Committee** on 1 October 2015 due to the following:

1. It is noted that general permission was given to use the data for scientific publication, however, permission from Prof Susan Howie is specifically required for the purpose of secondary data analysis. The permission letter must state the title of the study and the name of the researcher.

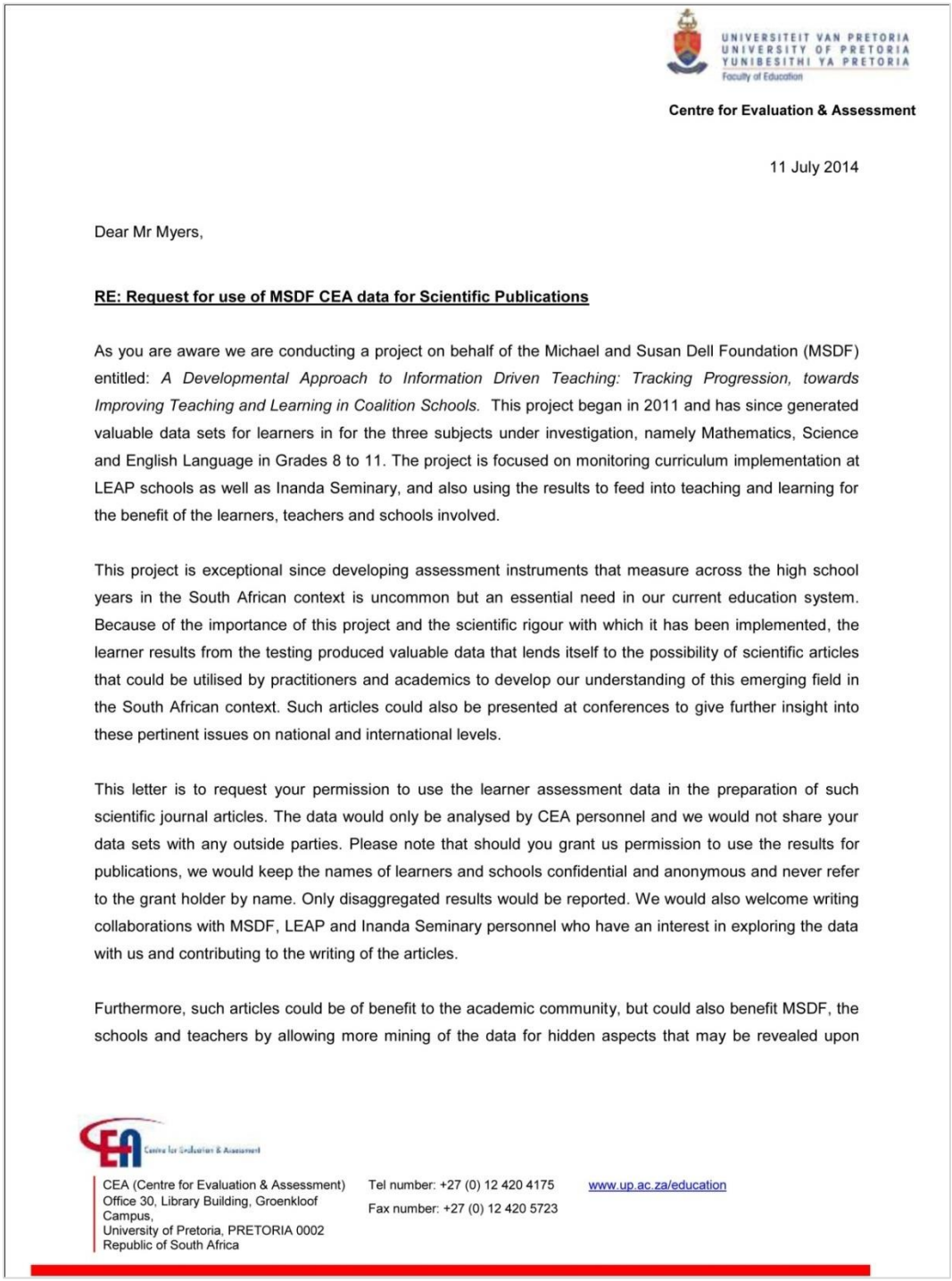
Please note that data collection may not commence prior to the above issue being resolved to the satisfaction of and full ethical clearance being granted by this Committee. The Committee requests that you respond at your earliest convenience to: Ms Tracey Andrew at tracey.andrew@up.ac.za / Room 7-27./

Sincerely

Prof Karen Harris
Acting Chair: Research Ethics Committee
Faculty of Humanities
UNIVERSITY OF PRETORIA
e-mail: karen.harris@up.ac.za
Kindly note that your original signed approval certificate will be sent to your supervisor via the Head of Department. Please liaise with your supervisor.

