A PSYCHOMETRIC INVESTIGATION INTO THE USE OF AN ADAPTATION OF THE GHISELLI PREDICTABILITY INDEX IN PERSONNEL SELECTION

Liesle Twigge

THESIS PRESENTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF COMMERCE AT THE UNIVERSITY OF STELLENBOSCH

Supervisor: Prof CC Theron

December 2003

Stellenbosch University http://scholar.sun.ac.za

DECLARATION

I, the undersigned, hereby declare that the work contained in this thesis is my own original work and that I have not previously in its entirety or in part, submitted it at any university for a degree.

SIGNATURE

DATE

Stellenbosch University http://scholar.sun.ac.za

A Psychometric Investigation into the Use of an Adaptation of the Ghiselli Predictability Index in Personnel Selection

Liesle Twigge, Department of Industrial Psychology, University of Stellenbosch, South Africa

Supervisor: Prof C.C. Theron, M.A., D.Phil. (Stell.)

Abstract

The field of human resources involves continuous decision-making regarding the matching of the workforce with the workplace, since this match determines individuals' motivation to perform the actions associated with the workplace.

If, at the time of the decision, the decision maker could obtain information on end performance, the chances of achieving the desired results would be increased. However, personnel selection is complicated by the obvious fact that information on end performance is not available at the time of the selection decision. All such decisions thus involve predictions about people's performance. The classic validity model forms the foundation of all prediction in as far as the strength of the relationship between the predictor of performance and the actual performance determines the accuracy of the predictor.

Over time, numerous possibilities have been considered on how to increase the magnitude of this relationship as experienced through the validity coefficient, mostly involving modifications and/or extensions to the standard regression model. An interesting and challenging alternative to the usual multiple-regression based attempts may be found in the work of Ghiselli (1956, 1960a, 1960b). He has chosen to improve prediction directly through the development of a composite predictability index that explains variance in the prediction errors resulting from an existing prediction model. It would, however, appear as if the procedure has found very little, if any, practical acceptance, partly attributed to the fact that the predictability index failed to significantly

Stellenbosch University http://scholar.sun.ac.za

explain unique variance in the criterion when added to a model already containing one or more predictors.

Resultantly, based on the Ghiselli idea, this research investigates the possibility of modifying such a predictability index so that it does significantly explain unique variance in the criterion when added to a model already containing one or more predictors. In addition, the study investigates whether the expansion of the prediction model is warranted by examining the effect the increase in subject predictability has on the predictive validity of the selection procedure, as well as the monetary effect it has on the utility of the procedure. Hypotheses are tested to determine the possibility of developing an index from a personality measurement that shows a strong and significant correlation with the residuals computed from the regression of the criterion on an ability predictor; to determine if the addition of the index to an ability predictor significantly explains variance in the criterion measurement that is not yet explained by the ability predictor relationships, and to determine whether this ability is affected by the direction in which the index has been developed. Furthermore, hypotheses are tested to determine the increment on validity and selection utility.

The data for the analysis was obtained from Psytech (SA), where a validation study was performed at the Gordon Institute of Business Science using the Apil-B ability test, the Critical Reasoning Test Battery and the Organisational Personality Profile measurements to predict the performance of 100 MBA students.

The results of the analysis confirmed Ghiselli's earlier findings that the traditional predictability index does not significantly explain variance in the criterion residual when added to the selection battery. However, by modifying the Ghiselli procedure, the study found that the index was able to significantly explain variance when added to a battery already containing the predictor. When the index is based on the real values of the residuals, the addition of the predictability index to the model significantly explains unique variance in the criterion, but not so when based on the absolute values of the residuals. It also indicated that the inclusion of the predictability index to the prediction

Stellenbosch University http://scholar.sun.ac.za

model created a substantial increase in the validity of the selection procedure and that the increase in validity translated into a noteworthy improvement in utility.

Conclusions are drawn from the obtained results and recommendations are made for future research.

Stellenbosch University http://scholar.sun.ac.za

'n Psigometriese Ondersoek na die Gebruik van 'n Aanpassing van die Ghiselli Voorspellingsindeks in Personeelkeuring

Liesle Twigge, Department Bedryfsielkunde, Universiteit van Stellenbosch, Suid-Afrika

Studieleier: Prof C.C. Theron, M.A., D.Phil (Stell.)

Opsomming

Die veld van menslike hulpbronne sluit 'n aaneenlopende besluitnemingsproses aangaande die passing van die arbeidsmag met die werkplek in, aangesien hierdie passing die individu se motivering met betrekking tot optredes wat met die werkplek geassossieer word, bepaal.

Indien die besluitnemer ten tye van die besluitneming alreeds oor inligting rakende die eindprestasie van die individu beskik, sal die moontlikheid verhoog word om die gewenste resultate uit die besluitneming te verkry. Personeelkeuring word egter gekompliseer deur die voor die hand liggende feit dat inligting rakende die eindprestasie nie beskikbaar is ten tye van die keuringsbesluit nie. Alle besluite van hierdie aard sluit dus voorspellings oor individue se prestasie in. Die klassieke geldigheidsmodel vorm die basis van alle voorspellings gebaseer op die sterkte van die verwantskap tussen die voorspeller van prestasie en die werklike prestasie van die individu.

Oor die jare is verskeie moontlikhede oorweeg om die sterkte van die hierdie verwantskap soos uitgedruk deur die geldigheidskoëffisiënt te verhoog, hoofsaaklik deur middel van aanpassings en/of verlengings van die standaardregressiemodel. 'n Interessante en uitdagende alternatief vir die pogings gebaseer op meervoudige regessie kan gevind word in die werk van Ghiselli (1956, 1960a, 1960b). Hy poog om voorspelling direk te verbeter deur die ontwikkeling van 'n saamgestelde voorspellingsindeks wat variansie verklaar in die voorspellingsfoute verkry uit 'n bestaande voorspellingsmodel. Dit wil egter voorkom asof die voorspellingsindeks

Stellenbosch University http://scholar.sun.ac.za

gefaal het om unieke variansie in die kriterium te verklaar wanneer dit toegevoeg word tot 'n model wat alreeds een of meer voorspellers bevat.

Gebaseer op die Ghiselli-idee, ondersoek hierdie navorsing dus die moontlikheid om die voorspellingsindeks aan te pas sodat dit beduidend unieke variansie in die kriterium verklaar wanneer dit toegevoeg word tot 'n model wat alreeds een of meer voorspellers bevat. Die studie ondersoek enersyds ook die regverdiging van die uitbreiding van die voorspellingsmodel deur die impak van die verbetering in voorspelling op die voorspellingsgeldigheid van die keuringsprosedure, en andersyds bestudeer dit ook die monetêre effek op die nutwaarde van die prosedure. Hipoteses word getoets om die moontlikheid van 'n indeks, wat uit 'n persoonlikheidsmeting ontwikkel, is en wat sterk en beduidend met die residue wat uit die regressie van die kriterium op die vermoënsvoorspeller bereken is, te bepaal. Daar word ook getoets of die toevoeging van die indeks tot 'n vermoënsvoorspeller beduidende variansie in die kriteriummeting verklaar wat nie alreeds deur die vermoënsvoorspeller verklaar word nie. Daar word verder bepaal of hierdie vermoë geaffekteer word deur die rigting waarin die indeks ontwikkel is. Verder word hipoteses getoets aangaande die impak op beide die geldigheid en die nutwaarde van die keuringsprosedure.

Die data vir die analises is verkry by Psytech SA, waar 'n valideringstudie uitgevoer is by die Gordon Institute of Business Science deur die gebruik van die Apil-B vermoënstoets, die Critical Reasoning Test Battery en die Organisational Personality Profile metings om die prestasie van 100 MBA studente te voorspel.

Die resultate van die analise bevestig Ghiselli se vroeëre bevindings dat die tradisioneel ontwikkelde indeks nie beduidend variansie in die kriteriumresidue verklaar wanneer dit toegevoeg word tot die keuringsbattery nie. Deur egter die oorspronklike Ghiselli prosedure aan te pas word gevind dat die toevoeging van die indeks tot die regressiemodel wel beduidend unieke variansie verklaar. Die vermoë van die indeks om variansie te verklaar wanneer dit tot die battery toegevoeg word, is beduidend wanneer die indeks gebaseer word op die werklike waardes van die residue, maar toon geen

Stellenbosch University http://scholar.sun.ac.za

beduidendheid wanneer dit gebaseer word op die absolute waardes van die residue nie. Die resultate dui ook daarop dat die insluiting van die voorspellingsindeks in die model 'n betekenisvolle toename in die voorspellingsgeldigheid van die keuringsprosedure teweegbring, en dat die toename in voorspellingsgeldigheid vertaal na 'n substantiewe styging in nut.

Gevolgtrekkings word uit die verkreë resultate afgelei, en aanbevelings vir toekomstige navorsing word gemaak.

Stellenbosch University http://scholar.sun.ac.za

ACKNOWLEDGEMENTS

I would like to give acknowledgement to Prof. Callie Theron for his continued wisdom, guidance, enthusiasm and support during this study.

Appreciation is extended to Nanette Tredoux of Psytech SA for permitting access to the raw data, which was collected for a validation study at a post-graduate institution in South Africa.

I would further like to offer gratitude to Mareth Hugo for assistance in the linguistic preparation of the manuscript.

Finally, I extend my sincerest thanks to my parents for their love, encouragement and support.

Stellenbosch University http://scholar.sun.ac.za

Dedicated to my beloved Father and Mother

Stellenbosch University http://scholar.sun.ac.za

TABLE OF CONTENTS

Stellenbosch University http://scholar.sun.ac.za

Stellenbosch University http://scholar.sun.ac.za

CHAPTER 4

RESULTS OF ANALYSIS

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

Stellenbosch University http://scholar.sun.ac.za

LIST OF TABLES

Stellenbosch University http://scholar.sun.ac.za

LIST OF FIGURES

Stellenbosch University http://scholar.sun.ac.za

CHAPTER 1
INTRODUCTION, OBJECTIVES AND OVERVIEW OF THE STUDY

1.1. Introduction

Man's very existence evolves around a continuous economic cycle of production and consumption. Money is the force by which this sequence is kept dynamic. By converting money into the production of goods and services for consumption, organisations are the vital instruments for enabling these human behaviours. Organisations, on one account, exist to provide the society in which they function with essential goods and services by capitalising on its scarce resources. Conversely, organisations, in its very core, exist to provide its stakeholders with maximum profits. By its existence, organisations form the heart of the economic cycle.

However, organisations are more than that which is physically observable and which occupies physical space. Organisations are about people; specifically the behaviour of people. In essence, an organisation exists through and is constituted by its people. To an enormous degree, the effectiveness of an organisation depends on the effectiveness of its employees. Without a high quality labour force, an organisation is destined to fail to reach performance of high regard.

To aid an organisation in reaching its full potential, an organisation's human resources must be utilized and managed as effectively as possible. Human resource management is therefore undoubtedly an irreplaceable function to design and implement policies and programmes that enhance employee performance and improve the organisation's overall effectiveness.

Human resource management constitutes an array of interventions that guide a workforce to achieve the goals set for an organisation. The selection of appropriate human resources is one of these functions, and can logically be said to be at the basis of the

Stellenbosch University http://scholar.sun.ac.za

success of these interventions, as it regulates the movement of employees into, through and out of the organisation. Selection, as it is most simply interpreted, is the process of selecting from a particular group of recruits the individual best suited for that particular position.

First and foremost, selection thus represents a potentially powerful instrument through which the human resources function could add value to an organisation. Furthermore, it also represents a relatively visible mechanism through which opportunities within the organisation can be regulated. This latter aspect puts selection, more than any other human resource intervention, under constant scrutiny, in that it should entail efficient, fair and equitable practices (Theron, 1999).

Effective selection decisions strive to enhance its contribution to the organisation's overall efficiency by maximising the economic value added to the organisation by selecting those employees best suited for their positions. The value added is determined by the rand-and-cent value of the improvement in performance an organisation will experience if its human resource selection decisions result in hiring the most appropriate applicants for its vacancies and the cost of affecting this improvement. Attempts to improve selection procedures must therefore be evaluated in terms of the financial utility of the decisions in which it results.

> Personnel decisions centre around the assignment (or non-assignment) of one or more individuals to treatments whose outcomes are of importance to institutions or to the individuals so assigned (Wiggins, 1973, p. 224).

If the decision maker knew beforehand how well each individual was qualified for each treatment and thereby could anticipate the outcome of any assignment, no selection problem would exist, and for that matter, no such research as the present would be necessary. In a Utopia all organisations would be filled with employees perfectly fitted to their positions. The ideal would be to base selection decisions on measurements of the final criterion, performance, at the time of selection. The ideal situation, however, never occurs. Moreover, the lack of information regarding the performance on assignments or

Stellenbosch University http://scholar.sun.ac.za

the outcomes of the assignments, force decision makers to predict the performance and outcomes of individuals (Cronbach & Gleser, 1965; Wiggins, 1973). To make better-than-chance assignments based on predicted performance certain, a priori information must be available to the decision maker when the predictions are made (Ghiselli, Campbell & Zedeck, 1981). The decision maker has to utilize information that will enable the forecasting of outcomes most accurately. The task of the decision maker is to make predictions from a priori and assessment data with the possible outcomes having values assigned to it, in such a manner that the overriding purpose of the organisation is maximised (Wiggins, 1973).

An accurate estimation of performance will be possible from substitute information to the extent to which the substitute correlates with a measure of performance and the nature of the relationship is known. In the absence of the required information at the time of decision-making, only two possible options exist to obtain relevant substitute information for the criterion (Binning & Barrett, 1989). Such substitute information could be considered relevant to the extent to which it permits an accurate estimate of performance.

Under the first option the job in question would be systematically analysed with the purpose of inferring presumed critical incumbent attributes. These attributes are believed to be determinants of the level of criterion performance that would be attained from the description of the job content and context. The presumed interrelationships between these hypothesised determinants and the way they collectively combine in the criterion are postulated in a nomological network or latent structure (Campbell, 1991; Kerlinger & Lee, 2000) as a complex hypothesis explaining criterion performance in the job in question. These hypothesised determinants of criterion performance, or a person centred subset thereof, could, to the extent that the tentative performance theory is indeed valid, serve in combined form as a suitable substitute measure for the, still to be realised, actual criterion scores. The way these hypothesised determinants of performance should be combined is suggested by the way these determinants are linked in the postulated nomological network (Theron, 1999). Therefore, should it be possible to validly and reliably operationalise the person-centred constructs required performing successfully on

Stellenbosch University http://scholar.sun.ac.za

the job, and these measures would be combined in a manner that agrees with the relationships that exist in the nomological network, a relevant substitute measure for the actual criterion scores would be obtained. The first option could be termed a construct orientated approach (Binning & Barrettt, 1989).

In the second option the job in question would again be systematically analysed via one or more of the available job analysis techniques (Gatewood & Feild, 1994) to identify and define the behaviours that collectively denote job success if exhibited on the job. Substitute information would then be obtained through low or high fidelity simulations of the demands that need to be met on the job to be considered successful. These simulations in a selection context necessarily occur off the job and prior to the selection decision. Such simulations would elicit behaviour that, if in future exhibited on the job, it would denote a specific level of job performance. The second option could be termed a content orientated approach (Binning & Barrettt, 1989).

Both options obtain substitute information through observable behaviour elicited by a stimulus set. In the construct orientated approach, the stimuli are designed so that the testee's response to them is primarily a function of a specific, defined construct. Owen and Taljaard (1998) regard these stimuli (psychological tests) as sets of items that serve the purpose of deriving very specific behaviour with regards to a specific construct that is being tested, in determining testees characteristics with regards to aspects such as mental ability, aptitude, interests and personality structure and performance. These sets of stimuli comprise methods of evaluation and selection by way of scores with acceptable psychometric properties such as satisfactory validity and reliability coefficients.

In the content orientated approach the stimuli are designed to elicit the same response as actual facets of the job would elicit. Although the reaction to the stimulus set is again determined by a network of constructs, the nature of these constructs are not (necessarily) known. The extent to which effective substitute criterion measures are obtained through these two options should be the subject of empirical validation investigations. The nature of the evidence required to justify the use of the substitute X differs across these two

Stellenbosch University http://scholar.sun.ac.za

options. Option 1 requires proof that X provides a construct valid measure of ξ; that Y provides a construct valid measure of η and that X significantly explains variance in Y and thus by implication in η. Option 2 requires proof that X represents a representative sample of the demands that collectively constitute the job content, that Y provides a construct valid measure of η and that X significantly explains variance in Y and thus by implication in η (Binning & Barrettt, 1989; Theron, 1999).

Clearly important differences exist between the logic underlying these two options in terms of which substitute criterion measures are generated. Most pertinent, is the fact that the first option requires the clarification of an underlying performance theory whilst the second option can proceed without any noteworthy understanding as to why inter-individual performance differences exist (Theron, 1999). The two arguments, however, would agree that effective, though not necessarily value-adding, selection would be possible if the substitute for the ultimate criterion showed a statistically describable relationship with a valid operational measure of the ultimate criterion. Both arguments, moreover, maintain that the same condition represents a necessary, but again not sufficient, condition to achieve fair employee selection.

The extent to which the substitute succeeds in representing the ultimate criterion is in both cases described by a validity coefficient. In both cases the validity coefficient would be a multiple correlation calculated between a composite intermediate criterion and a weighted combination of the indicators or predictors of performance ($R_{Y,E[Y|X_i]}$). A perfect correlation would mean that the selector has a perfect understanding of the performance structural model (Campbell, 1991); can obtain perfectly reliable and valid measures of all relevant latent variables and thus could, with perfect precision and complete certainty, predict values on the intermediate criterion from the combined substitute measures. Selection would be straight forward if this would be the case, because it would mean that the actual outcomes that would result for any applicant, should such an applicant be accepted, can be predicted with complete certainty. For such a perfectly informed selector there would be no unforeseen consequences and therefore also no risk and no decision errors (Theron, 1999). This is, however, never the case

Stellenbosch University http://scholar.sun.ac.za

(March & Simon, 1958). The condition, under which the selector in reality has to make selection decisions, is characterised by relevant, limited and psychometrically imperfect information. Relevant but limited and psychometrically flawed information would therefore result in the typical imperfectly correlated, bivariate distribution of composite criterion and composite predictor/substitute criterion scores (Boudreau, 1991; Campbell, 1991; Cronbach & Gleser, 1965; Theron, 1999). This classic validity model forms the foundation of all selection procedures (Boudreau, 1991; Campbell, 1991). The selector's lack of perfect understanding of what affects criterion performance and how this determines criterion performance, combined with his inability to measure the relevant person characteristics without error, therefore prevents him from anticipating selection outcomes with complete certainty. His access to relevant, but limited, and psychometrically flawed information on applicants, however, still allows him the possibility of statistically describing the conditional criterion distribution in terms of its mean and standard deviation. Thus the decision maker can only base his decision whether to accept an applicant on the expected criterion performance conditional on information on the applicant or, if a minimally acceptable criterion performance level can be defined, the conditional probability of success (or failure) given information on the applicant (Theron, 1999).

Cronbach and Gleser (1965) acknowledge that our society continually confronts people with decisions for which they have inadequate information. Psychological tests and other assessment techniques are used to provide information for decision-making. Cronbach and Gleser (1965) vigorously advocate the inability of traditional measurement and test theory, due to its emphasis on the instrument and precision of measurement, to provide an adequate conceptual framework from which to assess the practical usefulness of tests in decision-making.

Personnel selection essentially is a form of applied decision-making. The focus thus should be on the quality of the selection decisions and not on the psychometric properties of the measuring instruments used to provide the information for the decision-making. Cronbach and Gleser (1965) acknowledge the usefulness of tests for accurate estimation

Stellenbosch University http://scholar.sun.ac.za

of an underlying latent variable, but suggest that the value of a selection procedure depends on many other qualities in addition to the reliability and validity with which the critical attributes are being measured. Especially to be considered is the relevance of a measurement to a particular decision in which it results and the loss resulting from an erroneous decision. They maintain a view that the ultimate purpose of any personnel testing is to arrive at qualitative decisions. Cronbach and Gleser (1965, pp. 135-136) point out the inadequacy of traditional measurement theory as a conceptual vehicle to evaluate the usefulness of selection instruments by stating:

> The traditional theory views the test as measuring instrument intended to assign accurate numerical values to some quantitative attribute of the individual. It therefore stresses, as the prime value, precision of measurement and estimation. .... In pure science it is reasonable to regard the value of a measurement as proportional to its ability to reduce uncertainty about the true value of some quantity. .... In practical testing, however, a quantitative estimate is not the real desideratum. A choice between two or more discrete treatments must be made. The tester is to allocate each person to the proper category, and accuracy of measurement is valuable only insofar as it aids in this qualitative decision.

This should, however, not be interpreted to mean that classical measurement and test theory should be regarded as irrelevant and outmoded. Although it would be wrong to equate quality of decision-making to the magnitude of the validity coefficient, the latter nonetheless still influences the former. If the other pertinent factors affecting selection decision quality are held constant, selection decision quality increases as the absolute value of the validity coefficient increases. Utility is a positive linear function of validity, and for zero cost, is proportional to validity (Brogden, 1946; Brogden, 1949a, 1949b). The validity coefficients typically encountered in validation studies are, however, disappointingly low. Validity coefficients typically fall below 0, 50 and only very seldom reach values as high as 0, 70 (Campbell, 1991). Typically selection instruments thus explain only 25% of the variance in the criterion (Campbell, 1991). The validity ceiling first identified by Hull (Hull, 1928) seemingly still persists. Numerous possibilities have been considered on how to affect an increase in the magnitude of the validity coefficient (Campbell, 1991; Ghiselli et al, 1981; Guion, 1991). A survey of

Stellenbosch University http://scholar.sun.ac.za

these will be subsequently presented. Most of these attempts revolved around modifications and/or extensions to the regression strategy (Gatewood & Feild, 1994).

An interesting and provocative alternative to the usual multiple-regression based attempts may be found in the work of Ghiselli (1956, 1960a, 1960b). Rather than expanding on the basic mathematical model of multiple-regression, Ghiselli has chosen to attack the problem of improved prediction directly by the use of empirical procedures (Ghiselli, 1956, 1960a, 1960b). The essence of the proposed procedure revolves around the development of a composite predictability index that explains variance in the prediction errors or residuals resulting from an existing prediction model. It would, however, appear as if the procedure has found very little if any practical acceptance.

The actuarial nature of the procedure could probably to a large extent account for it not being utilized in the practical development of selection procedures. The lack of general acceptance must, however, also be attributed in part to the fact that the predictability index originally proposed by Ghiselli (1956, 1960a, 1960b) failed to significantly explain unique variance in the criterion when added to a model already containing one or more predictors (Wiggins, 1973). The predictability index thus only serves the purpose of isolating a subset of individuals for whom the model provides relatively accurate criterion estimates. The selection problem, however, requires the assignment of each and every member of the total applicant sample (and not only a subset of the applicant group) to one of two possible treatments based on their estimated criterion performance.

Based on the original idea proposed by Ghiselli (1956, 1960a, 1960b), the objective of this research is to investigate the possibility that the differentiation between subjects on the basis of the predictability of their criterion performance could be used to increase the accuracy of the criterion estimates for the total applicant sample. If the addition of a modified predictability index does significantly explain unique variance in the criterion when added to a model already containing one or more predictors, the study in addition will try to determine whether the expansion of the prediction model is warranted, by examining the effect the increase in subject predictability has on the predictive validity of

Stellenbosch University http://scholar.sun.ac.za

the selection procedure, as well as the monetary effect it has on the utility of the procedure.

1.2. Research Objectives

More specifically, the objectives of the study are:

- to propose a modification to the Ghiselli procedure that would solve the aforementioned problem experienced by Ghiselli (1956, 1960a, 1960b) in his original studies;
- to corroborate the earlier finding of Ghiselli (1956, 1960a, 1960b) that the development of a predictability index that significantly explains variance in the criterion residual, is practically possible;
- to demonstrate that this relationship is persistent in as far as it cross-validates to representative hold-out samples;
- to examine the factor structure of the predictability index to establish whether substantive theoretical meaning could be attached to the predictability index;
- to examine the incremental validity resulting from the inclusion of the predictability index in the prediction model;
- to examine the impact of the inclusion of the predictability index in the prediction model on selection utility.

1.3. Outline of the Study

The manuscript will commence with an in-depth study of the relevant literature on the various approaches that have been employed to increase the correlation between predicted and eventual criterion performance. Special attention will be devoted to a procedure suggested by Ghiselli (1956, 1960a, 1960b). The rationale behind a modification of the original procedure will be put forward. The research problems and substantive research hypotheses will subsequently be stated. A discussion of the research methodology will put forward the research design, statistical hypotheses, statistical analyses, the computer package utilised, as well as the sampling design. The manuscript

Stellenbosch University http://scholar.sun.ac.za

will conclude with a discussion of the observed results and the conclusions, and in addition, propose recommendations for further studies.

Stellenbosch University http://scholar.sun.ac.za

CHAPTER 2
LITERATURE STUDY

2.1. The Essential Logic Underlying Personnel Selection

Any person working in the field of human resources is continually making decisions regarding the matching of the workforce with the workplace. Human resources activities match individuals and jobs. Individuals bring particular skills, knowledge, aptitudes, needs and values to the employment relationship. Jobs have a certain content or duties, tasks, behaviours, functions and responsibilities necessary for satisfactory performance. They also have returns or results of membership and performance, such as pay, status, and social relationships. The worker-job match affects efficiency and equity. Regarding efficiency, the match between the individual's skills, knowledge and aptitudes and the job's content determines the individual's ability to accomplish work behaviours such as performance, attendance and tenure. The match between the individual's needs and values, behaviours, and the job's returns determines the individual's motivation to engage in the work behaviours (Milkovich & Boudreau, 1988). If the decision maker obtains better information before making his decision, he will have a better chance of attaining the results he desires. All decisions involve prediction about some difference among people's performance (Cronbach, 1960).

Selection traditionally involves evaluating inter-individual differences among job applicants on the basis of their knowledge base, skill level, intellectual abilities, personality attributes, and disposition to maximise organisational pay-offs such as productivity. These inter-individual differences are the basis for predicting an applicant's job performance and are the division line between the one that is chosen and the rest who are declined (Ackerman & Humphreys, 1990; Cook, 1998; Guion, 1991).

Stellenbosch University http://scholar.sun.ac.za

Personnel selection is necessitated by the combined effect of inter-individual differences amongst applicants on those attributes that would determine their eventual job performance and the selecting organisation's desire to maximise performance. The desire to maximise performance implies work success as the ultimate/final institutional criterion in terms of which applicants for employment should ideally be evaluated and on which they should ideally be compared so as to arrive at an institutionally rational selection decision. Personnel selection is, however, complicated by the obvious fact that information on the ultimate institutional criterion can never be available at the time of the selection decision. The only solution to this dilemma, apart from reducing selection to random assignment, is to base the decision on relevant substitute information that is assessable prior to the selection decision (Ghiselli et al., 1981; Theron, 1999). Even if no direct information on the criterion ever enters the selection decision making process, the criterion nonetheless always remains the focus of interest and interpretation in selection assessment. Substitute information can be considered relevant to the extent to which it correlates with a valid operationalisation of the ultimate criterion. The identification of relevant substitute information therefore creates the possibility of estimating the expected criterion performance and/or probability of success/failure conditional of the information content.

Earlier two basic options have been identified in terms of which such substitute information can be generated. The focus of the subsequent discussion, aimed at identifying various possible approaches that could be pursued to enhance the accuracy with which criterion performance is predicted from information obtained during selection, will be the construct orientated approach (Binning & Barrettt, 1989).

Although behaviour of working man is an extremely complex phenomenon, the construct orientated approach assumes that just as in the rest of nature, things happen in an orderly, systematic fashion as a function of a set of determining factors in accordance with laws. The behaviour of working man is also the result of the lawful working of a set of determining factors characterising the individual and the context in which the behaviour occurs and not simply a random walk through the workplace.

Stellenbosch University http://scholar.sun.ac.za

According to Kerlinger and Lee (2000) nothing in nature, not even the roll of a dice, and thus by implication, nothing in the behaviour of working man, occurs in an absolute sense by chance. Determinism, as a philosophical assumption, represents the view that all phenomena are necessary results of previously existing conditions (Goodwin, 1995). The construct orientated approach to selection must make this assumption in order to justify its objective to explain the behaviour of working man, as well as its objective to influence the performance of working man by regulating the flow of employees in, through and out of the organization based on such explanations.

The deterministic assumption made by the construct orientated approach to selection implies that the behaviour of working man should in principle be explicable in terms of behavioural laws of the basic form "if ξ (changes) then η (changes along with ξ)" where ξ represents an exogenous latent variable that affects an endogenous latent variable (Diamantopoulos & Sigauw, 2000). Explaining the behaviour of working man thus means uncovering the relevant exogenous and endogenous latent variables and the nature and strength between them (Goodwin, 1995).

Scientific theory represents a set of interrelated constructs, their definitions and proven statements (in the sense that they have survived the opportunity to be refuted) on the nature of the relationship between constructs of the basic form "if ξ then η" as an explanation of a phenomenon in nature, with the objective of science to provide valid and credible explanations for the sake of the practical utility of knowledge (Kerlinger & Lee, 2000). Effective selection under the construct orientated approach to selection thus requires the explication of a performance theory. A valid performance theory constitutes a fundamental and indispensable, though not sufficient, prerequisite for efficient and equitable human resource selection (Guion, 1991; Milkovich & Boudreau, 1988; Theron, 1999). Stated more bluntly, measuring the wrong attributes well will result in ineffective selection just as surely as measuring the correct attributes poorly will result in ineffective selection. More specifically efficient selection will be possible to the extent to which:

Stellenbosch University http://scholar.sun.ac.za

a) the identity of the full spectrum of latent variables (ξ_i) determining performance (η) are known;

b) the nature of the relationship between the criterion construct (η) and the latent variables influencing it (ξ_i) are correctly understood;

c) the latent variables determining performance (ξ_i) can be reliably and validly measured (X_i);

d) the nature of the relationship between the criterion construct (η) and the latent variables influencing it (ξ_i) can be accurately captured in a prediction/decision rule.

To substantiate the claim that actual job performance can be inferred from information obtained from selection techniques, the nomological network or latent structure (Binning & Barrettt, 1989; Campbell, 1991; Guion, 1991) explaining criterion performance should be tested empirically. To establish the legitimacy of the performance hypothesis, an operational hypothesis is deductively derived from the substantive performance hypothesis by operationally defining the performance construct (η) and the explanatory psychological constructs (ξ_i). The operational definition (Y) of the performance construct constitutes a premise in the aforementioned deductive argument, as do the operational definitions (X_i) of the explanatory psychological constructs. The validity of the deductive argument depends on the validity of these premises (Copi & Cohen, 1990; Mouton & Marais, 1985). In a valid deductive argument the premises provide conclusive grounds for the truth of the conclusion (Copi & Cohen, 1990). The justifiability of the claim that the operational performance hypothesis constitutes a valid testable representation of the theoretical performance hypothesis thus depends on the construct validity (Kaplan & Saccuzzo, 2001) of the operational measures of the performance construct and the explanatory psychological determinants. Should empirical support for the operational performance hypothesis be found (assuming that the aforementioned deductive argument was in fact valid), the substantive performance hypothesis may be regarded as corroborated since it has survived an opportunity to be refuted (Popper, 1972). The validity of the substantive performance hypothesis, together with evidence on the construct validity of the operational measures of the explanatory person centred latent

Stellenbosch University http://scholar.sun.ac.za

variables, provides support for the assertion that job performance (η) can be predicted from a set of predictors (X_i) developed through a construct-related approach. If it can be shown that an instrument validly measures (X_i) a specific construct (ξ_i) that has been shown to be vital for job performance (η), then certain inferences about job performance from the test scores are, by logical implication, possible (Binning & Barrett, 1989; Nunnally & Bernstein, 1994; Thorndike, 1982). If this can be shown then it could be said that the selection procedure has been successfully validated.

2.2. Validity of Selection Decision Making

Validity is a concept of considerable complexity. Validity, at the same time is a concept that is quite often misunderstood (Binning & Barrett, 1989; Kaplan & Saccuzzo, 2001; Schmitt & Landy, 1993). Since at least the early 1950's, test validity has been broken into three distinct types, one of which comprises two subtypes (Messick, 1989). These are the familiar trinity of content validity, criterion related validity (subsuming predictive and concurrent validity) and construct validity (Ellis & Blustein, 1991; Landy, 1986; Kaplan & Saccuzzo, 2001; Messick, 1989, Schmitt & Landy, 1993; Schuler & Guldin, 1991). The taxonomy itself is not fundamentally flawed (Kaplan & Saccuzzo, 2001; Landy, 1986) in as far as it suggests that different inferences can be made from test scores. The linkage of these validity concepts to specific aims of testing by the American Psychological Association in their technical recommendations on psychological testing (American Psychological Association, 1954, 1966, 1974), in conjunction with Title VII litigation case law (Landy, 1986), did however create the false belief that only a single validation type or strategy needs to be employed to justify inferences made from test scores in any given situation.

One should, however, not think of the three so-called types of validity as standing for discrete and independent processes. The three so-called types of validity should rather be seen as representing parts of a larger system that addresses the goal of hypothesis testing (Landy, 1986). The different validity analysis strategies are not alternatives but rather form supplementary facets of a single unitary validity concept (Binning & Barrett, 1989;

Stellenbosch University http://scholar.sun.ac.za

Ellis & Blustein, 1991; Guion, 1991; Messick, 1989; Schmitt & Landy, 1993). The validation process is hereby meant not to be regarded as one in which the available validity approaches are independent of one another, as is suggested by the Trinitarian approach, but rather to adhere to a coherent validity concept of employing the relevant validity approaches as a union. Critics of the Trinitarian approach (Guion, 1980; Landy, 1986; Dunnette & Borman, 1979) plead that bolder steps must be taken to break away from the Trinitarian doctrine of validity. Thus, instead of using them as different methods of validation, they should be employed as different analyses, all of which are essential to the validation process (Nunnally & Bernstein, 1994). Schmitt and Landy (1993, p. 286) clearly affirm the foregoing position by stating:

> Marshalling evidence of validity is now seen as a process of theory development and testing (Binning & Barrett, 1989; Landy, 1986). We must develop and articulate theories of job performance and define logically the constructs that are central to these theories. We must establish a 'nomological network' that relates constructs important in the job performance domain to the constructs we choose to identify qualified job applicants. This requires evidence that the measures we use to operationalize constructs in the predictor and performance domains possess a logical relationship to these constructs and empirically consistent relationships to other measures of the construct.

The validation process is therefore not so much directed towards the integrity of tests as they are directed towards the inferences that can be made about the attributes of the people who have produced those test and criterion scores (Guion, 1980; Landy, 1986). According to Binning and Barrett (1989), validity is not a characteristic of an assessment procedure, but rather of the inferences derived from the information from such a procedure. The validity of a selection procedure thus refers to the extent to which inferences about the criterion construct from assessment procedures are justifiable. But to justify such criterion referenced inferences requires proof that construct referenced inferences are permissible from the predictor and the criterion measures. Binning and Barrett (1989) consequently propose five inferences or hypotheses to be central to the validation of a personnel selection procedure, namely:

Stellenbosch University http://scholar.sun.ac.za

a) The performance/criterion construct (η) is related to (and thus could in principle be inferred from) an array of systematically interrelated predictor or person-centred constructs (ξ_i);
b) an operational criterion measure (Y) provides a reliable and valid empirical measure of the performance construct (η) so that it is possible to infer the state of η from Y;
c) a set of predictors (X_i) provide valid and reliable measures of the corresponding predictor constructs (ξ_i) so as to enable the inference of the latter from the former; and consequently
d) the operationalised performance/criterion construct (Y) is systematically related to (and therefore can be predicted from) the set of predictors (X_i) measuring the person-centred constructs (ξ_i) on which the performance construct depends, and consequently
e) the performance construct (η) is related to (and therefore could be inferred from) the set of predictors (X_i) measuring the person-centred constructs (ξ_i) on which the performance construct depends

Criterion-related validity thus necessitates strong evidence not only about the relationship between the predictor and criterion measures, but also the relationship between the criterion measure and the performance domain, as well as the relationship between the predictor measure and the predictor construct (Binning & Barrett, 1989; Nunnally & Bernstein, 1994; Thorndike, 1982). The rationale for the expanded or unificationist view of the validation process stems from the fact that although the purpose of employment testing is prediction, a simple criterion-related design is not sufficient to support the inference that people who do better on the test will perform better on the job. Some assurance is needed that the criterion, performance, is measured in some reasonable way, and whether it does is determined via construct validation. Furthermore, in choosing one criterion rather than another, it is assumed that the criterion is either representative of, or pre-eminent among the many criteria that might have been chosen. This assumption implies content-orientated validity (Landy, 1986).

Stellenbosch University http://scholar.sun.ac.za

2.3. Selection Decision Strategies

Measurement data, once obtained, is translated into decisions in accordance to some strategy for decision-making (Cronbach, 1960). A decision strategy describes how scores from tests are to be combined with non-test information, and what decision will be made for any given combination of facts. A strategy is thus a rule for arriving at selection decisions used by a decision maker in any possible contingency (Cronbach & Gleser, 1965). It consists of a set of specified conditional probabilities (typically either zero or unity) which reflects the policy of the decision-maker. In the final analysis it is the selection decision strategy which should be evaluated in terms of its predictive validity - in other words terms of the correspondence that exists between the criterion referenced inferences made via the decision rule from the available predictor information and the actual criterion performance achieved. Demonstrating that the available predictor variables individually correlate significantly with the criterion thus constitutes insufficient evidence to justify the use of the predictor variables for selection decision-making. This important realisation often seems to be absent in validation studies which combines selection information in accordance with a clinical or judgemental strategy (Gatewood & Feild, 1994).

Several selection decision-making strategies exist that range from pure clinical to pure mechanical combinations of data available to the decision maker (Kleinmutz, 1990; Murphy & Davidshofer, 1988). The problem thus becomes determining which of the strategies are superior in providing the most accurate predictions to the decision-maker.

Clinical prediction involves combining information from test scores and measures obtained from interviews and observations covertly in terms of an implicit combination rule imbedded in the mind of a clinician to arrive at a judgment about the expected criterion performance of the individual being assessed (Murphy & Davidshofer, 1988). Mechanical prediction involves using the information overtly in terms of an explicit combination rule to arrive at a judgment about the expected criterion performance of the individual being assessed (Murphy & Davidshofer, 1988). An actuarial system of

Stellenbosch University http://scholar.sun.ac.za

prediction represents a mechanical method of combining information to arrive at an overall inference about the expected criterion performance of an individual that was objectively derived via statistical or mathematical analysis from actual criterion and predictor data sets (Meehl, 1954; Murphy & Davidshofer, 1988). Wiggins (1973, p. 200) very clearly states that:

> Statistical combination of input data qualifies as actuarial prediction if and only if the combination is completely determined by empirical regularities that have been demonstrated to exist between the input data and the criterion to be predicted.

The actuarially derived decision rule should, therefore reflect the nature of the relationship that exists between the various latent predictor variables and the criterion construct.

The accuracy of clinical and actuarial prediction has been studied widely (Dawes, 1971; Dawes & Corrigan, 1974; Goldberg, 1970; Kleinmutz, 1990; Meehl, 1954, 1957; Murphy & Davidshofer, 1988). These reviews seem to suggest that clinicians very rarely make better predictions that can be made using actuarially derived prediction methods, that statistical methods are in many cases more accurate in predicting relevant criteria than are highly trained clinicians, and that clinical judgement should be replaced, wherever possible, by mechanical methods of integrating the information used in forming predictions (Murphy & Davidshofer, 1988).

The debate surrounding the use of clinical versus actuarial decision making has been maintained for many years. The most valuable outcome of this debate was that the assessment and decision making process should be broken down into several subtasks and that some of these tasks are done most efficiently by using statistical techniques. Rather than abandoning the use of the clinical mind in the assessment and decision making process, it should be used to perform those activities it excels in, so that the two approaches complement each other in a way that enhance the decision making quality. Statistical methods are superior to clinical methods when it comes to tasks such as standardized data collection, data analysis and integration of information, but abandoning

Stellenbosch University http://scholar.sun.ac.za

clinical judgement would preclude the use of behavioural observation data and, especially important, would negate the importance of theorization and hypothesis formation. The combination of these methods, and thus leaving room for a certain degree of clinical judgement, seems to be preferable to the exclusion of one from the other (Murphy & Davidshofer, 1988; Goldberg, 1970).

Efficient selection will be possible under the construct orientated approach to selection to the extent to which the nature of the relationship between the criterion construct (η) and the latent variables influencing it (ξ_i) can be accurately captured in an explicit mechanical prediction/decision rule. One of the primary objectives of selection validation research is thus to actuarially derive a model/description of the relationship between the criterion construct (η) and the latent variables influencing it (ξ_i) to allow the researcher to accurately predict criterion performance on the basis of knowledge about predictor variables. In the derivation of such a model the researcher would typically engage in regression analysis.