Research Ethics Committee Members: Prof KL Harris(Acting Chair); Dr L Blokland; Dr JEH Grobler; Ms H Klopper; Dr C Panebianco-Warrens; Dr C Puttergill; Prof GM Spies; Dr Y Spies; Prof E Taljard; Ms KT Andrew (Committee Admin), Mr V Sithole (Committee Admin)

10.3 Appendix C: Permission letter for external funding agency



UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA
Faculty of Education

Centre for Evaluation & Assessment

11 July 2014

Dear Mr Myers,

RE: Request for use of MSDF CEA data for Scientific Publications

As you are aware we are conducting a project on behalf of the Michael and Susan Dell Foundation (MSDF) entitled: *A Developmental Approach to Information Driven Teaching: Tracking Progression, towards Improving Teaching and Learning in Coalition Schools.* This project began in 2011 and has since generated valuable data sets for learners in for the three subjects under investigation, namely Mathematics, Science and English Language in Grades 8 to 11. The project is focused on monitoring curriculum implementation at LEAP schools as well as Inanda Seminary, and also using the results to feed into teaching and learning for the benefit of the learners, teachers and schools involved.

This project is exceptional since developing assessment instruments that measure across the high school years in the South African context is uncommon but an essential need in our current education system. Because of the importance of this project and the scientific rigour with which it has been implemented, the learner results from the testing produced valuable data that lends itself to the possibility of scientific articles that could be utilised by practitioners and academics to develop our understanding of this emerging field in the South African context. Such articles could also be presented at conferences to give further insight into these pertinent issues on national and international levels.

This letter is to request your permission to use the learner assessment data in the preparation of such scientific journal articles. The data would only be analysed by CEA personnel and we would not share your data sets with any outside parties. Please note that should you grant us permission to use the results for publications, we would keep the names of learners and schools confidential and anonymous and never refer to the grant holder by name. Only disaggregated results would be reported. We would also welcome writing collaborations with MSDF, LEAP and Inanda Seminary personnel who have an interest in exploring the data with us and contributing to the writing of the articles.

Furthermore, such articles could be of benefit to the academic community, but could also benefit MSDF, the schools and teachers by allowing more mining of the data for hidden aspects that may be revealed upon

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University of Pretoria, PRETORIA 0002
Republic of South Africa

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further analysis. The preparation of the articles would not impinge in any way on our successful completion of the planned deliverables for the current grant.

If you are willing to allow us to use the MSDF data sets generated by our project for publication and further analysis, please sign below.

Sincerely yours,

Professor Sarah Jane Howie
Director of Centre for Evaluation and Assessment
Tel: +27 12 420 4175 (PA)
Sarah.Howie@up.ac.za

The Michael and Susan Dell Foundation gives the Centre for Evaluation and Assessment permission to use the data sets generated by the project: *A Developmental Approach to Information Driven Teaching: Tracking Progression, towards Improving Teaching and Learning in Coalition Schools* for further analysis and scientific publications provided the stipulations mentioned in this letter are adhered to.

Jarred Brad Myers

Jarred Myers
Program Officer
Michael & Susan Dell Foundation
TEL +27 (21) 831-7514
FAX +27 (21) 831-7501
jarred.myers@msdf.org

10.4 Appendix D: Permission letter to learners and parents

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
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Faculty of Education

Centre for Evaluation & Assessment

17 January 2013

Dear Learner

RE: REQUEST FOR PERMISSION TO USE TEST RESULTS FOR RESEARCH PURPOSES

The Michael and Susan Dell Foundation (MSDF) which is involved in the improvement of teaching and learning at your school, approached the Centre for Evaluation and Assessment (CEA) at the Faculty of Education, University of Pretoria to develop and administer English Language, Science and Mathematics tests which all learners in your grade will be asked to complete. CEA staff members will visit your school during January and November 2013. During the testing time you will complete the following tests:

- A Science test
- An English Language test
- A Mathematics test

There is nothing to study for the tests as they will be used to check which aspects of the curriculum for each subject you have had exposure to. You just need to try your best. The goal of the tests is to monitor your progress in these subjects at school and to help teachers at your school with the planning of teaching and learning tasks.