Regression analysis provides the basis of a decision making strategy by typically forming a linear combination of predictors in an actuarial manner by regressing performance assessments on a weighted linear combination of predictors. The multiple regression strategy minimizes error in prediction and combines the predictors optimally to yield the most efficient estimate of criterion status (Hair, Anderson, Tatham & Black, 1995; Howell, 1992). Regression models can be modified to handle nominal data, non-linear relationships and both linear and non-linear interactions (Hair et al., 1995; Howell, 1992).

Given the pivotal role of regression analysis in the derivation of a model/description of the relationship between the criterion construct (η) and the latent variables influencing it (ξ_i), the underlying principles and functioning of this technique will be subsequently examined.

Stellenbosch University http://scholar.sun.ac.za

2.4. The Traditional Linear Regression Model:

2.4.1. Simple Linear Regression:

Psychological assessment in personnel selection has the aim of generating predictions about critical aspects of work behaviour that will contribute to decisions regarding the assignment of individuals to appropriate treatments (Cronbach & Gleser, 1965; Wiggins, 1973). It is for this reason that explanatory models are developed which seek to explain variance in the criterion. Regression is concerned with prediction, that is, the ability to build a statistical model which uses information about a set of independent or predictor variables in order to estimate the expected value of some dependent or response variable (Berenson, Levine & Goldstein, 1983; Bobko, 2001).

Prediction of the criterion in personnel selection via regression analysis traditionally modelled the prediction problem in a manner that simplifies the statistical analysis and inference involved. According to Campbell (1991), nothing more is meant by the term "classic prediction model" than the familiar bivariate normal distribution. Campbell (1991) goes on to state that the classic prediction model makes a number of rather demanding assertions about selection prediction which simultaneously reflect the four assumptions of simple linear regression (Berenson et al., 1983; Bobko, 2001) underlying the prediction model:

- There is a single continuous normally distributed predictor variable (X) with interval scale properties.
- There is one continuous normally distributed criterion variable (Y) measured on an interval scale.
- The joint X-Y distribution is bivariate normal and therefore linear and homoscedastic.
- The product-moment correlation coefficient is the preferred index of predictive success.

Stellenbosch University http://scholar.sun.ac.za

These four assumptions of simple linear regression (Berenson et al., 1983; Bobko, 2001; Osborne & Waters, 2002) underlying the classic prediction model are discussed next.

1. Normality

The first assumption that the criterion distribution conditional on the value of the predictor follows a normal distribution is necessary for the purpose of inference. In regression analysis the independent variable X is considered to be fixed at specific levels. Moreover, at each fixed X the dependent variable Y is considered a random variable following a specific probability density function denoted by $f(Y \mid X)$ with mean $\mu_{y \mid x}$ and variance $\sigma^2_{y \mid x}$. The population is therefore divided into several subpopulations – one for each fixed X, in which the random criterion variable Y follows a specific density $f(Y \mid X)$. Generally it is assumed that at each fixed X the subpopulation of criterion values follows a normal distribution. For a fixed value of the predictor X, therefore:

$$Y|X_i \sim f(Y \mid X_i) = N_{(\mu_{y \mid x}, \sigma^2_{y \mid x})} \text{.-------------------- } 1$$

2. Linearity

The second assumption is that the functional relationship between the predictor X and the criterion Y is linear. This means that at each fixed value of X the corresponding mean of the criterion Y ($\mu_{y \mid x}$) is a straight-line function of X.

3. Independence

The third assumption of independence is that the observed criterion values are independent of one another for each value of the predictor X. More formally this is regarded as the independence of error assumption. If the Y values are independent and normally distributed at each fixed level of X, then the residual difference values between observed and predicted values of Y are also independent and normally distributed.

Stellenbosch University http://scholar.sun.ac.za

4. *Homoscedasticity*

The fourth assumption is that the variance in the criterion measures around the conditional mean $\mu_{y|x}$ (that is $\sigma^2_{y|x}$) be constant for all values of X. This means that Y varies the same amount when X is fixed at a low value as when X is fixed at a high value.

It should be noted that these assumptions apply to regression as a statistical tool in its entirety, and therefore are essentially also the assumptions (although in an expanded form) underlying multiple regression.

Prediction becomes possible when the relationship between two variables can be specified by means of an equation of the general form $Y = f(X)$. Therefore, for every value of X, a value can be generated for the criterion variable Y by performing the appropriate mathematical operations on the value of X (Bobko, 2001; Hair et al., 1995; Kerlinger & Lee, 2000; Myers, Montgomery & Vining, 2002; Wiggins, 1973). In a simple linear regression analysis the objective is to develop a linear model from which the values of a dependent variable can be predicted based on the observed values of a single independent variable. To develop the model a sample of n independent pairs of observations $(X_1, Y_1), (X_2, Y_2), \ldots, (X_n, Y_n)$ are obtained, where X_i represents the ith value of the independent or predictor variable X and where Y_i represents the corresponding response – that is, the ith value of the dependent variable Y (Berenson et al., 1983; Hair et al., 1995; Kerlinger & Lee, 2000; Muchinsky, 1993; Myers et al., 2002).

To study the possible underlying relationship between X and Y, the n individual pairs of observations can be plotted on a two-dimensional scatter diagram. The dependent variable Y is plotted on the vertical axis, while the independent variable X is plotted on the horizontal axis (Bobko, 2001; Hair et al., 1995; Myers et al., 2002). According to Berenson et al., (1983), Muchinsky (1993), and Muchinsky, Kriek and Schreuder (1998), the scatter diagram aids the researcher in selecting an appropriate regression model. By examining the plotted sample points, the researcher attempts to project the underlying mathematical relationship that may exist between X and Y.

Stellenbosch University http://scholar.sun.ac.za

In a simple population regression model containing a single predictor variable X, this functional relationship can be expressed as:

$$Y_i = f(X_i) + \varepsilon_i \; ; \; i = 1,2,\ldots,n \text{ ----------------------2}$$

where any observed value Y_i in the population would be a function of the true mathematical model $f(X_i)$ plus some residual error ε. The error term represents the scatter of observed Y_i values above and below the regression line; ε_i therefore equals $Y_i - f(X_i)$.

If the scatter diagram would indicate the appropriateness of a linear relationship between X and Y, the population regression model can be re-expressed as:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i; \; i = 1, 2, n \text{ ---------------------3}$$

where the two unknown parameters β_0 and β_1 are required to specify the straight line relationship assumed to exist between the predictor and the criterion. The regression coefficient β_0 is the true intercept, a constant factor in the regression model representing the expected value of Y when $X = 0$. The regression coefficient β_1 is the true slope and represents the amount that Y changes (either positively or negatively) per unit change in X (Berenson et al., 1983; Bobko, 2001; Hair et al., 1995; Kerlinger & Lee, 2000; Muchinsky, 1993; Myers et al., 2002). The regression coefficients would be determined so as to minimize $\Sigma\varepsilon^2_i$.

Normally access to the entire population is not possible. The parameters β_0 and β_1 consequently cannot be calculated directly and the population regression model therefore cannot be obtained directly. The objective then becomes one of obtaining estimates b_0 (for β_0) and b_1 (for β_1) from a randomly selected sample. Usually these estimates are obtained by employing the method of least squares. With this method the statistics b_0 and b_1 are computed from the sample in such a manner that the best possible fit within the constraints of the least squares model is achieved. That is, the following linear regression equation is obtained:

$$E(Y|X_i) = b_0 + b_1 X_i; \; i = 1, 2, n \text{ -------------------4}$$

such that equation 5 is minimized.

$$\sum_{i=1}^{n} (Y_i - E(Y|X_i))^2 = \sum_{i=1}^{n} e_i^2 \text{ --------------5}$$

Stellenbosch University http://scholar.sun.ac.za

The least squares method satisfies the condition set by equation 5 by developing the following two normal equations:

$$\sum_{i=1}^{n} Y_i = nb_0 + b_1 \sum_{i=1}^{n} X_i \text{-------------------------} 6$$

$$\sum_{i=1}^{n} I_x i_a = b_0 \sum_{i=1}^{n} i + b_1 \sum_{i=1}^{n} X_i \ldots\ldots\ldots\ldots\ldots\ldots 7$$

Solving simultaneously for b_1 and b_0, equations 8 and 9 are obtained:

$$b_1 = \{ n\sum_{i=1}^{n} I_x i_a - (\sum_{i=1}^{n} X_i)(\sum_{i=1}^{n} Y_i)\} / \{(n\sum_{i=1}^{n} X_i^2 - (\sum_{i=1}^{n} X_i)^2\} \text{----} 8$$

$$b_0 = \mathrm{E}(Y) - b_1\mathrm{E}(X)$$

$$= (\sum_{i=1}^{n} Y_i/n) - b_1 (\sum_{i=1}^{n} X_i/n) \text{----------------------} 9$$

The sample regression equation shown as equation 10 is thus obtained (Berenson et al., 1983; Bobko, 2001; Hair et al., 1995; Muchinsky, 1993; Myers et al., 2002):

$$\mathrm{E}\,(Y|X_i) = b_0 + b_1 X_i \text{--------------------------------} 10$$

2.4.2. Testing the Significance of the Linear Relationship

The significance of the linear relationship expressed as equation 10 can be tested by using either an ANOVA approach or a t-test. The results of such a test would indicate whether a linear model satisfactorily captures the relationship between the predictor and the criterion. If the linear model failed to account for the variance in Y, the possibility that a curvilinear relationship between *X* and *Y* might be more appropriate, should be examined. Should various non-linear models also fail to significantly explain variance in the criterion, it would be better to seek other predictor variables and/or perhaps even develop a multiple regression model.

Stellenbosch University http://scholar.sun.ac.za

In an ANOVA approach the following statistical null hypothesis is tested (Berenson et al., 1983; Bobko, 2001):

H_0: $\beta_1 = 0$ (no simple linear regression is present),

H_1: $\beta_1 \neq 0$ (there is a significant simple linear regression present).

The F ratio is obtained by solving equation 11:

$F = \text{MSR/MSE} \sim F_{1,\, n\text{-}2}$-----------------------------11

And, using an α level of significance, the null hypothesis is rejected if:

$F \geq F_{1\text{-}\alpha;\, 1,\, \text{n-2}}$.

In using the t-test approach, the same null hypothesis is tested by the test statistic shown as equation 12:

$t = b_1 - \beta_1 / S_{bi} \sim t_{n\text{-}2}$---------------------------------12

By using a α level of significance, the null hypothesis is rejected if (Berenson et al., 1983; Bobko, 2001; Hair et al., 1995; Muchinsky, 1993):

$t \geq t_{1\text{-}\alpha/2;\, n\text{-}2}$ or if $t \leq t_{\alpha/2;\, n\text{-}2}$

2.4.3. Examining the Fit of the Model

The fitted model should be examined in terms of the extent to which it adheres to the underlying assumptions of simple linear regression, i.e. the model should be evaluated whether at each fixed level of X, the subpopulations of Y values follow a normal distribution, whether the functional relationship between X and Y is linear, whether the observed Y values are independent of each other for each value of X and whether the scatter around the regression line is constant for all values of X. Regardless of the result of the test for the significance of the simple linear relationship, it is still necessary to determine the extent to which a linear model provides an appropriate fit.

To test the appropriateness of the simple linear relationship, the unexplained error sum of squares (SSE) must be partitioned in its two sources: *lack of fit* and *pure error*. *Lack of fit* is that segment of unexplained variance due to (1) the inappropriate choice of the

Stellenbosch University http://scholar.sun.ac.za

nature of the model (for example, a linear model instead of a non-linear model) or (2) the exclusion of important predictor variables. On the other hand, pure error is that segment of unexplained variance which reflects the inherent random fluctuations in the response variables. Thus (Berenson et al., 1983; Bobko, 2001) the sum of squares error (SSE) equals the sum of squares error due to lack of fit (SSLF) plus the sum of squares pure error (SSPE), or:

$$\text{SSE} = \text{SSLF} + \text{SSPE} \text{ -------------------------------} 13$$

The pure error sum of squares can be computed only if it can be assumed that X is fixed at X_j where there exist n_j independent Y values. The expected value of Y conditional on X_j is computed E $(Y|X_j)$. The sum of the squared deviations of the observed criterion values around the expected value is subsequently computed $\sum_{k=1}^{nj} (Y_{jk} - E\ (Y|X_j))^2$. Summing these results together over all l levels of X, SSPE is obtained through equation 14:

$$\text{SSPE} = \sum_{j=1}^{l} \sum_{k=1}^{nj} (Y_{jk} - E\ (Y_j))^2 \text{ ------------------} 14$$

For any particular fixed level of X, the degrees of freedom are $n_j - 1$. The mean squares pure error (MPSE) is thus computed as equation 15:

$$\text{MPSE} = \text{SSPE}/\sum_{j=1}^{l} n_j - 1 \text{ ------------------------} 15$$

The sum of squares error due to lack of fit in turn is computed by subtraction:

$$\text{SSLF} = \text{SSE} - \text{SSPE} \text{ -------------------------------} 16$$

The degrees of freedom associated with lack of fit are also determined by subtraction:

$$(\text{LOF d.f.}) = (\text{Error d.f.}) - (\text{Pure Error d.f.})$$

$$= (n\ \text{-}2) - (\sum_{j=1}^{l} n_j - 1) \text{----------------------------} 17$$

The means square error lack of fit (MSLF) thus is given by equation 18:

$$\text{MSLF} = \text{SSLF}/\ ((\text{n -2}) - (\sum_{j=1}^{l} n_j - 1)) \text{ ---------} 18$$

Stellenbosch University http://scholar.sun.ac.za

An ANOVA table adjusted for the decomposition of the unexplained variance (error) term is used to test the null hypothesis

H_0: the simple linear model fits the data

H_1: the simple linear model does not fit the data

When H_0 is true, both MSLF and MSPE are estimating the inherent variability in the Y values. Except for chance, the fit value should equal 1. On the other hand, if H_0 is false, *MSLF* is estimating this inherent variability in addition to lack of fit and the fit value will significantly exceed 1 (Berenson et al., 1983; Bobko, 2001).

Pure error can only be estimated if the sample contains at least one level of X for which at least two independent measurements on Y have been obtained. If each of the n sample observations have differing X values, the fit of the regression model cannot be tested, but should then rather be evaluated by examining the residuals $(Y_i - E(Y|X_i)$. Residual analysis provides an invaluable aid to the researcher in the model-building process. The appropriateness of the fitted model can be evaluated by studying residuals for possible violations of the assumptions of normality, linearity, and homoscedasticity (Berenson et al., 1983; Tabachnick & Fidell, 1989).

The appropriateness of the fitted regression model can be best evaluated by plotting the residuals on the vertical axis against the corresponding values of the independent variable X on the horizontal axis for all n observations. If a pattern in the residuals can be observed, the fitted model would be deemed inappropriate. By plotting the residuals $e_{i=}$ $(Y_i - E(Y|X_i)$ against X_i, the linear effect β_1 is removed or filtered out (Berenson et al., 1983; Bobko, 2001) thus revealing any initially hidden trend not adequately captured by the linear, homoscedastic regression model.

When the aforementioned assumptions underlying simple linear regression are met, the residuals will appear as a pile-up in the centre of the plot at each value of predicted score. If, on the other hand, the residuals distribution is skewed, the assumption of normality has failed (Berenson et al., 1983; Bobko, 2001; Tabachnick & Fidell, 1989). If the homoscedasticity assumption is satisfied, the residuals tend to fluctuate uniformly around

Stellenbosch University http://scholar.sun.ac.za

zero for all values of *X*. A lack of homoscedasticity can be observed if the residuals seem to "fan out" as *X* increases, thereby demonstrating a lack of homogeneity in the variances of the *Y* values at each level of *X* (Berenson et al., 1983; Bobko, 2001; Tabachnick & Fidell, 1989). In some instances, the assumption that errors of prediction are independent of one another is violated as a function of something associated with the order of cases. Any resulting patterns which visually emerge through a scatter plot of the order in which observes data were collected would indicate a potential violation in the independence assumption (Berenson et al., 1983; Bobko, 2001; Tabachnick & Fidell, 1989).

To increase the probability that a fitted model will satisfy the assumptions underlying regression, it becomes important to examine the issues that could cause such deviations prior to fitting the model to the data. An issue that requires attention when evaluating model fit, is the presence of outliers, which, when present, tends to degrade the homoscedasticity of the regression of the criterion on the predictor and also tends to negatively influence the normality of the distribution of Y values for each fixed value of X.

2.4.4. The Effect of Outliers on Model Fit

According to Tabachnick and Fidell (1989) and Bobko (2001) the presence of outliers is an important issue in regression analyses. Certain cases in research data have such extreme values on one or a combination of variables that they disproportionately influence the statistics that define the regression model. These cases are labelled as univariate or multivariate outliers. They are observations with a unique combination of characteristics identifiable as distinctly different from other observations. Outliers cannot be positively characterized as either beneficial or problematic but instead must be viewed within the context of the analysis and should be evaluated by the types of information they may provide regarding the phenomenon under study. When beneficial, outliers, although different from the majority of the sample, may be indicative of exotic cases in the population that have a relative low incidence but which could legitimately appear in a sample. In contrast, problematic outliers are not representative of the population but

Stellenbosch University http://scholar.sun.ac.za

rather a reflection of measurement or data capturing errors and therefore can seriously distort statistical tests (Hair et al., 1995; Howell, 1992).

There are at least four possible explanations for the presence of an outlier. Firstly, an outlier could represent an error in measurement procedure such as an incorrect data recording or entry. Secondly, an outlier could occur due to the failure to specify missing value codes in computer control language so that it is read as real data. The third reason could be that the outlier is not part of the population from which the sample is drawn. Finally an outlier could occur if the observation is part of the population but that the distribution for the variable in the population has more extreme values than a normal distribution (Bobko, 2001; Hair et al., 1995; Howell, 1992).

Outliers are found in univariate, bivariate and multivariate situations. The univariate perspective for detecting outliers examines the distribution of observations via for example box plots, selecting as outliers those distinctive cases that fall at the outer ranges of the distribution. In addition to univariate assessment, pairs of variables can be assessed jointly through a scatter plot. Cases that fall markedly outside the range of other observations can be noted as isolated points in the scatter plot. The third perspective for identifying outliers involves a multivariate assessment of each observation across a set of variables. Because most multivariate analyses involve more than two variables, an objective means of measuring the multidimensional position of each observation relative to some common point, needs to be made. The Mahalanobis D^2 is a measure of the distance in multidimensional space of each observation from the centre of the observations. While providing a common measure of multidimensional centrality, it also has statistical properties that allow for significance testing (Bobko, 2001; Hair et al., 1995; Howell, 1992; Tabachnick & Fidell, 1989).

Once outliers are identified there exist several strategies for reducing their influence. The most preliminary measure is to examine the data for the case so as to ensure that they have been correctly entered into the data file, after which the possibility exists that one variable could be responsible for most of the outliers, which, if highly correlated with

Stellenbosch University http://scholar.sun.ac.za

other variables and not critical in the analysis, can be eliminated to reduce the number of outliers. If a simple alternative is not possible, the outliers can be examined in terms of the population of the sample from which it is intended to be drawn. If cases are deemed not to be part of the population, they can be deleted with no loss in generalizability of results to the target population. If outliers are part of the target population and are therefore retained in the analysis, steps can be taken to reduce their influence by either transforming variables or changing scores. When variable transformation is undertaken, the objective is to consider outliers as part of a non-normal distribution with tails that are too high so that there are too many cases at extreme values of the distribution. By transforming the shape of the distribution to an approximately normal distribution the number of cases with extreme values should be reduced. A second option exists to change the score(s) on the important variables for outlying cases to be less deviant. In selecting the appropriate strategy, the researcher should be guided by the purpose to accommodate outliers in the analysis but without them seriously distorting the analysis (Hair et al., 1995; Howell, 1992; Tabachnick & Fidell, 1989).

2.5. Extensions to the Basic Regression Model to Increase Predictive Validity

The predictive limits that have been reached in applications of the basic prediction model seem to have inspired many workers to experiment with extensions to this basic model. The present section considers a number of instances in which the linear regression equation itself is challenged as being incomplete for the prediction of human behaviour and in which extended mathematical procedures have been employed.

2.5.1. Expanding the Number of Predictors via Multiple Linear Regression

It has been argued throughout the previous section that, since the fundamental task of science is to explain phenomena, its basic aim is to discover general explanations of natural events, and in the case of Industrial Psychology, to explain the behaviour of working man. But, natural phenomena, and by implication, the behaviour of working man are complex. Complex, in this context, means at least that behaviour has several

Stellenbosch University http://scholar.sun.ac.za

facets and causes, thus several sources of variation (Pedhazur, 1982). In an attempt to explain the behaviour of working man, the researcher must therefore elaborate on the basic deterministic assumption of Industrial Psychology that behaviour is explicable in terms of behavioural laws in the basic form, "if ξ then η", by taking into account that this behaviour is complexly determined by a large number of determinants. The researcher should rather think of behaviour in terms of "if ξ_1, ξ_2, ξ_3, ξ_n then η, given ξ_{m1}, ξ_{m2}, ξ_{m3}, ξ_{mn}" portrayed as a complex nomological network of independent and dependent latent variables (Bobko, 2001; Kerlinger & Lee, 2000; Myers et al., 2002; Theron, 1999). Explaining the behaviour of working man thus means uncovering the identity of the exogenous and endogenous latent variables, the nature of the relationships that exist between them and the strength of these relationships.

The behavioural researcher is concerned, basically, with propositions of the "if ξ then η" kind. Such propositions explain phenomena in terms of a simple equation in which a single dependent variable is regressed on a single independent variable. However, considering the multitude of determinants affecting the criterion construct, this is hardly enough. Even if empirical evidence would support hypothesized one-dimensional linkages, individual predictor variables will in all probability not go far in explaining variance in the criterion, since numerous additional independent variables that influence the criterion construct η are ignored. Simple linear regression cannot be employed to treat such cases successfully, and therefore multiple regression should be engaged in assisting the researcher in fruitfully examining more complex performance hypotheses (Guion, 1991; Kerlinger & Lee, 2000).

According to Kerlinger and Lee (2000) and Hair et al. (1995), multiple regression analysis can be conceived as a refined and powerful method of controlling variance when estimating the relative influence of various sources of variance on Y, through analysis of the interrelations between all the variables. It reveals how much variance in Y could be regarded as due to X_1, X_2, Xp. It gives some idea of the relative amounts of influence of the X's. Multiple regression analysis is a valuable and powerful technique for studying the complex interrelations between independent variables and a dependent variable and

Stellenbosch University http://scholar.sun.ac.za

thereby providing a more comprehensive account of the variance observed in the dependent variable (Bobko, 2001; Myers et al., 2002; Tabachnick & Fidell, 1989).

The problem of multiple regression is that of finding a regression equation to predict Y on the basis of p predictors (X_1, X_2, X_3, Xp). For any particular investigation, when there are several independent variables present, the simple linear regression model can be extended if a linear relationship between each independent variable and the dependent variable can be assumed. The multiple linear regression model can hereby be expressed as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \varepsilon_i$$

$$E\,(Y|X) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \varepsilon_i \text{ -----} 19$$

Where: β_0 = Y intercept

β_1 = slope of Y with variable X_1 holding all the X-variables constant;

β_2 = slope of Y with variable X_2 holding all the X-variables constant; and

ε_i = random error in Y for observation i.

The slope β_1 represents the unit change in Y per unit change in X_1, taking into account the effects of all the other X-variables and therefore could be termed a partial regression coefficient (Bobko, 2001; Howell, 1992; Kerlinger & Lee, 2000; Myers et al., 2002; Tabachnick & Fidell, 1989).

The principle of least-squares is again employed to find those β values that would minimise the sums of squares of the residuals so as to increase the predictive power of the model.

Solutions of the b weights enable the determination of the regression and residual sum of squares by the formulas (Bobko, 2001; Howell, 1992; Kerlinger & Lee, 2000; Myers et al., 2002; Tabachnick & Fidell, 1989):

$$SS_{reg} = b_0 \sum Y_i + b_1 \sum X_1 Y_i + \ldots + b_p \sum X_p Y_i - (\sum Y_i / n) \text{ ----} 20$$

$$SS_{res} = \sum Y^2_i - b_0 \sum Y_i - b_1 \sum X_1 Y_i - \ldots - b_p \sum X_p Y_i \text{ ----------} 21$$

Stellenbosch University http://scholar.sun.ac.za

2.5.1.1. Testing the Significance of the Linear Relationship

Once the regression model has been fitted to data, it can be determined whether there is a significant relationship between the dependent variable and the set of independent variables. Assuming p independent variables, the null and alternative hypothesis is set up as:

H_0: $\beta_1 = \beta_2 = \ldots = \beta_p = 0$

(there is no linear relationship between the dependent variable and the independent variables)

H_1: $\beta_1 \neq \beta_2 \neq \ldots \neq \beta_p = 0$

(at least one regression coefficient is not equal to zero)

The null hypothesis is tested by subdividing the total variance in the *Y* values (SST) into two components, variation due to regression (SSR) and variance due to error (SSE). An F-test statistic would be calculated to test the null hypotheses:

$$F = (SS_{reg}/df_1)/SS_{res}/df_2) \text{ ----------------------------- } 22$$

If df_1 and df_2, the degrees of freedom for the numerator and the denominator of the *F*-ratio, are defined, a formula to test the significance of any multiple regression problem emerges as:

$$F = (SS_{reg}/p)/\ (SS_{res}/\ (n\text{-}p\text{-}1)) \text{ ---------------------- } 23$$

Where p = number of independent variables, and n = sample size. Depending on the α level of significance used, the null hypothesis may be rejected if $F \geq F_{1-\alpha;\, p,\, n-p-1}$, implying that at least one of the independent variables are related to the dependent variable (Bobko, 2001; Hair et al., 1995 ; Kerlinger & Lee, 2000; Myers et al., 2002; Tabachnick & Fidell, 1989).

In the development of a multiple regression model, the objective is to include only those independent variables that are useful in the prediction of a dependent variable, i.e. to include only those independent variables that significantly explain variance in the criterion that is not yet explained by the remaining variables in the model. If an independent variable does not obey to this principle it should be deleted from the model and a simpler model with fewer independent variables should be utilized. This principle,

Stellenbosch University http://scholar.sun.ac.za

however, sometimes seems to be forgotten by test developers in the pursuit of an impressive R-square (Psytech, 2003). The contribution of each independent variable can be assessed by either comparing successive regression models, or basing the evaluation of the contribution made by each independent variable on the *t*-test of the slope (Berenson et al., 1983; Bobko, 2001; Hair et al., 1995; Myers, 2002).

In comparing successive regression models, a partial *F*-test criterion is used which determines the contribution to the regression sum of squares (SS_{reg}) made by each independent variable after all independent variables have been included in the model. The new independent variable would only be included if it significantly improved the explanatory power of the existing model. To determine the contribution of a particular variable k, given that all other variables have already been included in the model, the following equation would provide the appropriate information (Berenson et al., 1983; Bobko, 2001; Hair et al., 1995; Myers et al., 2002):

$$SS_{reg}\,(b_k \mid \text{slopes of all variables except } k)$$
$$= SS_{reg}\,(\text{slopes of all variables including } k) - SS_{reg}\,(\text{slopes of all variables except } k) \text{ ------------------------------24}$$

To test for the contribution of the kth independent variable to the model, the relevant null and alternative hypothesis would be:

H_0: variable X_k does not significantly improve the simple model given that variables $X_1, X_2, X_3 \ldots X_{k-1}$ have been included

H_1: variable X_k significantly improves the model already containing variables $X_1, X_2, X_3 \ldots X_{k-1}$.

The partial *F*-test criterion is expressed by:

$$F = SS_{reg}\,(b_k \mid \text{slopes of all variables except } k)/MSE \quad 25$$

Where:

$$F \sim F_{1,\,n-p-1}$$

And, by using an α level of significance, the null hypothesis may be rejected if (Berenson et al., 1983; Bobko, 2001; Hair et al., 1995; Myers et al., 2002):

$$F \geq F_{1-\alpha;\,1,\,n-p-1}$$

Stellenbosch University http://scholar.sun.ac.za

The second approach to evaluating the contribution of an independent variable involves the test of a hypothesis for the slope. To test the hypothesis regarding the contribution of the kth predictor variable the following test statistic would apply:

$$t = b_k / S_{bk} \quad \text{---} 26$$

Where $t \sim t_{n-p-1}$ and where p is the number of independent variables in the regression equation, and S_{bk} is the standard error of the regression coefficient b_k. Using an α level of significance, the decision rule to reject the null hypothesis is (Berenson et al., 1983; Bobko, 2001; Hair et al., 1995; Myers et al., 2002):

$$t > |t_{1-\alpha/2;\, n-p-1}|$$

2.5.1.2. Examining the Fit of the Model

When trying to improve the prediction of a dependent variable by adding independent variables to the linear model, the same assumptions which had to be met in the simple linear regression model (linearity, homoscedasticity, independence, and normality) also apply in an extended sense to the multiple regression model. The assumptions underlying multiple regression analysis apply both to the individual variables and to the relationship as a whole (Hair et al., 1995; Tabachnick & Fidell, 1989).

For the multiple regression model, the likelihood of performing a test of lack of fit becomes less probable as more independent variables and/or additional levels of the independent variables are introduced. To test for lack of fit, at least two independent measurements of Y are needed for at least one specific combination of levels of the independent variables. Due to the need for an excessive sample size and due to fact that the levels of the independent variables can often not be controlled, a test for the lack of fit can often not be performed, in which case an analysis of the residuals in terms of patterns in residual plots, as proposed in simple linear regression, is particularly useful (Berenson et al., 1983; Bobko, 2001; Hair et al., 1995).

Stellenbosch University http://scholar.sun.ac.za

However, when at least two independent measures of Y can be found for at least one specific combination of the levels of the independent variables, a test for lack of fit can be performed by extending the procedure developed for the simple linear regression equation. For the multiple regression model, the pure error sum of squares (SSPE) can be computed as:

$$\text{SSPE} = \sum_{j=1}^{l} \sum_{k=1}^{nj} (Y_{jk} - E(Y_j))^2 \text{------------------}27$$

$E(Y_j)$ would in this case represent the mean of Y for the j^{th} combination of X_1, X_2, X_p, assuming p predictor variables in the regression model (Berenson et al., 1983; Bobko, 2001; Hair et al., 1995).

2.5.1.3. Multicollinearity

According to Berenson et al. (1983), the objective of a multiple regression analysis is best served when the explanatory variables comprising the model are themselves uncorrelated. When strong interrelationships exist, it becomes increasingly difficult, if not impossible, to measure the unique impacts of individual explanatory variables on the criterion variable. Multicollinearity is a situation in which the explanatory variables in the model are themselves highly correlated, which causes difficulty when estimating the partial regression coefficients. Multicollinearity causes the multiple regression method to lose its accuracy, and, by implication, its reliability, since the test would not provide the same results over time due to the interrelationships between the predictor variables (Breakwell, Hammond & Fife-Schaw, 2000; Jaccard, 2001). Non-orthogonality in the explanatory variables can result in such highly unstable regression coefficients that their values will be subject to dramatic change as a result of additions or deletions of variables or small changes in data points.

The impact of muticollinearity is to reduce the impact of the predictive power of any individual variable by the extent to which it is associated with other independent variables. Multicollinearity is not a problem of misspecification, but rather of the data itself, and requires extreme caution in the interpretation of the meaning of all estimates

Stellenbosch University http://scholar.sun.ac.za

generated. Multicollinearity can be highlighted by a number of signals of which the most obvious indicator is the correlation matrix calculated from the set of explanatory variables. Large correlations indicate strong linear associations, implying that certain variables may be surrogates for others with little or no additional predictive power themselves. Two other indicators of multicollinearity exist. Regression coefficients with signs the reverse of what is expected, represent one sign of possible problems regarding multicollinearity. Important regression coefficients having large standard errors, represent another danger signal (Berenson et al., 1983; Hair et al., 1995; Jaccard, 2001; Tabachnick & Fidell 1989).

The problem of multicollinearity can be addressed by one of several possible options. Some of these are to omit one or more highly correlated variables and identify other predictor variables to help prediction; to use the model with highly correlated predictors for prediction only with no attempt to interpret the partial regression coefficients, to use the simple correlations between each predictor and the criterion to understand the individual relationships, or to regress the criterion on orthogonal principle components underlying the predictors (Hair et al., 1995; Howell, 1992; Jaccard, 2001; Tabachnick & Fidell, 1989).

2.5.1.4. Other Limitations in Regression Analysis

Regression analysis poses a number of additional problems to the behavioural researcher in the calculation and interpretation of estimates in the regression model. In any given regression model, R, R^2 and the partial regression weights will be the same no matter what the order of the variables. However, if one or more predictor variable(s) would be eliminated from the regression equation, these values would change. This does not mean, however, that the order in which the variables are entered into the equation does not matter. On the contrary, order of entrance is very important when the independent variables are correlated. The proportion of unique variance in the criterion variable that a predictor variable can account for, which is not explained by the predictors that entered the regression model earlier, can change dramatically with different orders of entry of the

Stellenbosch University http://scholar.sun.ac.za

independent variables (Berenson et al., 1983; Kerlinger & Lee, 2000; Tabachnick & Fidell, 1989).

Another important fact is that there usually is limited utility to adding new predictor variables to a regression equation. Because many variables in behavioural research are at least moderately correlated, it becomes increasingly difficult to explain unique variance in the criterion not already explained by those predictors in the model. The fact is that after a number of predictor variables have been included in the regression model, the additions of further variables tend to become redundant (Berenson et al., 1983; Kerlinger & Lee, 2000).

2.5.2. Suppressor Variables

Extending the classic prediction model requires the addition of independent predictor variables that are highly related to the criterion, but in general unrelated to each other. Ideally, a set of independent variables of high criterion relevance would have average inter-correlations that are close to zero. Under these circumstances each independent variable would explain a different component of the criterion with minimum overlap in the criterion variance explained by each predictor. The addition of predictors meeting the requirements of the regression model should result in significant increases in the proportion of criterion variance explained by the model and therefore its predictive accuracy (Guion, 1991). In practice, however, it is highly improbable to obtain more than a couple of independent predictors that are highly valid yet do not share variance with other valid predictors (Wiggins, 1973).

According to Wiggins (1973, p.30), Horst (1941) was the pioneer in attracting attention to the fact that predictor variables may not always function in the manner outlined above but still contribute to the predictive ability of the multiple regression equation. Certain variables, called suppressor variables, have exactly the contradictory properties than conventional predictor variables, but nonetheless still produce impressive increases in the prediction of a criterion variable (Bobko, 2001). A suppressor variable has an

Stellenbosch University http://scholar.sun.ac.za

insignificant correlation with the criterion, but a high, significant correlation with a predictor which does correlate significantly with the criterion (Anastasi & Urbina, 1997; Ghiselli, et al, 1981; Stockburger, 2001). Such variables are useful in predicting the criterion by advantage of its correlations with other predictor variables, because they suppress variance that is irrelevant to prediction of the criterion. Suppressor variables are detected where all variables in a multiple regression equation are randomly scored to be positively related to the criterion, and whereby all the resulting regression coefficients are expected to be positive. It may however be found that, occasionally, a certain regression coefficient(s) is significantly negative, indicating a suppressor variable (Anastasi & Urbina, 1997; Bobko, 2001; Guion, 1991; Howell, 1992; Stockburger, 2001; Tabachnick and Fidell 1989; Wiggins 1973).

At first glance, the inclusion of suppressor variables in a multiple regression model may seem unreasonable due to its lack of predictive validity and its high apparent disuse with other predictors. By assigning the regression coefficient of the suppressor variable with a negative value in the regression equation, an increase on the suppressor variable would result in a decrease in $E(Y|X_i)$. However, the apparent conflicting implementation of suppressor variables provide the useful purpose of, although not directly increasing the variance explained in the criterion, decreasing the extraneous variance in the predictors, as it deducts the unrelated variance in a predictor from the regression equation (Bobko, 2001; Howell, 1992; Tabachnick and Fidell 1989; Wiggins, 1973). Suppressor variables therefore prevent high predicted criterion scores resulting from high scores on the predictor for the wrong reasons as it were.

In an attempt to conclude the rationale for using suppressor variables, Wiggins (1973, p.32) states that:

> Although the use of suppressor variables does not require a departure from the multiple regression prediction model, the decision to use such variables requires a revision of the usual criteria for "good" predictors. Traditionally, predictor variables that are uncorrelated with the criterion of interest are automatically excluded from further consideration. The class of variables that are uncorrelated with significant criteria is, unfortunately, a very large one, and

Stellenbosch University http://scholar.sun.ac.za

> some rationale must guide the identification of those variables which have suppressor properties. Further, since suppressor methodology is a somewhat costly departure from standard procedures, the use of suppressor variables should lead to a practical increment in predictive validity. For this reason, it is appropriate to consider the available evidence relating to the empirical effectiveness of suppressor variables in predicting socially relevant criterion measures.

Thorndike (1982) and Ghiselli, et al. (1981) are of the opinion that suppressor variables are only rarely encountered in psychological measurement. Although occasionally found, suppressor effects are also only rarely replicated (Cook, 1998). Although conceptually appealing, the use of suppressor variables to enhance predictive accuracy does not seem extremely promising

2.5.3. Moderators

The conventional deterministic assumption of science is that the various exogenous predictor variables function independent of each other in their explanation of the endogenous criterion variable. This implies that each of the exogenous variables do not interact with any of the other exogenous variables in their effect on the endogenous criterion variable. The nature of human behaviour, however, hardly ever justifies this assumption, since the nomological network of latent variables underlying work performance, is not only complex in the number of latent variables, but these variables are extremely complex in their interaction with one another.

In conventional prediction, the endogenous criterion variable is typically assumed to be a mathematical additive function of *n* unique exogenous predictor variables. Differences in the value of the endogenous criterion variable across individuals would therefore be assumed to be due to the differences in each unique endogenous variable across individuals. But the underlying complex nomological network of variables fundamental to behaviour also is made up of interactions between exogenous variables (Bobko, 2001; Jaccard, 2001). These interaction effects in essence constitute additional independent

Stellenbosch University http://scholar.sun.ac.za

predictor effects which explain unique variance in the endogenous criterion variable because they reflect the fact that the nature of the relationship between exogenous predictor variables and the endogenous criterion variable change as a function of the condition of moderator variables (Kerlinger & Lee, 2000).

Ghiselli et al. (1981, p. 478) define a moderator variable as:

> A variable that has been found to be linearly uncorrelated with both the predictor variable and the criterion variable yet increases the multiple correlation beyond that obtained for only the predictor and criterion. Moderator variables increase prediction because of the non-linear, interactive effects of the predictor and the moderator.

When a moderator-predictor interaction effect is added to a regression model containing main effects only this additional variable could explain differences in the value of the endogenous criterion variable that is not explicable in terms of the main effects, if the slope of the regression of the criterion on the predictor in question differs across different conditions of the moderator variables. The conventional main effect regression model would not be able to account adequately for differential rates of change in the criterion accompanying one unit change in the predictor across different conditions of the moderator variable. Therefore, if a situation should occur in which special patterns of predictor-criterion data points are associated with unique values of the moderator variable, the main effects multiple regression model should be extended to do justice to it (Bobko, 2001; Jaccard, 2001; Wiggins, 1973). Modifying equation 4 by adding an interaction effect (ZX) in addition to a moderator main effect (Z) (which needs not necessarily be included) would result in equation 28:

$$E(Y|X_i) = b_0 + b_1X_i + b_1Z_i + b_1ZX_i \;; i = 1,2,...,n \qquad 28$$

Frederiksen and Melville (1954) set the stage for moderator variables when they called attention to the "differential predictability" phenomenon. This refers to a situation in which the correlation between a predictor and criterion, r_{x1y}, can be shown to vary as a function of classification on a third variable x_2, in which situation the third variable is coined a moderator variable (Saunders, 1956). Saunders applied a joint linear function to

Stellenbosch University http://scholar.sun.ac.za

the Frederiksen-Melville data by using a third term to express the interaction between the predictor and the moderator variable. Although the use of such a moderated regression was found to be superior to the conventional regression method in some cases, the increments in predictive validity were small and the relationship judged to be unstable (Bobko, 2001; Jaccard, 2001; Wiggins, 1973). Cook (1998) and Guion (1991) come to similar conclusions. Moderators are not widely found; do not dramatically enhance predictability of the criterion and do replicate well. Guion (1991, p. 337), nonetheless, puts forward a valid point of view when he argues:

> Abandonment of the search for moderators seems premature. Most moderator searches have relied on serendipity rather than rational thought, so failure is not surprising. A well developed theory of the criterion is needed to postulate and design research to test for specifically expected moderators; there is no reason to expect vague, unfocused searches to be productive

Earlier it has been argued that a valid performance theory constitutes a fundamental and indispensable though not sufficient prerequisite for efficient and equitable human resource selection (Milkovich and Boudreau, 1988, Theron, 1999). More specifically, efficient selection will be possible to the extent to which such a performance theory encompasses the full spectrum of latent variables (ξ_i) determining criterion performance (η), and the extent to which the nature of the relationship between the criterion construct (η) and the latent variables influencing it (ξ_i) is correctly understood. If the underlying performance theory would explain criterion performance in terms of one or more interaction effects, inclusion of the appropriate cross product terms in a moderated regression equation should enhance the proportion of criterion variance explained and predictive accuracy.