The Michael and Susan Dell Foundation would also like to use your results from the tests to determine how best to assist with their support at your school. We, at the University, will thus be using your results from these tests to assist the MSDF and your school with these goals. We will provide feedback to the MSDF, your school and teachers regarding your results but will not disclose your results to anyone else without your permission. Your name and the name of your school will be kept confidential during any discussions we may have about the tests. We would therefore like your permission to use your test results for research purposes. If you are willing to let us use your test results confidentially for research purposes, please sign the letter below.

For and on behalf of the CEA,

Prof. Sarah Howie
Director of Centre for Evaluation and Assessment
Tel: +27 12 420 4175 (PA)

I, (name) _____ in Grade___, give my permission for the University to use the results of the tests I complete for research purposes.

LEARNER SIGNATURE:	……
DATE:	……

Centre for Evaluation & Assessment

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UNIVERSITEIT VAN PRETORIA
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Faculty of Education

Centre for Evaluation & Assessment

17 January 2013

Dear Parent/ Guardian

RE: ENGLISH LANGUAGE, SCIENCE AND MATHEMATICS TESTING PROGRAMME

The Michael and Susan Dell Foundation (MSDF) which is involved in the improvement of teaching and learning at your child's school, approached the Centre for Evaluation and Assessment (CEA) at the Faculty of Education, University of Pretoria to develop and administer English Language, Science and Mathematics tests which all learners in your child's grade will be asked to complete. CEA staff members will visit the school in January and November this year.

There is nothing specific for your child to study for the tests as they will be used to check which aspects of the curriculum for each subject they have had exposure to. They will just need to try their best. The goal of the tests is to monitor their progress in these subjects at school and to help teachers at the school with the planning of teaching and learning tasks. The Michael and Susan Dell Foundation would also like to use the results from the tests to determine how best to assist with their educational support at the school. We, at the University, will thus be using the results from these tests to assist the MSDF and the school with these goals. Under no circumstances, will your child face negative consequences resulting from their completion of the tests or from their results. The results will only be used to support their learning and the learning environment in the school.

We will provide feedback to the MSDF, the school and teachers regarding your child's results but will not disclose the results to anyone else without permission. Your child's name and the name of the school will be kept confidential during any discussions we may have about the tests with anyone other than the MSDF and the teachers at the school. Your child has been sent a letter requesting his or her permission to use his/ her test results for these purposes. We would also like your permission to use your test results for research purposes.

If you are willing to let us use your child's test results confidentially for research purposes, please sign the letter below.

For and on behalf of the CEA,

Prof. Sarah Howie
Director of Centre for Evaluation and Assessment
Tel: +27 12 420 4175 (PA)

I, parent/ guardian of (name) _____ in Grade___, hereby give my permission for the University to use his/ her results of these tests for research purposes.

PARENT/ GUARDIAN SIGNATURE: ……

DATE: ……

Centre for Evaluation & Assessment

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10.5 Appendix E: Evaluating anchor items study - removed items

Passage name: The Hitchhiker. The items were based on a fictional story written by a South African author. The story is an adaption of the urban legend of a ghost that hitches a ride. The driver only realises that his passenger was a ghost after he had dropped her off. He notices that she has left her jacket in the car. As he wants to return the jacket, he goes to the address where he left her. There he finds out that his passenger was a woman who had died some years ago. The story concludes with the driver visiting her grave. Total number of words in the passage: 731.

Anchor item 5

Figure 9.1 Item 5 removed from instrument based on analysis

Anchor item 15

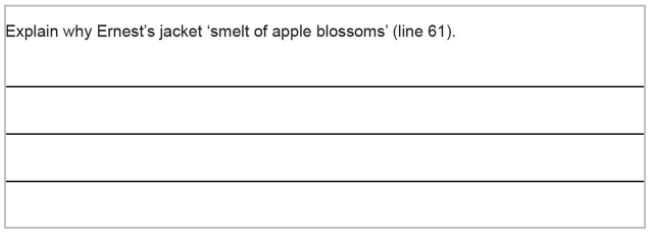

Figure 9.2 Item 15 removed from instrument based on analysis