2.5.4. Higher-Order Functions:

Effective selection is possible because the performance level achieved by any individual on the job or in training is not a random event. There exists a systematic relationship between specific person-centred characteristics and the level of success achieved on the job or in training. Effective selection is possible to the extent to which the identity of the

Stellenbosch University http://scholar.sun.ac.za

person centred determinants of job or training performance are known and the manner in which they collectively combine in the criterion is accurately captured in a nomological network or latent structure (Campbell, 1991; Kerlinger & Lee, 2000). These person-centred determinants of criterion performance, could serve in combined form as a suitable substitute measure for the, still to be realised, actual criterion scores. The way in which measures of these determinants of performance should be combined, is suggested by the way these determinants are linked in the nomological network (Theron, 1999). Typically the assumption is made that the linkages in the nomological network are linear. This need however not necessarily be the case. To the extent that the linearity assumption is in error, the accuracy of prediction will suffer.

The moderated regression equation discussed previously, represents only one of an extremely large family of possible equations for expressing a criterion variable as a non-linear function of two or more predictors. By including product, quadratic or tertiary terms in the regression equation, the model remains linear in the partial regression coefficients and therefore can still be solved through traditional linear regression procedures (Ghiselli et al., 1981). Alternatively, the regression model can be specified in terms of an equation which is non-linear in the regression coefficients like a logistic or exponential function for example. There are, of course, no limits to the complexity of the expression (Wiggins, 1973). The aim is however to obtain the most parsimonious model which explains the maximum variance in the criterion, when the model is cross validated on a holdout sample.

In derivation samples increases in the complexity of the prediction equation are quite often associated with corresponding increases in predictive accuracy. However, when the same regression weights are applied to predictors in a cross-validation sample, increases in the complexity of the prediction accuracy are often associated with corresponding decreases in predictive accuracy (Wiggins, 1973).

Stellenbosch University http://scholar.sun.ac.za

2.5.5. Neural Networks:

The assumption that the relationship between the latent predictor variables and the latent criterion is linear (so as to simplify analysis) or at worst curvilinear, but expressible in terms of a familiar and solvable mathematical function could, however, still be insufficient to model the relationship accurately. If a highly contorted hyper plane defining the value of an latent criterion variable over a space of *n* exogenous latent predictor variables would be assumed, such that for any combinations of conditions of the exogenous predictor variables the endogenous criterion latent variable has a specific value, the reaction of η to changes in the ξ's would seem random, even though η is strictly determined by the *n* ξ's. A linear or even a known curvilinear model fitted to the data would probably confirm this chaotic impression. One would thus have a strict determinism masquerading as chaos so to speak (Theron, 2001). Should such a situation exist, it would suggest the building of neural networks as the methodological avenue to pursue, rather than the conventional approach of fitting known, normally linear, mathematical models, via regression analysis, to the data.

The fields of statistics and neural networks are closely related, although they differ in the linearity of the problems they wish to solve. Traditionally, statistics are concerned with linear problems, whilst neural networks have been developed to deal with nonlinearities of any form. Most closely, these two fields touch in the area of backpropagation, as it serves as a statistical modelling tool (Abdi, Valentin & Edelman, 1999; Anderson, 1995; Smith 1993).

Backpropagation provide a way of using examples of a target function (in this case a nonlinear hyper plane defining the value of an endogenous criterion latent criterion variable over a space of *n* exogenous latent predictor variables) to acquire the coefficients that cause a certain mapping function to estimate the target function as closely as possible. The mapping function used in backpropagation is rather complex. A neural network is made up of simple nodes that are processors arranged in three layers: input nodes, by which the networks receives the independent variable values; output nodes, by

Stellenbosch University http://scholar.sun.ac.za

which the network delivers its estimates of the dependent variable values; and the "hidden nodes" in between input and output nodes, which do the processing of the independent variable values to estimates of dependent variable values. The nodes in each layer are connected to the next layer by means of links by which values are passed. Outputs in one layer serve as inputs in the next. The network is fully connected in that there are links between all the nodes in adjacent layers. The network has the ability to estimate both quantitative variables and class variables. It has the analogy to regression which estimates quantities (Abdi et al., 1999; Anderson, 1995; Smith 1993).

A neural network operates in two modes, namely mapping and learning. During the mapping mode, information passes through the network from the input to the output nodes, whereby the network processes one example of a target function at a time, producing an estimate of the dependent variable values based on the independent variable values for that example. The input nodes receive the set of values of the independent variables, whereby the hidden nodes calculate the weighted sum of the inputs using its unique connection strengths as weights. Each hidden node computes a sigmoid function of its sum by simply squashing the value down to a limited range. Each output node computes a similar calculation to the hidden nodes to result in a value that is the estimate of the independent variable it represents (Abdi et al., 1999; Anderson, 1995). The nature of the mapping carried out by the network depends on the value of the weights. Backpropagation is the method of finding the optimum values for these connection strengths. It involves training the network for examples for which the correct output values are known (Smith 1993).

During the learning node, the network has to carry out a computation for each example, by firstly performing the mapping procedure. Thereafter, the output nodes are informed of the target values for that specific example. Based on the difference between the current outputs and the target outputs (termed the error), each output node determines the direction as well as the amount of change in which each of its weights would have to move to reduce the error, through its links to the hidden nodes. In the learning node, training begins with arbitrary values for the weights, which may be random numbers, and

Stellenbosch University http://scholar.sun.ac.za

it proceeds iteratively, with each iteration called an epoch. The network processes all the examples and adjusts the weights in the direction that reduces the error. Although the weights are normally changed after all the examples have been processed, it is also possible to change the weights as each example is processed. As the incremental adjustments are made, the weights gradually converge on the optimal set of values. The key insight in backpropagation is that the hidden nodes are able to adjust the weights through the error information that is received from the output nodes by the method of gradient descent. This method is designed to produce the set of coefficients that reduces the mean squared error of the model, synonymous to those used in the traditional regression method (Smith 1993).

According to Smith (1993), the advantage of neural networks in being able to model any relationship is at the same time also its disadvantage. The power of a neural network is influenced by the number of hidden nodes. The number of input and output nodes are determined by the number of dependent and independent variables, but that of the hidden nodes must be decided on by the developer of the network. The risk lies therein that the network can approximate a target function of any complexity as long as it has enough hidden nodes. Smith, 1993, p. 25, however warns:

> This power has its price. Given a limited sample size and enough noise in the data, a network with too many hidden nodes can overfit – that is, it can model the accidental structure of the noise in the sample as well as the inherent structure of the target function.

2.5.6. Statistical Corrections For Measurement Error

When developing a selection procedure the objective is to model the relationship between the latent criterion construct and fallible measures of the predictor constructs that determine job performance as it exists in the applicant population on which the selection procedure will be eventually used. In reality, however, the relationship between a fallible measure of the criterion construct and fallible measures of the predictor constructs is modelled on a biased sample selected from the applicant population. The extent to which the operationalised criterion contains random measurement error and the extent to which

Stellenbosch University http://scholar.sun.ac.za

the validation sample is a too homogenous and thus unrepresentative, biased, sample from the applicant population, will affect the validity coefficient (Campbell, 1991; Crocker & Algina, 1986; Lord & Novick, 1968; Messick, 1989; Schepers, 1996). Both factors will attenuate the validity coefficient. It thus follows that, to the extent that the aforementioned two factors did operate in the validation study but do not apply to the actual area of application, the obtained validity coefficient cannot, without formal consideration of these factors, be generalised to the actual area of application. The obtained validity coefficient thus cannot, without appropriate corrections, be considered an unbiased estimate of the actual validity coefficient of interest. Campbell (1991, p. 701) consequently recommends that:

> If the point of central interest is the validity of a specific selection procedure for predicting performance over a relatively long time period for the population of job applicants to follow, then it is necessary to correct for restriction of range *(and)* criterion unreliability .... Not to do so is to introduce considerable bias into the estimation process.

Appropriate formulas to correct the validity coefficient for criterion unreliability and restriction of range have been derived from classical measurement theory (Crocker & Algina, 1986; Lord & Novick, 1968; Kaplan & Saccuzzo, 2001; Schepers, 1996; Theron, 1999). If these corrections would be applied, the validity coefficient would be adjusted, but that would still leave the prediction equation, in terms of which the criterion estimates are derived, unaffected. The prediction equation actually used to derive the expected criterion estimates for decision-making is thus still the one derived from the validation study data, which, however, is not fully representative of the actual application (Theron, 1999). This, however, begs the questions of whether the characteristics in terms of the context in which the prediction equation is actually applied, do in any way differ from the context in which it was developed; if this will affect the prediction equation, and if so, in which way(s).

Stellenbosch University http://scholar.sun.ac.za

If the considerations underlying the corrections previously applied to the correlation coefficient do in fact also affect one or more of the facets of the prediction equation, corrections to the decision rule would then also be required. Theron (1999, p. 29) expresses his concern in this regard as follows:

> The decision function is probably the pivot of the selection procedure because it firstly captures the underlying performance theory, but more importantly from a practical perspective, because it guides the actual accept and reject choices of applicants [i.e. it forms the basis of the strategy matrix]. Restricting the statistical corrections to the validity coefficient would leave the decision function unaltered even though it might also be distorted by the same factors affecting the validity coefficient. Basically the same logic also applies to the evaluation of the decision rule in terms of selection utility and fairness. Correcting only the validity coefficient would leave the "bottom-line" evaluation of the selection procedure unaltered. Restricting the statistical corrections to the validity coefficient basically means that practically speaking nothing really changes.

2.5.7. The Prediction of Predictability

Classic psychometric theory holds that errors of measurement and of prediction are characteristics of the measuring device rather than the testee and that these errors are distributed randomly across individuals. Interactive effects between the measuring device and the person being assessed are not recognized, and the psychological structure of all individuals is taken to be the same. To increase reliability and validity of measurement, then, attention is entirely focused on improvement of measurement devices. However, a substantial body of evidence indicates there are systematic individual differences in error, and in the importance that a given trait has in determining a particular performance (Ghiselli, 1963).

If it could be demonstrated that these differences, or some other measure of error, such as the standard error or the correlation coefficient, were related to another variable then some modification of classic psychometric theory would appear to be in order. Ghiselli (1960b) has called this other variable a predictability variable, but Saunders (1956) has

Stellenbosch University http://scholar.sun.ac.za

better termed it a moderator thus drawing attention to its interactive effects. Such a position would not require all variation to be predictable by the moderator, but only a portion of it. The remainder would still be thought of as being random error.

> An interesting and provocative alternative to the use of the multiple-regression method of prediction is found in the work of Ghiselli. He emphasizes the fact that the goal of prediction is to develop a method that will forecast criterion scores, y', as little different as possible from actually obtained criterion scores, y. That is, the goal of prediction is to minimize the absolute difference $|y - y'|$. These differences are absolute since Ghiselli views the direction of such differences as unimportant as under- or overestimates both merely count as "errors". Any procedure which minimizes $|y - y'|$ is therefore, by definition, a good procedure (Wiggins, 1973, p. 61).

Ghiselli (1960b) has proposed a method whereby a moderator variable may be developed for a specific prediction situation. Ghiselli (1956) has investigated the possibility of differentiating by some other means, perhaps another test, those individuals whose test and criterion scores show small absolute discrepancies from those individuals whose test and criterion scores are markedly different. In a derivation sample, the absolute differences between predicted and actual criterion scores are obtained. The subjects are then divided into two groups on the basis of their high or low predictability. Correlation analysis is subsequently performed to identify items from a separate item pool that discriminate between high and low predictability. The items that correlate significantly with the absolute residual are then linearly combined in a predictability index. To the extent to which the predictability index correlated with the absolute residuals, it should be possible to separate those subjects for whom the regression model provides accurate criterion estimates from those for whom the model performs less well. The index of predictability should therefore function as a moderator (Anastasi & Urbina, 1997; Wiggins, 1973).

Stellenbosch University http://scholar.sun.ac.za

Knowledge of the predictability of an individual's criterion score should have considerable practical value. In an actual applicant sample, applicants would be ordered on the predictability index, and predictions would be made from the original predictors for the most predictable subset of applicants only. As predictions would be limited to an increasingly smaller proportion of the applicant sample, the validity of the predictor should approach unity. Selection procedures therefore can be improved not only by the addition of highly valid predictors to present procedures, but also by the addition of devices to screen out individuals whose levels of aptitude and job proficiency show little correspondence. Ghiselli (1956, 1960a, 1960b, 1963) has provided a number of convincing demonstrations of the utility of this approach and of variations on it (Wiggins, 1973).

As stated by Ghiselli (1963), there is a substantial body of empirical evidence indicating that moderator effects do occur. With respect to validity, the function of the moderator is to predict the weight a test carries in determining criterion performance for a given individual. Moderators are most attractive since they promise significant improvements in measurement accuracy and especially in predictive validity.

However, it appears (Wiggins, 1973) that a combination of predictor and predictability index scores in multiple regression does not improve prediction over that given by the predictor scores alone. The value of predictability index scores lies solely in providing an index of the extent to which prediction of criterion scores from a particular test will be in error. The method does not provide for an alternative means of predicting those individuals who have been screened out because of their low predictability. Personnel selection however requires that each and every applicant should be assigned to either an accept or a reject treatment (Cronbach & Gleser, 1965).

An important aspect in the original Ghiselli proposal that could hold the key to overcoming this shortcoming is the direction of the differences between actual and predicted scores of performance. Ghiselli viewed this as unimportant as both over- and underestimates count as "errors" (Wiggins, 1973). However, the question that arises is

Stellenbosch University http://scholar.sun.ac.za

whether the direction of the prediction error should be taken into account when developing a predictability index. The addition of such an index to a selection battery could conceivably add to the predictive validity of the battery.

Based on the original proposal of Ghiselli, this research is therefore devoted to the investigation of the possibility of differentiating between individuals in terms of their predictability in such a manner that the addition of a predictability index would enhance the predictive validity of a selection battery. What is required to improve predictive accuracy is the addition of a predictor to the regression model which functions by way of analogy like an observation post adjusting the distance and angle of mortar or artillery fire onto a target. The predictors in the model provide criterion estimates that are in most cases too high or too low. If a predictive index could be developed which would provide feedback on the magnitude of the prediction error derived from the regression model as well as the direction of the error, then the inclusion of such an index in the regression equation as an additional main effect, should logically enhance the predictive validity of the selection battery. This would however mean that the predictive index should be developed from the real differences between actual and predicted criterion scores of subjects, rather than the absolute difference as Ghiselli (1956, 1960a, 1960b, 1963) originally proposed.

If the development of a predictability index to predict the algebraic residual would prove possible and the inclusion of the predictability index would significantly explain criterion variance not explained by the predictors already in the model, the question arises whether the predictability index and its effect in the regression model would successfully cross validate on a holdout sample. This seems an especially pertinent question given the poor replication of moderator effects generally (Cook, 1998).

Stellenbosch University http://scholar.sun.ac.za

2.6. Quality of Decision-Making

Accuracy of prediction in and by itself is not the ultimate objective of research in personnel selection. Throughout this literature study the emphasis has been placed on the importance of arriving at qualitative decisions as the ultimate purpose of personnel testing as proposed by Cronbach and Gleser (1965). The challenge for any study into the improvement of personnel testing therefore ultimately lies in demonstrating that the quality of decision making benefits from the proposed improvement.

In selection the choice exists between accepting an individual into an institution and rejecting that individual. In general, the aim of the decision maker is to accept those individuals whose expected pay-off is the highest, within the limits placed upon him. A selection strategy serves the purpose of guiding numerous decisions about applicants made by human resource managers and therefore should be evaluated by "its total contribution when applied to a large number of decisions" (Cronbach & Gleser, 1965, p. 23). Thus the focus should now be placed on strategic decisions about selection procedures rather than on operational decisions about individual applicants (Boudreau, 1991; Cascio, 1991). The decision options under consideration are therefore not individual applicants, but rather different possible procedures or strategies that could be used to assign applicants to treatments (Boudreau, 1991; Cronbach & Gleser, 1965). The selection strategy chosen by the decision maker therefore needs to be evaluated by its total contribution when applied to a number of decisions. The expected pay-off from an individual has little meaning if the decision making strategy has not been evaluated in terms of its utility in terms of predictive validity (Bobko, 2001; Cascio, 1991; Guion, 1991).

In general the concept of utility refers to the increase in employee quality affected by the selection procedure over random selection. In the context of selection, the concept of utility can probably be best defined as the Rand-cent value of the increase in performance brought about by a selection procedure over random selection, weighed up against the costs incurred in bringing about such an improvement (Cascio, 1991; Cronbach & Gleser,

Stellenbosch University http://scholar.sun.ac.za

1965). The money spent on the development, validation and use of a selection procedure should not be viewed as merely an expense, but indeed as an investment. The resulting question that needs to be asked thus is what the return on such an investment is, and how this compares with alternative investment possibilities.

It therefore follows that selection by means of any selection procedure, regardless of the effectiveness of the procedure itself, only has meaning if the utility of the procedure is significantly positive. Utility is influenced by three factors, of which selection effectiveness is but one of such a factor. The two other factors that influence utility are the costs involved in the use of a particular measuring instrument per applicant (C), and the Rand-cent value of one unit increase in performance as measured by means of the criterion (i.e. the standard deviation of the criterion distribution expressed in monetary terms, SD_y). Selection effectiveness, in turn, is influenced by the selection ratio (ϕ), the base rate or criterion standard deviation, and the validity coefficient (Bobko, 2001; Cascio, 1991).

The utility of a selection procedure can be calculated empirically by means of regression procedures, provided that the standard deviation of the criterion distribution expressed in monetary terms is known. Various procedures exist whereby this amount can be estimated (Schmidt & Hunter, 1983; Cascio & Ramos, 1986).

Several utility models can be distinguished to determine the total utility of a selection procedure, whereby the best known models are those of Taylor-Russell (1939), Naylor-Shine (1965) and Brogden (1946) and Cronbach and Gleser (1965). The Taylor-Russell model describes the usefulness of a selection procedure in terms of the success ratio, i.e. the probability of success on the criterion conditional on surpassing the critical cut-off on the predictor. This model assumes that a continuous criterion is dichotomized by a criterion cut-off Y_k and that a continuous predictor is dichotomized by an unrestricted (explicit) or restricted (implicit) selection cut-off X_k. The success ratio can therefore be increased by either an increase in the validity coefficient, a decrease in the selection ratio, or an increase in the base rate.

Stellenbosch University http://scholar.sun.ac.za

The Naylor-Shine utility model interprets selection utility in terms of the expected standardised criterion performance of the selected group of applicants. This model is based on the fact that, if normality of the predictor distribution is assumed, it can be shown that the expected standardised predictor performance of the top-down selected applicants is equal to the height of an ordinate under the standardized normal distribution at the cut point divided by the proportion of applicants falling above it (λ/ϕ). The expected standardised criterion performance of the selected group of applicants would then be given by:

$$Z_{y\_selected} = r_{xy}(\lambda/\phi) \qquad 29$$

The Brogden-Cronbach-Gleser continuous variable utility model is potentially the most versatile utility model available (Cascio, 1991). It interprets selection utility in terms of the performance improvement achieved by the selection procedure expressed on a criterion scaled in monetary value (Bobko, 2001). It assumes a linear, homoscedastic regression of a normally distributed criterion, scaled in an appropriate monetary unit, on a normally distributed standardised predictor. The resulting equation that gives the total utility of the use of a selection instrument for a single period if N_s individuals are selected, with a cost of C involved in the testing of a single applicant and a selection ratio of ϕ is:

$$\Delta U = N_s r_{xy} SD_y(\lambda/\phi) - N_s(C/\phi) \qquad 30$$

Each of the described models is potentially useful only by understanding their appropriate applications. The Taylor-Russell model is the most appropriate under the following circumstances:

(1) Differences in ability beyond the minimum necessary to perform the job do not yield differences in benefit.

(2) Individuals are placed into two or more groups based on their scores on a procedure.

(3) Differences in output are believed to occur, but are presently immeasurable.

Stellenbosch University http://scholar.sun.ac.za

The Naylor-Shine model is most appropriate when differences in criterion performance cannot be expressed in monetary terms, but when it can be assumed that the function relating pay-off to the predictor score is linear. The Brogden-Cronbach-Gleser model is most appropriate in situations where linear regression of the criterion on the predictor can be assumed. This model provides a direct estimate of the monetary value of a selection programme by making use of a monetary criterion (Bobko, 2001; Cascio 1991).

Brogden (1946; 1949a; 1949b) and Cochran (1951) have shown that selection utility is a linear function of test validity, and that total selection utility could therefore be enhanced by an improvement in total validity. The objective of this study is not only to examine the increase in predictive validity achieved by the inclusion of the proposed predictability index in the regression model, but ultimately to describe the extent to which the utility of a selection strategy would be improved by the inclusion of such an index. If the predictive validity can be significantly increased by the inclusion of the proposed predictability index in the regression model, the total utility of the selection procedure should subsequently increase despite the investment in the administration of an additional test from which the items for the predictability index will be harvested. This increase in utility would in the final analysis determine whether the use of the proposed predictability index would contribute to the ultimate aim of effective selection in organisations, namely to contribute to the efficiency of the business in terms of monetary value.

Stellenbosch University http://scholar.sun.ac.za

CHAPTER 3
RESEARCH METHODOLOGY

The validity coefficients typically encountered in validation studies are disappointingly low. Validity coefficients typically fall below 0,50 and only very seldom reach values as high as 0,70 (Campbell, 1991). Selection instruments therefore typically explain only 25% of the variance in the criterion (Campbell, 1991). Numerous possibilities have been considered on how to affect an increase in the magnitude of the validity coefficient (Campbell, 1991; Ghiselli et al., 1981; Guion, 1991). A survey of these has been presented in Chapter 2. Most of these attempts revolved around modifications and/or extensions to the regression strategy (Gatewood & Feild, 1994).

An interesting and provocative alternative to the usual multiple-regression based attempts has been suggested by Ghiselli (1956, 1960a, 1960b). The essence of the proposed procedure revolves around the development of a composite predictability index that explains variance in the prediction errors or residuals resulting from an existing prediction model. It would, however appear as if the procedure has found very little if any practical acceptance. The actuarial nature of the procedure could probably account to a large extent for it not being utilized in the practical development of selection procedures. The lack of general acceptance must however also be attributed in part to the fact that the predictability index originally proposed by Ghiselli (1956, 1960a, 1960b) failed to significantly explain unique variance in the criterion when added to a model already containing one or more predictors (Wiggins, 1973). The predictability index thus only serves the purpose of isolating a subset of individuals for whom the model provides relatively accurate criterion estimates. The selection problem, however, requires the assignment of each and every member of the total applicant sample (and not only subsets of the applicant group) to one of two possible treatments based on their estimated criterion performance.

Stellenbosch University http://scholar.sun.ac.za

In the preceding literature study is has been argued that the key to overcoming this shortcoming could be found in the nature of the differences between actual and predicted scores of performance. Ghiselli viewed overestimates as important an error as underestimates (Wiggins, 1973), and thus based the development of his predictability index on the absolute residuals. However, if the direction of the prediction error would be taken into account when developing a predictability index, large positive values on the index would signal large positive residuals (underestimation) and large negative values (or low positive values) would signal large negative residuals (overestimation), assuming a positive correlation between the predictability index and $(Y\text{-}E[Y|X_i])$. The addition of this index to a regression model should enhance the predictive validity of the selection procedure, because its values would provide feedback on the magnitude of the prediction error derived from the regression model as well as the direction of the error. The partial regression coefficient associated with the predictability index in the expanded regression model should be positive. An initial estimate derived from the original model which is too low (underestimate) should therefore be elevated in the subsequent estimate derived from the expanded regression model due to the influence of the positive predictability index value. Conversely an initial estimate derived from the original model which is too high should be lower in the subsequent estimate derived from the expanded regression model due to the influence of the negative predictability index value. The same principle should still apply even if the predictability index scale would be linearly transformed to run from zero to some positive upper limit.

The foregoing argument brings a number of pertinent questions to the fore. Is the development of a predictability index to predict the algebraic residual feasible? Would the inclusion of the predictability index significantly explain criterion variance not explained by the predictors already in the model? Would the predictability index, and its effect in the regression model, successfully cross validate on a holdout sample? Would the utility of the increase in validity affected by the inclusion of the predictability index in the regression model warrant its inclusion? To be able to empirically answer these questions, however, requires that they be directed at a specific selection application.

Stellenbosch University http://scholar.sun.ac.za

The empirical investigation into the modification proposed to the Ghiselli procedure will be performed on the use of the APIL Battery (Psytech, 2003; Taylor, 1994) for the prediction of overall academic performance in an MBA programme. The predictability index will be developed from the items of the Organisational Personality Profile (OPP) test (Psytech, 2003).

3.1. Research Problems

The following research problems can therefore be formulated.

1. Is average MBA performance (η) significantly influenced by learning potential (ξ_1)?

2. Is it possible to develop a predictability index from the items of a personality measure that shows a strong and significant correlation with the real, algebraic residuals ($Y - E[Y|X_1]$) computed from the regression of the criterion on a learning potential predictor?

3. If so, will the addition of the predictability index, based on the real, algebraic values of the residuals, to the regression model significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor?

4. Is it possible to develop a predictability index from the items of a personality measure that shows a strong and significant correlation with the absolute residuals $|(Y - E[Y|X])|$ computed from the regression of the criterion on a learning potential predictor?

Stellenbosch University http://scholar.sun.ac.za

5. If so, will the addition of the predictability index (based on the absolute values of the residuals) to the regression model significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor?

6. If it is possible to develop a predictability index based on the real, algebraic values of the residuals and the addition of the index to the regression model significantly explain unique variance in the criterion measure, are these relationships persistent in as far as they cross-validate to a representative hold-out sample?

7. Would an examination of the factor structure underlying the items comprising the predictability index provide evidence that substantive theoretical meaning could be attached to the predictability index?

8. If the addition of the predictability index, based on the real, algebraic values of the residuals, to the regression model significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor, what will the impact of the inclusion of the predictability index in the prediction model be on selection utility?

3.2. Substantive Research Hypotheses

The literature study would suggest the following substantive research hypotheses.

1. Average MBA performance (η) is significantly influenced by learning potential (ξ_1).

2. A predictability index can be developed from the items of a personality measure that shows a strong and significant correlation with the real, algebraic residuals ($Y - E[Y|X_1]$) computed from the regression of the criterion on a learning potential predictor.

Stellenbosch University http://scholar.sun.ac.za

3. The addition of the predictability index, based on the real, algebraic values of the residuals, to the regression model will significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor.

4. A predictability index can be developed from the items of a personality measure that shows a strong and significant correlation with the absolute residuals $|(Y - E[Y|X])|$ computed from the regression of the criterion on a learning potential predictor.

5. The addition of the predictability index (based on the absolute values of the residuals) to the regression model will not significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor.

6. The predictability index, developed on the derivation sample will correlate significantly with the real, algebraic residuals obtained from fitting a new basic regression model on a representative holdout sample taken from the same population.

7. The addition of the predictability index, based on the real, algebraic values of the residuals, to the holdout regression model will significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor.[1]

8. The factor structure underlying the items comprising the predictability index provides evidence that a clear substantive theoretical interpretation could be attached to the predictability index.

---

[1] The further cross validation question as to whether the expanded regression model (including the predictability index) developed on the derivation sample would succeed in accurately predicting the criterion scores of the holdout sample with little shrinkage, has not been addressed.

Stellenbosch University http://scholar.sun.ac.za

9. The addition of the predictability index, based on the real, algebraic values of the residuals, to the regression model will significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor, will increase the predictive validity of the selection procedure and thereby increase selection utility.

3.3. Description of the Sample

To serve the analytical purposes of this study, the data had to meet a number of specific requirements. The data set, firstly, had to contain an explicit criterion measure and a predictor measure which correlate significantly with the criterion. The data set, secondly, had to contain the results of a second predictor, but in this case measures were required on the item level. The items of the second predictor had to provide the data from which the predictability index could be harvested. The data set, thirdly, had to be large enough to allow the formation of a derivation sample on which the predictability index would initially be developed, and a holdout sample on which the predictability index would be cross validated.

A data set was obtained from Psytech SA that satisfied the first two of the aforementioned requirements. Psytech SA obtained data from the Gordon's Institute of Business Science (GIBS) on 101 MBA students between 1990 and 1991. A highly selected non-probability sample was chosen from students with average or above average interim MBA performance levels. The variance on the MBA examination scores was therefore typically low. The available information on the demographic profile of the derivation sample is presented in Tables 3.1. to 3.4.

Stellenbosch University http://scholar.sun.ac.za

Table 3.1. The Race Composition of the Derivation Sample

		Frequency	Percentage	Valid Percentage	Cumulative Percentage
Valid	Black	21	20,8	21,4	21,4
	White	68	67.3	69,4	90,8
	Asian	9	8,9	9,2	100,0
	Total	98	97,0	100,0	
Missing	-9999	3	3,0		
Total		101	100,0		

Table 3.2. The Gender Composition of the Derivation Sample

		Frequency	Percentage	Valid Percentage	Cumulative Percentage
Valid	Female	30	29,7	29,7	29,7
	Male	71	70,3	70,3	100,0
	Total	101	100,0	100,0	

Table 3.3. The Home Language Composition of the Derivation Sample

		Frequency	Percentage	Valid Percentage	Cumulative Percentage
Valid	Eng	53	52,5	55,8	55,8
	Afr	21	20,8	22,1	77,9
	Shona	1	1,0	1,1	78,9
	Sesotho	1	1,0	1,1	80,0
	Zulu	3	3,0	3,2	83,2
	Danish	1	1,0	1,1	84,2
	Xhosa	4	4,0	4,2	88,4
	Nsotho	2	2,0	2,1	90,5
	Ssotho	2	2,0	2,1	92,6
	Sotho	2	2,0	2,1	94,7
	Tswana	3	3,0	3,2	97,9
	German	1	1,0	1,1	98,9
	Italian	1	1,0	1,1	100.0

Stellenbosch University http://scholar.sun.ac.za

	Total	95	94,1	100,.0	
Missing	-9999	6	5,9		
		101	100,0		

Table 3.4. Descriptive Statistics on the Age Distribution

N	**Valid**	**100**
	Missing	1
Mean		33,13
Median		33,00
Mode		34
Std. Deviation		5,165
Variance		26,680
Skewness		,556
Std. Error of Skewness		,241
Kurtosis		,266
Std. Error of Kurtosis		,478
Minimum		24
Maximum		49

a Multiple modes exist. The smallest value is shown

Average interim MBA performance was utilized as the criterion in the study. The Apil battery was utilized as the predictor. Descriptive statistics on the criterion and the predictor is shown in Table 3.5. The Organisational Personality Profile (OPP) Questionnaire (Psytech, 2003), along with the Critical Reasoning Test Battery Version 2 (CRTB2) (Psytech, 2003) has also been administered to the sample. The initial intention was to use only the items of the OPP for the development of the two predictability indices. It, however, subsequently become necessary also to use the items of the CRTB2 for the development of the predictability index based on the absolute residuals.

Stellenbosch University http://scholar.sun.ac.za

Table 3.5. Descriptive Statistics on the Apil and MBA Performance Distributions

		Apil general learning potential score	MBA Average to date
N	Valid	101	101
	Missing	0	0
Mean		63,16198	67,86144
Median		63,47000	67,43750
Mode		65,000	64,000
Std. Deviation		10,554199	4,502512
Variance		111,391124	20,272610
Skewness		-,359	,423
Std. Error of Skewness		,240	,240
Kurtosis		-,570	,055
Std. Error of Kurtosis		,476	,476
Minimum		37,000	58,750
Maximum		83,000	81,000

More detailed information regarding the sampling methodology was not available from Psytech. The nature of the sampling methodology is however not critical in arriving at valid and credible conclusions on the merits of the modifications proposed to the original Ghiselli procedure.

The data set obtained from Psytech was too small to permit the formation of a derivation sample and a holdout sample. In terms of Cohen's statistical power tables (Cohen, 1988), however, the sample size of 101 for the derivation sample can be regarded as adequate. The required number of participants to achieve statistical power of 0,80 in testing the significance of a sample product moment r, given a medium effect size of $\rho = 0.30$, a 5% significance level and a directional alternative hypothesis, is n=68. At a 1% significance level the required n increases to 107. For a non-directional alternative hypothesis the

Stellenbosch University http://scholar.sun.ac.za

Cohen tables recommend sample sizes of 84 (p=0,05) and 124 (p=0,01), assuming the same effect size as before.

3.4. Psychometric Evaluation Of Measuring Instruments

The following section provides a brief description of the instruments used in the evaluation of the proposed modification to the original Ghiselli procedure. The psychometric properties of the measuring instruments used in the assessment will also be examined.

3.4.1. The Apil Battery

The Apil Battery (Apil-B), initially designed by Terry Taylor in 1995 was utilised as the primary predictor of MBA performance in as far as it predicts the academic performance of the subjects still to be described. The Apil-B is published and distributed by APROLAB and is designed with the intention of measuring learning potential of people from Grade 12 and up in a manner essentially designed to diminish the influence of the impact of verbal abilities, cultural connotations and educational qualifications.

The hallmark of this test is that testees learn new skills, by which they are also measured, while they are being assessed. This test assesses the following dimensions:

- Abstract thinking/concept formation (fluid intelligence)
- Automisation of learning (efficiency of learning new cognitive skills)
- Transfer of learning to new concepts
- Performance gain in a learning task based on memory (using rote and/or logical principles in organising memory in a curve of learning)
- Final level of learning performance
- Processing depth (concept memorisation and mastery)
- Speed of information processing
- Accuracy of information processing
- Cognitive flexibility

Stellenbosch University http://scholar.sun.ac.za

The instrument has been successfully implemented in a number of human resource fields, including selection and development, skills development and capacity building, multi-skilling, career pathing, and bursary selection (Psytech, 2003).

This instrument has been widely tested in South African industry and academic institutions in the country as described in section 3.3.1.1. The Kuder-Richardson 20 reliability coefficient of most of the Apil-B tests ranged between 0,82 and 0,92 (Psytech, 2003).

The predictive validities of the Apil-B, claimed by Jooste (2001), are good. In a recent study done at Deloitte and Touche on 100 employees, the Apil-B overall score correlated 0,61 with performance ratings, indicating its high concurrent validity (Psytech, 2003).

3.4.2. The Critical Reasoning Test Battery Version 2 (CRTB2)

The Critical Reasoning Test Battery Version 2 (CRTB2), designed and published by Psytech SA (Psytech, 2003), was employed in the original study as the primary ability measure of subjects. Its purpose is to assess high level critical reasoning ability. This instrument was specifically designed to assess management and provides a detailed and specific measure of critical reasoning. It consists of two tests aiming at measuring both verbal (VCR2) and numerical (NCR2) critical reasoning. The passages and tables, on which the items are based, have been composed to reflect current, real world topics. The items consist of the type of material that managerial, professional and technical staff is likely to encounter in the course of their work.

The reliability of the instrument was tested on insurance sales consultants and business school applicants. In both cases very high reliabilities were found, with the Cronbach alpha coefficients of the Verbal Critical Reasoning subtests being 0,88 and 0,84 respectively, and that of the Numerical Critical reasoning subtests being 0,84 and 0,80 respectively. These cases constituted mean alpha coefficients of between 0,82 and 0,86.

Stellenbosch University http://scholar.sun.ac.za

Validation studies done on the instrument in the prediction of MBA students' performance at a business school in Gauteng indicated that the Verbal Critical reasoning correlated significantly with most of the subject scores and with the average academic score. The Numerical Critical Reasoning test only correlated significantly with two subjects and in both cases negatively. It must be taken into account that the MBA students were, as previously stated, pre-selected by academic achievement and work experience, which would serve to reduce the variance for ability tests.

3.4.3. The Organisational Personality Profile Test (OPP)

The Organisational Personality Profile test (OPP) also designed and published by Psytech SA, was used for the measurement of subjects' personality profiles. Items from this test that correlated strongly and significantly with the residuals resulting from the regression of MBA averages on the Apil-B, were used to construct the predictability indices under discussion. The OPP has ninety eight items from which the predictability indices could be constructed. The main purpose of this test is to obtain an accurate measure of occupationally relevant personality traits. The OPP sets out to measure the following nine bipolar traits:

- Accommodating / Assertive
- Detail conscious / Flexible
- Cynical / Trusting
- Emotional / Phlegmatic
- Reserved / Gregarious
- Genuine / Persuasive
- Composed / Contesting
- Optimistic / Pessimistic (internal-external locus of control)
- Abstract / Pragmatic

From these basic traits, detailed assessments of interpersonal style, thinking style and patterns of coping with stress can be made.

Stellenbosch University http://scholar.sun.ac.za

A combined sample from various smaller groups that have been tested in South Africa by Psytech and users of the OPP in various settings since 1996, indicated Cronbach alpha scores of between 0,64 and 0,70. The predictive validity of the OPP that was tested by predicting MBA course results in students in various institutions, showed multiple correlation coefficients of between 0,342 and 0,665. However, not all of the personality scales included in the regression model significantly explained variance in the criterion not explained by the remainder of the predictors in the model (Psytech, 2003). Correlational analysis with various other personality measures indicated positive evidence for the construct validity of the OPP and supports the contention that the OPP scales measure what they claim to measure (Psytech, 2003).

3.5. Research Design

An ex post facto correlational design is used

3.6. Statistical Hypotheses

Hypothesis 1:

Average MBA performance (Y) is significantly influenced by learning potential (X_1).

H_{01}: $\rho[Y,X_1] = 0$

H_{a1}: $\rho[T,X_1] > 0$

Hypothesis 2:

A predictability index (X_2) can be developed from the items of a personality measure that shows a strong and significant correlation with the real, algebraic residuals ($Y - E[Y|X_1]$) (Y_{res}) computed from the regression of the criterion on a learning potential predictor

H_{02}: $\rho[Y_{res}, X_2] = 0$

H_{a2}: $\rho[Y_{res}, X_2] > 0$

Hypothesis 3:

Stellenbosch University http://scholar.sun.ac.za

The addition of the predictability index, based on the real, algebraic values of the residuals (X_2), to the regression model will significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor (X_1).

H_{03}: $\beta_2[X_2] = 0 \mid \beta_1[X_1] \neq 0$

H_{a3}: $\beta_2[X_2] > 0 \mid \beta_1[X_1] \neq 0$

Hypothesis 4:

A predictability index (X_3) can be developed from the items of a personality measure that shows a strong and significant correlation with the absolute residuals $|(Y - E[Y|X_1])|$ ($|Y_{res}|$) computed from the regression of the criterion on a learning potential predictor.

H_{04}: $\rho[|Y_{res},X_3|] = 0$

H_{a4}: $\rho[|Y_{res},X_3|] > 0$

Hypothesis 5:

The addition of the predictability index, based on the absolute values of the residuals (X_3), to the regression model will not significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor (X_1).

H_{05}: $\beta_2[X_3] = 0 \mid \beta_1[X_1] \neq 0$

H_{a5}: $\beta_2[X_3] > 0 \mid \beta_1[X_1] \neq 0$

Hypothesis 6:[2]

The predictability index, developed on the derivation sample (X_2) will correlate significantly with the real, algebraic residuals (Y_{res_h}) obtained from fitting a new basic regression model on a representative holdout sample taken from the same population.

H_{06}: $\rho[Y_{res\_h},X_2] = 0$

H_{a6}: $\rho[Y_{res\_h},X_2] > 0$

Hypothesis 7:

[2] H_{06} and H_{07} will not be tested due to insufficient observations to form a holdout sample.

Stellenbosch University http://scholar.sun.ac.za

The addition of the predictability index, based on the real, algebraic values of the residuals (X_2), to the holdout regression model will significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor (X_1).

H_{07}: $\beta_2[X_2] = 0 \mid \beta_1[X_1] \neq 0$

H_{a7}: $\beta_2[X_2] > 0 \mid \beta_1[X_1] \neq 0$

Hypotheses 8 and 9 are descriptive hypotheses and no corresponding statistical hypotheses are therefore formulated.

3.7. Statistical Analysis

The Statistical Package for Social Sciences (SPSS) version 11.0 will be employed to analyse the data. The specific analyses performed and the logic underlying the sequence of analyses will be outlined below.

Correlation analysis will be used to establish whether the Apil–B could be used as the primary predictor of average MBA performance. Should the resultant Pearson correlation coefficient $r[Y,X_1]$ be significant and H_{01} could therefore be rejected, the MBA averages will be regressed on the learning potential predictor.

The real, algebraic residuals ($Y\text{-}E[Y|X_1]$) as well as the absolute residuals ($|Y\text{-}E[Y|X_1]|$), of the predicted MBA results from the regression will subsequently be computed, using the appropriate regression equation obtained earlier to derive the criterion estimates $E[Y|X_1]$.

The items of the OPP will then be correlated with the absolute and real residuals computed in steps 3 and 4 to establish a matrix of zero-order Pearson correlation coefficients and the corresponding conditional probabilities $P[|r_{ij}| \geq r_c|H_0:\rho_{ij}=0]$.

For each residual variable (absolute and real residuals), those OPP items that correlated significantly with that specific residual variable, will be identified. These items will be

Stellenbosch University http://scholar.sun.ac.za

linearly combined for each residual variable to create the two predictability indices, i.e. an absolute residual predictability index (X_3) and a real residual predictability index (X_2). The predictive validity of these two predictability indices will then be evaluated by correlating the indices with the residuals they are meant to predict. Should H_{02} and H_{04} be rejected, it would imply that it is possible to develop predictability indices from the items of the OPP.

To establish whether the predictability index, based on the real, algebraic values of the residuals (X_2), when added to the basic regression model, will significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor (X_1), H_{03} will be tested by fitting the following multiple regression model to the data using standard multiple regression:

$$E[Y|X_1,X_2] = \alpha + \beta_1[X_1] + \beta_2[X_2]$$

To establish whether the predictability index, based on the absolute values of the residuals (X_3), when added to the basic regression model, will significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor (X_1), H_{05} will be tested by fitting the following multiple regression model to the data using standard multiple regression:

$$E[Y|X_1,X_3] = \alpha + \beta_1[X_1] + \beta_2[X_3]$$

If the addition of the predictability index based, on the real, algebraic values of the residuals (X_2), to the basic regression model, significantly explains unique variance in the criterion measure that is not explained by the learning potential predictor (X_1), the question arises whether substantive meaning could be attached to the index scores. The residuals in part reflect the influence of variables that systematically affect the criterion but which were not included in the original model. Are the items included in the predictability index indicators of one or more underlying latent variables that conceptually could be expected to explain variance in the criterion? Or, alternatively, is

Stellenbosch University http://scholar.sun.ac.za

the predictability index nothing more than an incoherent, meaningless collection of items that have nothing more in common than their correlation with the regression residuals. Exploratory principal component analysis will be performed on the set of OPP items, to explicate the factor structure underlying the index. The Eigen-value greater than one rule will be used to decide on the number of factors to extract. Varimax rotation will be used to rotate the obtained solution to simple structure. Depending on the results of the principal component analysis, item analysis will be performed on the items comprising the index to assess the extent to which internally consistent descriptions of the latent variables underlying the index are obtained.

If, contrary to expectation, the addition of predictability index based on the absolute values of the residuals (X_3) to the basic regression model, significantly explains unique variance in the criterion measure that is not explained by the learning potential predictor (X_1), similar analyses will be performed on the items comprising this index as well.

If the addition of predictability index based, on the real, algebraic values of the residuals (X_2), to the basic regression model, significantly explains unique variance in the criterion measure that is not explained by the learning potential predictor (X_1), the proportion of criterion variance explained by the expanded regression model $R^2(Y, E[Y|X_1,X_2])$ will be greater than that explained by the basic model $r^2(Y,X_1)$. The question is what the effect of this increase in predictive validity is on the quality of selection decision-making. The Taylor-Russell (Cascio, 1991), Naylor-Shine (Cascio, 1991) and Brogden-Cronbach-Gleser (Brogden, 1949a; Cascio, 1991; Cronbach & Gleser, 1965) utility models will be employed to describe the effect of the incremental validity of the predictive index on the quality of selection decision-making.

Stellenbosch University http://scholar.sun.ac.za

The improvement in the proportion of the selected applicants succeeding on the criterion (i.e., the success ratio, S_v) affected by the inclusion of the predictability index in the regression model, assuming a selection ratio of ϕ and a base rate BR, will be given by:

$$\Delta S_v = (S_v[X_1,X_2] - BR) - (Sv[X_1] - BR)$$
$$= S_v[X_1,X_2] - S_v[X_1] \qquad 31$$

The improvement in the mean standardized criterion performance of the selected group affected by the inclusion of the predictability index in the regression model, assuming a selection ratio of ϕ, will be given (in standard deviation units) by:

$$\Delta E[Z_y|\text{selected}] = [R(Y, E[Y|X_1,X_2])(\lambda/\phi)] - [r(Y,X_1)(\lambda/\phi)]$$
$$= [R(Y, E[Y|X_1,X_2] - r(Y,X_1)][\lambda/\phi] \qquad 32$$

The R-c value of the improvement in the mean standardized criterion performance of the selected group affected by the addition of the predictability index to the basic regression model, assuming a selection ratio of ϕ, an average tenure of T years, a cohort of N_s applicants selected out of N_a, a R-c scaled standard deviation SD_y, a per applicant cost of C_1 associated with the Apil and a per applicant cost of C_2 associated with the OPP will be given (in R-c) by:

$$\Delta U = TN_s\, R(Y, E[Y|X_1,X_2]SD_y(\lambda/\phi) - C_1N_a - TN_s r(Y,X_1)SD_y(\lambda/\phi) - C_1N_a$$
$$= TN_sSD_y(\lambda/\phi)(R(Y, E[Y|X_1,X_2] - r(Y,X_1)) - N_a(C_2 + C_1) \quad 33$$

The incremental validity produced by the inclusion of the predictability index in the basic regression model will be determined empirically. Arbitrary, but realistic illustrative values will be chosen for the other parameters affecting the improvement in the quality of selection decision-making in each of the utility models to describe the effect of the incremental validity of the predictive index on the quality of selection decision-making.

Stellenbosch University http://scholar.sun.ac.za

CHAPTER 4
RESULTS OF ANALYSES

Ghiselli (1956, 1960a, 1960b) proposed an interesting and provocative procedure on how to affect an increase in the magnitude of the validity coefficient of a selection procedure. This study proposed and motivated specific modifications to the original Ghiselli procedure, so as to circumvent specific shortcomings associated with the original procedure. Chapter 3 outlined the specific research problems, substantive research hypotheses and statistical hypotheses emanating from the proposed modification, and described the intentions on how to analyse the data statistically so as to shed light on the validity of the hypotheses. Chapter 4 will report on the results of these analyses.

4.1. The Relationship Between Average MBA Performance and Learning Potential

To be able to investigate the feasibility of the proposed modifications to the original Ghiselli procedure, a significant linear relationship between a criterion and at least one predictor is required. It had been hypothesized that MBA performance should be systematically related to learning potential as measured by the Apil. Hypotheses 1 was tested by calculating the zero-order Pearson correlation between average MBA performance and performance of the Apil and the corresponding conditional probabilities $P[|r_{ij}| \geq r_c|H_0: \rho[Y,X_1] = 0]$. Given a 5% significance level and directional alternative hypotheses, H_{01} will be rejected if $P[|r_{ij}| \geq r_c|H_{01} : \rho[Y,X_1] = 0] < 0{,}05$. The matrix of zero-order Pearson correlation coefficients and the corresponding conditional probabilities is portrayed in Table 4.2.

The convention proposed by Guilford (cited in Tredoux & Durrheim, 2002, p. 184) and portrayed in Table 4.1. will be used to interpret sample correlation coefficients. Although somewhat arbitrary and although it ignores the normative question about the magnitude

Stellenbosch University http://scholar.sun.ac.za

of values typically encountered in a particular context, it nonetheless fosters consistency in interpretation.

Table 4.1. Guilford's Interpretation of the Magnitude of a Significant r

Absolute value of r	Interpretation
< 0,19	Slight; almost no relationship
0,20 – 0,39	Low correlation; definite but small relationship
0,40 – 0,69	Moderate correlation; substantial relationship
0,70 – 0,89	High correlation; strong relationship
0,90 – 1,00	Very high correlation; very dependable relationship

(Tredoux & Durrheim, 2002, p.184)

The correlation analysis of the Apil-B ability test (X_1) and the MBA performance (Y) confirmed that the Apil-B can be used as the primary predictor of MBA performance, in that it showed a moderate (0,416) and significant ($p<0,05$) correlation with the criterion (Table 4.2.). H_{01} can therefore be rejected. The substantial relationship, which exists between learning potential and MBA performance, can thus be used as a platform to empirically investigate the proposed modifications to the original Ghiselli procedure.

Average MBA performance was subsequently regressed on the Apil-B ability test (X_1) by fitting the following regression model on the data:

$$E(Y|X1) = \alpha + \beta[X1].$$

The results of the standard regression analysis are presented in Table 4.3. Approximately 17% of the variance in the criterion can be explained in terms of the linear regression of the MBA average to date on the primary predictor. Figure 4.1. depicts the linear relationship graphically.

Stellenbosch University http://scholar.sun.ac.za

Table 4.2. Correlation between the Apil-B Ability Test (X_1) and MBA Performance (Y)

		MBA Average to date (Y)	Apil general learning potential score (X_1)
MBA Average to date (Y)	Pearson Correlation	1	,416
	Sig. (1-tailed)	.	,000
	N	101	101
Apil general learning potential score (X_1)	Pearson Correlation	,416	1
	Sig. (1-tailed)	,000	.
	N	101	101

Table 4.3. Simple Linear Regression of Average MBA Performance on Learning Potential

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,416	,173	,164	4,15620

Predictors: (Constant), Apil general learning potential score (X_1)

Dependent Variable: MBA Average to date (Y)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	350,366	1	350,366	20,685	,000
	Residual	1676,895	99	16,938		
	Total	2027,261	100			

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
1	(Constant)	56,660	2,497		22,693	,000
	Apil general learning potential score	,177	,039	,416	4,548	,000

Stellenbosch University http://scholar.sun.ac.za

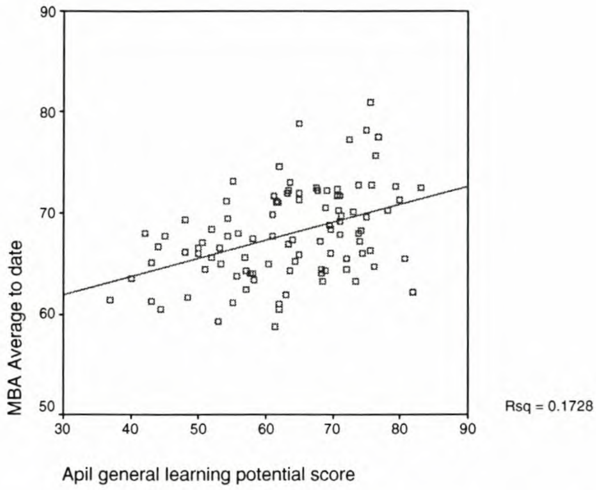

Figure 4.1. Simple Linear Regression of Average MBA Performance on Learning Potential

4.2 Development of Predictability Indices

The real, algebraic unstandardized residuals ($Y - E[Y|X_1]$) were then derived from the fitted regression model and written to the active data file (see Appendix A: res_1). Simultaneously, the absolute residuals $|(Y - E[Y|X_1])|$ (see Appendix A: abres_1) of the predicted MBA average results (see Appendix A: pre_1) were computed by extracting the predicted values $E[Y|X_1]$ from the appropriate equation in the regression analysis. The real, algebraic unstandardized residuals are plotted against the predictor in Figure 4.2. From Figure 4.2. it appears as if the linearity, normality and homoscedasticity assumption underlying the linear model have been reasonably well satisfied. The absolute unstandardized residuals are plotted against the predictor in Figure 4.3.

Descriptive statistics for the real, algebraic and absolute unstandardized residuals are shown in Table 4.4. In the case of the real residuals, the skewness and kurtosis statistics do not deviate significantly ($p>0,05$) from zero; thus supporting the inferences made from Figure 4.2.

Stellenbosch University http://scholar.sun.ac.za

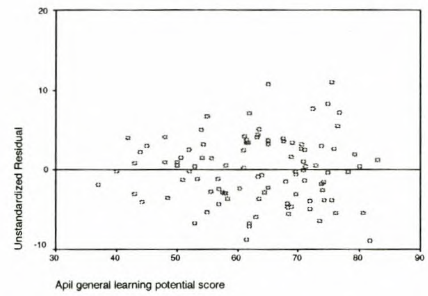

Figure 4.2. Real, Algebraic Unstandardized Residuals are Plotted against Learning Potential

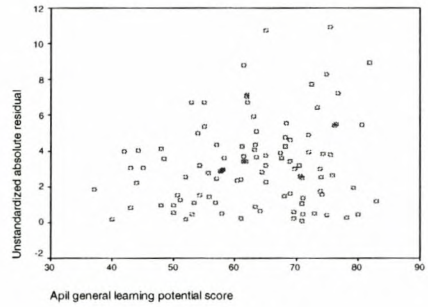

Figure 4.3. Absolute Unstandardized Residuals are Plotted against Learning Potential

Table 4.4. Descriptive Statistics For Real and Absolute Unstandardized Residuals

		Unstandardized Residual	Unstandardized absolute residual
N	Valid	101	101
	Missing	0	0
Mean		,0000000	3,3069266
Median		-,0640272	3,0156491
Std. Deviation		4,09499034	2,39245159
Variance		16,76894587	5,72382462
Skewness		,207	,955
Std. Error of Skewness		,240	,240
Kurtosis		-,118	,853
Std. Error of Kurtosis		,476	,476
Minimum		-8,92225	,06403
Maximum		10,94329	10,94329

Stellenbosch University http://scholar.sun.ac.za

The individual items of the OPP personality questionnaire were subsequently correlated with the real and absolute residuals computed from the fitted regression model (see correlation matrix in Appendix B). The OPP items that correlated significantly with the real residuals at the 0,05 level (see Appendix B) were flagged for inclusion in the predictability index (X_2). Nine items correlated significantly with the real residuals at this level, namely items 10, 18, 20, 25, 32, 33, 61, 73, and 96. In the case of the absolute residuals, however, only a single OPP item (item 55) presented itself as a significant predictor of the absolute prediction errors made by the fitted regression model. This clearly created a dilemma as far as the calculation of the second predictability index is concerned. The possibility of harvesting items from the Critical Reasoning Test Battery (CRTB2) was consequently examined. The items of the CRTB2 subtests were therefore correlated with the absolute residuals in a similar fashion to the OPP items (see correlation matrix in Appendix C). Again the yield was rather disappointing. Only three CRTB2 items correlated significantly with the absolute residuals at the 0,05 level. These were items 22 and 37 from the Verbal subscale and item 11 from the Numerical subscale. It is worthy of note that the CRTB2 items yielded eight significant predictors of the real residuals.

The selected nine OPP items for the real residual were subsequently combined in an unweighted linear composite by taking the mean of the qualifying items to form the predictability index (X_2) based on real residuals (see Appendix A). The selected three CRTB2 items were likewise combined in a unweighted linear composite by taking the mean of the qualifying items to form the predictability index (X_3) based on absolute residuals (see Appendix A).

Stellenbosch University http://scholar.sun.ac.za

4.3. Evaluation of Predictability Indices

The predictability index based on the real residuals (X_2) and the predictability index based on the absolute residuals were subsequently correlated with the unstandardized real and absolute residuals to determine the success with which the two predictability indices have been developed. In anticipation of the addition of the predictability indices to the basic regression model, the correlations of the two indices with the primary predictor and with the criterion were determined as well. The results are presented in Table 4.5.

Table 4.5. shows that the predictability index based on real residuals, (X_2), did correlate moderately (0,509) and significantly ($p<0,05$) with the real residuals derived from regressing the MBA averages on the Apil-B ability predictor. H_{02} can therefore be rejected in favour of H_{a2}, It is possible to develop a predictability index (X_2) from the items of a personality measure that shows a strong and significant correlation with the real, algebraic residuals ($Y - E[Y|X_1]$) computed from the regression of the criterion on a learning potential predictor. Table 4.5. in addition reveals that the absolute residual predictability index, based on the absolute residuals (X_3), did correlate moderately (0,508) and significantly ($p<0,05$) with the absolute residuals. H_{04} can therefore be rejected in favour of H_{a4}, if the initial assumption that the OPP would yield a sufficient number of items for the index, could be wavered. It is possible to develop a predictability index (X_3) from the items of a critical reasoning measure that shows a strong and significant correlation with the real, algebraic residuals $|(Y - E[Y|X_1])|$ computed from the regression of the criterion on a learning potential predictor.

The predictability index based on real residuals (X_2), correlated low (-0,002) and insignificantly ($p>0,05$) with the absolute residuals derived from regressing the MBA averages on the Apil-B ability predictor. Likewise the predictability index based on absolute residuals (X_3), correlated low (-0,047) and insignificantly ($p>0,05$) with the real residuals. Table 4.5. furthermore suggests that that the inclusion of X_2 alongside X_1 in a

Stellenbosch University http://scholar.sun.ac.za

multiple regression model is more likely to be meaningful than the addition of X_3 to a regression model already including X_1. X_2 correlated low (0,056) and insignificantly ($p>0,05$) with the Apil-B results while correlating moderately (0,487) and significantly ($p<0,05$) with the criterion. The predictability index based on real residuals (X_2) therefore seems to explain unique variance in the criterion not explained by the primary predictor. X_3 correlates low (0,242), but significantly ($p<0,05$) with the predictor while correlating low (0,058) and insignificantly ($p>0,05$) with the criterion. The predictability index based on absolute residuals (X_3) therefore seems not to explain unique variance in the criterion.

Table 4.5. Correlations between the Predictability Indices, the Primary Predictor and the Criterion

		X_2	X_3	Unstandardized Residual	Unstandardized absolute residual	Apil general learning potential score (X_1)	MBA Average to date (Y)
X_2	Pearson Correlation	1	-,028	,509	-,002	,056	,487
	Sig. (2-tailed)	.	,778	,000	,984	,576	,000
	N	101	101	101	101	101	101
X_3	Pearson Correlation	-,028	1	-,047	,508	,242	,058
	Sig. (2-tailed)	,778	.	,641	,000	,015	,565
	N	101	101	101	101	101	101
Unstandardized Residual	Pearson Correlation	,509	-,047	1	,075	,000	,909
	Sig. (2-tailed)	,000	,641	.	,456	1,000	,000
	N	101	101	101	101	101	101
Unstandardized absolute residual	Pearson Correlation	-,002	,508	,075	1	,190	,147
	Sig. (2-tailed)	,984	,000	,456	.	,057	,142
	N	101	101	101	101	101	101
Apil general learning potential score (X_1)	Pearson Correlation	,056	,242	,000	,190	1	,416
	Sig. (2-tailed)	,576	,015	1,000	,057	.	,000
	N	101	101	101	101	101	101
MBA Average to date (Y)	Pearson Correlation	,487	,058	,909	,147	,416	1
	Sig. (2-tailed)	,000	,565	,000	,142	,000	.
	N	101	101	101	101	101	101

Stellenbosch University http://scholar.sun.ac.za

Descriptive statistics for the two predictability indices are provided in Table 4.6. Two dummy variables (X_2D and X_3D) were subsequently created by dichotomising the index distributions into high and low prediction accuracy groups. In the case of X_2 the the cut-off points were chosen to distinguish those cases with residuals centred around zero from those with large positive or negative residuals. In the case of X_3 the cut-off point was chosen so as to include those cases with low absolute prediction errors.

Table 4.6. Descriptive Statistics for the Two Predictability Indices

		X2	X3
N	Valid	101	101
	Missing	0	0
Mean		3,0088	2,4422
Median		3,0000	2,5000
Std. Deviation		,44905	,46811
Variance		,20165	,21913
Skewness		-,038	,372
Std. Error of Skewness		,240	,240
Kurtosis		-,363	,171
Std. Error of Kurtosis		,476	,476
Percentiles	25	2,6667	2,0000
	50	3,0000	2,5000
	75	3,3333	3,0000

The relationship between the criterion and the predictor was subsequently graphically portrayed in Figure 4.4. and Figure 4.5. for the two levels of the dummy variable separately. Figures 4.4. and 4.5. seems to suggest that the predictability index based on the absolute residuals (X_3) is more effective in isolating a subset of individuals for whom the model provides more accurate criterion estimates than the predictability index based on real residuals. The two indices both correlate moderately strong (0,51) with the residuals from which it is derived. The superiority of one index over the other in separating the more accurate predictables from the less accurate predictables thus is somewhat surprising.

Stellenbosch University http://scholar.sun.ac.za

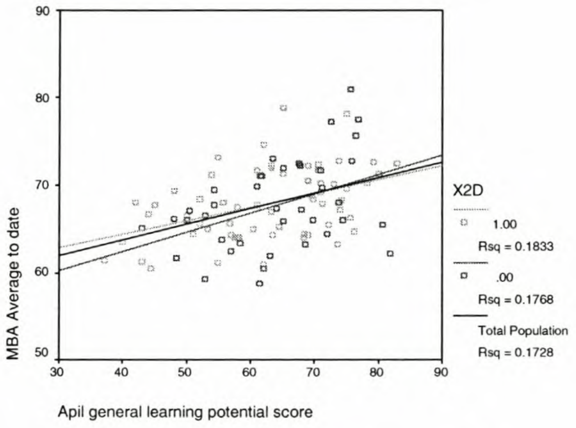

Figure 4.4. **MBA Average Performance as a Function of Learning Potential Depicted For High ($X_2D=1$) and Low Predictability ($X_2D=0$) Groups Separately**

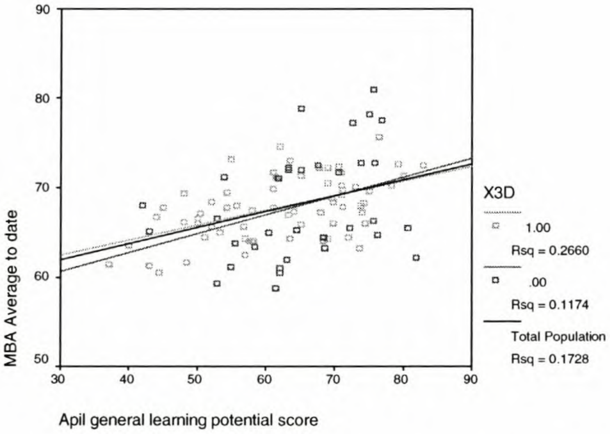

Figure 4.5. **MBA Average Performance as a Function of Learning Potential Depicted for High ($X_3D=1$) and Low Predictability ($X_3D=0$) Groups Separately**

Table 4.7. reveals that the addition of the predictability index, based on the real, algebraic values of the residuals (X_2), to the basic regression model significantly ($p<0,05$) explains unique variance in the criterion measure that is not explained by the learning potential predictor. H_{03} can thus be rejected in favour of H_{a3}. The original predictor still significantly ($p<0,05$) explains variance in the criterion not explained by the predictability index. The expanded regression model explains approximately 39% of the

Stellenbosch University http://scholar.sun.ac.za

variance in the criterion, compared to the approximately 17% explained by the basic model.

Table 4.7. shows that the unique variance in the predictability index (X_2) explains approximately 26% ($0,510^2$) of the unique variance in the criterion. The unique variance in the predictability index (X_2) explains approximately 22% ($0,464^2$) of the total variance in the criterion. Judged by the standardized partial regression coefficients and the partial and semi-partial correlation coefficients the predictability index is the more influential predictor in the regression model.

Table 4.7. Standard Multiple Regression of MBA Performance on Learning Potential and the Predictability Index Derived From Real Residuals (X_2)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,623	,388	,376	3,557492

a Predictors: (Constant), X2, Apil general learning potential score

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	786,998	2	393,499	31,092	,000
	Residual	1240,263	98	12,656		
	Total	2027,261	100			

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	*Correlations*		
Model		B	Std. Error	Beta			Zero-order	Partial	Part
1	(Constant)	43,342	3,130		13,846	,000			
	Apil general learning potential score (X_1)	,166	,034	,390	4,922	,000	,416	,445	,389
	X_2	4,661	,793	,465	5,874	,000	,487	,510	,464

Stellenbosch University http://scholar.sun.ac.za

Table 4.8. reveals that the addition of the predictability index based on the absolute values of the residuals (X_3), to the basic regression model does not significantly ($p>0,05$) explain unique variance in the criterion measure that is not explained by the learning potential predictor. H_{05} can thus not be rejected in favour of H_{a5}.

Table 4.8. Standard Multiple Regression of MBA Performance on Learning Potential and the Predictability Index Derived From Absolute Residuals (X_{23})

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,418	,175	,158	4,131730

a Predictors: (Constant), X3, Apil general learning potential score

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	354,284	2	177,142	10,377	,000
	Residual	1672,977	98	17,071		
	Total	2027,261	100			

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
Model		B	Std. Error	Beta			Zero-order	Partial	Part
1	(Constant)	57,429	2,977		19,293	,000			
	Apil general learning potential score (X_1)	,182	,040	,427	4,512	,000	,416	,415	,414
	X_3	-,436	,910	-,045	-,479	,633	,058	-,048	-,044

Stellenbosch University http://scholar.sun.ac.za

4.4 Substantive Meaning of Predictability Index Scores

Given that the addition of a predictability index based on the real, algebraic values of the residuals (X_2), to the basic regression model, significantly explains unique variance in the criterion measure that is not explained by the learning potential predictor (X_1), the question arises whether substantive meaning could be attached to the index scores. The objective was to determine if any theoretical meaning could be attached to the common factors underlying the index, if any were identified, and whether these interpretations would make sense in terms of the criterion. To shed light on this matter an exploratory principle component analysis was performed on the OPP items combined in the predictability index based on the real residuals. The Eigen value greater than one rule was used to decide on the number of factors to extract. Varimax rotation was used to rotate the obtained solution to simple structure.

Four factors were extracted (Figure 4.6. and Table 4.9.) and orthogonally rotated. The first four factors account for approximately 63% of the variance in the items (Table 4.9.). The rotated component matrix (Table 4.10.) should indicate whether the items comprising the predictability index systematically measured one or more underlying common construct(s) which could be linked to specific personality construct(s), or whether the predictability index is nothing more than an incoherent, meaningless collection of items that have nothing more in common than their correlation with the regression residuals.

Stellenbosch University http://scholar.sun.ac.za

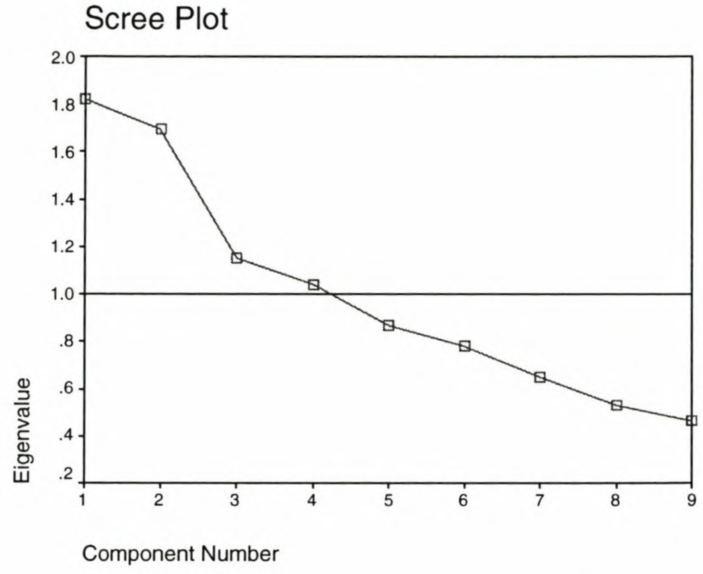

Figure 4. 6. Scree Plot

Table 4. 9. Principal Component Analysis Component Statistics

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	1,820	20,221	20,221	1,820	20,221	20,221	1,650	18,329	18,329
2	1,693	18,810	39,030	1,693	18,810	39,030	1,492	16,581	34,910
3	1,151	12,793	51,823	1,151	12,793	51,823	1,450	16,117	51,027
4	1,040	11,556	63,379	1,040	11,556	63,379	1,112	12,353	63,379
5	,871	9,674	73,054						
6	,784	8,709	81,762						
7	,647	7,192	88,954						
8	,530	5,891	94,845						
9	,464	5,155	100,000						

Extraction Method: Principal Component Analysis.

Stellenbosch University http://scholar.sun.ac.za

Table 4. 10. Rotated Factor Matrix

Item	Component			
	1	2	3	4
I rarely have time for lunch.	-8,236E-02	7,373E-02	**,797**	1,584E-02
I feel uncomfortable in crowded spaces (e.g. tube trains, lifts etc.).	-,353	**,613**	-7,243E-02	,122
If I am near a friend's house I will often drop in just to say hello.	4,831E-02	**,677**	,157	,300
Cleanliness is the greatest of all virtues.	,107	**,799**	7,285E-02	-,334
I often have difficulty remembering things.	**,667**	-7,153E-02	,018E-02	4,068E-02
There never seems to be enough hours in the day to get everything done.	,147	3,563E-02	**,809**	3,571E-02
I am inclined to get tense before important meetings, particularly if much is at stake.	**,735**	6,081E-02	,323	-,114
People are fundamentally goodhearted and kind.	-1,017E-02	6,081E-02	3,826E-02	**,937**
I find it easy to persuade people of my point of view.	**,706**	-3,181E-02	-,145	1,260E-02

Rotation Method: Varimax with Kaiser Normalization.

Rotation converged in 5 iterations.

However, no clear-cut picture emerges from Table 4.10. Although each item loads reasonably high on a single factor only, the common theme amongst the items loading on the same factor tends to be somewhat debatable. The first principle component could possibly be interpreted as a focus-intensity factor, the second principle component possibly as a compulsiveness factor and the third principle component possibly as a driven factor. These suggestions are however at best tenuous. Despite their questionable nature, these themes could conceivably play a role in the level of performance MBA students achieve. With the wisdom of hindsight, this could however probably have been said for any of the OPP items.

Item analyses were subsequently performed on the set of nine items derived from the correlation between the OPP personality measurement and the real residuals. Furthermore, the alpha coefficients were computed, taking into consideration the results of the principle component analysis. The results of the item analyses, shown in Table

Stellenbosch University http://scholar.sun.ac.za

4.11., Table 4.12. and Table 4.13. indicate modest internal consistency for the three item sets. This finding is however not surprising, given the limited number of items involved.

Table 4.11. Item Analysis on Component 1

R E L I A B I L I T Y   A N A L Y S I S - S C A L E(COMPONENT 1)

Correlation Matrix

	OPP_Q32	OPP_Q61	OPP_Q96
OPP_Q32	1,0000		
OPP_Q61	,3009	1,0000	
OPP_Q96	,2302	,3059	1,0000

N of Cases = 101,0

Statistics for	Mean	Variance	Std Dev	N of Variables
Scale	10,9010	3,9901	1,9975	3

Item-total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Alpha if Item Deleted
OPP_Q32	6,7723	2,4576	,3340	,1116	,4354
OPP_Q61	8,0396	1,184	,3865	,1497	,3730
OPP_Q96	6,9901	2,6099	,3378	,1146	,4414

Reliability Coefficients 3 items

Alpha = ,5241 Standardized item alpha = ,5372

Stellenbosch University http://scholar.sun.ac.za

Table 4.12. Item Analysis on Component 2

R E L I A B I L I T Y   A N A L Y S I S - S C A L E (COMPONENT 2)

Correlation Matrix

	OPP_Q18	OPP_Q20	OPP_Q25
OPP_Q18	1,0000		
OPP_Q20	,1716	1,0000	
OPP_Q25	,2652	,2979	1,0000

N of Cases = 101,0

Statistics for	Mean	Variance	Std Dev	N of Variables
Scale	8,2277	5,5176	2,3490	3

Item-total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Alpha if Item Deleted
OPP_Q18	6,0099	3,1099	,2712	,0797	,4591
OPP_Q20	5,3861	3,1794	,2934	,0980	,4189
OPP_Q25	5,0594	2,9364	,3673	,1360	,2927

Reliability Coefficients   3 items

Alpha = ,4919   Standardized item alpha = ,4932

Stellenbosch University http://scholar.sun.ac.za

Table 4.13. Item Analysis on Component 3

R E L I A B I L I T Y   A N A L Y S I S   -   S C A L E (COMPONENT 3)

Correlation Matrix

	OPP_Q10	OPP_Q33
OPP_Q10	1,0000	
OPP_Q33	,3596	1,0000

N of Cases = 101,0

Statistics for	Mean	Variance	Std Dev	N of Variables
Scale	5,4851	3,8523	1,9627	2

Item-total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Alpha if Item Deleted
OPP_Q10	2,6634	1,4255	,3596	,1293	.
OPP_Q33	2,8218	1,4079	,3596	,1293	.

Reliability Coefficients   2 items

Alpha = ,5289   Standardized item alpha = ,5289

Stellenbosch University http://scholar.sun.ac.za

4.5. The Effect of the Predictability Index on Utility

A definite increase in the proportion of criterion variance explained was found when adding the predictability index based on real residuals to the basic regression model. The question is what the effect of this increase in predictive validity is on the quality of selection decision-making. The Taylor-Russell (Cascio, 1991), Naylor-Shine (Cascio, 1991) and Brogden-Cronbach-Gleser (Brogden, 1949a; Cascio, 1991; Cronbach & Gleser, 1965) utility models will subsequently be employed to describe the effect of the incremental validity of the predictive index on the quality of selection decision-making.

The addition of the predictability index resulted in an increase in predictive validity from 0,416 to 0,623. To translate this increase in predictive validity to increases in decision quality in terms of the aforementioned three utility models however, requires addition assumptions on the other selection parameters characterizing the three models. Therefore, assume a big insurance company was to employ 100 sales representatives from an applicant pool of 2000, to be employed for an average of 5 years. Furthermore, assume the cost of the Apil battery per person to be R250 and that of the OPP R350. Assume the standard deviation of the criterion distribution expressed in a R-c metric to vary between 35% and 45% of average salary (Cascio, 1991). Assume average salary to be set at R100 000 per annum. Assume that 50% of the applicant pool could succeed if selected. Bivariate normality is assumed. The selection ratio ϕ would therefore equal 0,05 and the resulting λ value, obtained from the standardised normal probability table, would equal 0,103. The base rate (BR) would be 0,50.

The improvement in the proportion of the selected applicants succeeding on the criterion (i.e., the success ratio, S_v) affected by the inclusion of the predictability index in the regression model, would under the aforementioned assumptions be given by:

$$\begin{aligned}\Delta S_v &= (S_v[X_1,X_2] - BR) - (Sv[X_1] - BR)\\ &= S_v[X_1,X_2] - S_v[X_1]\\ &= 0{,}9434 - 0{,}82388\\ &= 0{,}11952\end{aligned}$$

Stellenbosch University http://scholar.sun.ac.za

$S_v[X_1,X_2]$ and $S_v[X_1]$ were calculated via SPSS by calculating $P[Z_y \geq 0$ and $Z_x \geq 1,64485]/P[Z_x \geq 1,64485]$ for the two validity coefficients, assuming multivariate normality. The addition of the predictability index (X_2) to the basic regression model would therefore, under the abovementioned scenario, result in an approximate 12% increase in the percentage selectees successful. This percentage would increase if larger increases in the validity coefficient could be affected. The improvement in the mean standardized criterion performance of the selected group affected by the inclusion of the predictability index in the regression model, assuming a selection ratio of ϕ, will under the abovementioned scenario be given (in standard deviation units) by:

$$\Delta E[Z_y|\text{selected}] = [R(Y, E[Y|X_1,X_2])(\lambda/\phi)] - [r(Y,X_1)(\lambda/\phi)]$$

$$= [R(Y, E[Y|X_1,X_2] - r(Y,X_1)][\lambda/\phi]$$

$$= [0,623\text{-}0,416][0,103/,05]$$

$$= 0,207[2,06]$$

$$= 0,42642$$

The addition of the predictability index (X_2) to the basic regression model would therefore, under the abovementioned scenario, result in an increase in average performance of approximately 0,43 standard deviation units. This might seem rather trivial but when extrapolated over selectees, time periods and the performance unit value of one standard deviation could amount to an impressive quantity.

The R-c value of the improvement in the mean standardized criterion performance of the selected group affected by the addition of the predictability index to the basic regression model is to be given (in R-c) by:

$$\Delta U = TN_s\, R(Y, E[Y|X_1,X_2]SD_y(\lambda/\phi) - C_1N_a - TN_s r(Y,X_1)SD_y(\lambda/\phi) - C_1N_a$$

$$= TN_sSD_y(\lambda/\phi)(R(Y, E[Y|X_1,X_2] - r(Y,X_1)) - N_a(C_2 + C_1)$$

$$= 5[100][40000][0,103/0,05]([0,623] - 0,416) - 100[250 + 350]$$

$$= 8528400 - 60000$$

$$= \text{R}8\ 468400\text{-}00$$

Stellenbosch University http://scholar.sun.ac.za

Where:

- ΔU = the increase in utility due to the addition of the predictability index;
- T = the average predicted tenure of the selected applicants;
- N_s = the number of people selected for a position using a selection battery to which the index computed in the study has been added;
- $R(Y, E[Y|X_1,X_2]$ = the correlation coefficient obtained by adding the index to a selection battery already containing the ability predictor;
- SD_y = the standard deviation of the criterion distribution expressed in a R-c metric;
- λ = the height of the ordinate cutting off an area under the standardised normal distribution corresponding to a selection ratio ϕ;
- ϕ = the selection ratio;
- C_1 = the per applicant cost for the Apil;
- $r(Y,X_1)$ = the validity coefficient of the basic regression model; and
- C_2 = the per applicant cost of the OPP.

The addition of the predictability index (X_2) to the basic regression model would therefore, under the abovementioned scenario, result in an increase in average performance worth R8 468400-00 over the average tenure of 5 years. This is a somewhat overoptimistic estimate in as far as it fails to reflect the time value of future earnings and the tax liability higher performance earnings would imply.

To illustrate the linear relationship between the increase in validity affected by the predictability index and utility, equation 33 has been solved for a range of possible values for SD_y and $R(Y, E[Y|X_1,X_2]$, while fixing the remaining utility parameters at their initially chosen values. Schmidt and Hunter's estimate of the standard deviation of the criterion distribution expressed in a R-c metric as 40 % of annual salary (Cascio, 1991) was varied with five percent up and down, resulting in the use of three values, i.e. 35%, 40% and 45%. The value of $R(Y, E[Y|X_1,X_2]$ was essentially varied in steps of 0,10 9 (see Table 4.14. and Figure 4.7.).

Stellenbosch University http://scholar.sun.ac.za

Figure 4.7. illustrates the resultant increase in the monetary utility as the correlation coefficient R(Y, E[Y|X_1,X_2] increased from 0,416 , as well the acceleration in the increase in the utility when the standard deviation of the criterion distribution expressed in a R-c metric increased from 35% of annual salary to 40% to 45%.

Table 4.14. Incremental Utility as a Function of R(Y, E[Y|X_1,X_2] and Sd_y

	N_s	T	Salary	Percentage	r_1	R_2	C_1	C_2	λ	ϕ	ΔU
1	100,00	5,00	100000,00	,40	,416	,623	250,00	350,00	,10	,05	8468400,00
2	100,00	5,00	100000,00	,40	,416	,723	250,00	350,00	,10	,05	12588400,00
3	100,00	5,00	100000,00	,40	,416	,823	250,00	350,00	,10	,05	16708400,00
4	100,00	5,00	100000,00	,40	,416	,923	250,00	350,00	,10	,05	20828400,00
5	100,00	5,00	100000,00	,40	,416	,523	250,00	350,00	,10	,05	4348400,00
6	100,00	5,00	100000,00	,40	,416	,423	250,00	350,00	,10	,05	228400,00
7	100,00	5,00	100000,00	,40	,416	,416	250,00	350,00	,10	,05	-60000,00
8	100,00	5,00	100000,00	,35	,416	,623	250,00	350,00	,10	,05	7402350,00
9	100,00	5,00	100000,00	,35	,416	,723	250,00	350,00	,10	,05	11007350,00
10	100,00	5,00	100000,00	,35	,416	,823	250,00	350,00	,10	,05	14612350,00
11	100,00	5,00	100000,00	,35	,416	,923	250,00	350,00	,10	,05	18217350,00
12	100,00	5,00	100000,00	,35	,416	,523	250,00	350,00	,10	,05	3797350,00
13	100,00	5,00	100000,00	,35	,416	,423	250,00	350,00	,10	,05	192350,00
14	100,00	5,00	100000,00	,35	,416	,416	250,00	350,00	,10	,05	-60000,00
15	100,00	5,00	100000,00	,45	,416	,623	250,00	350,00	,10	,05	9534450,00
16	100,00	5,00	100000,00	,45	,416	,723	250,00	350,00	,10	,05	14169450,00
17	100,00	5,00	100000,00	,45	,416	,823	250,00	350,00	,10	,05	18804450,00
18	100,00	5,00	100000,00	,45	,416	,923	250,00	350,00	,10	,05	23439450,00
19	100,00	5,00	100000,00	,45	,416	,523	250,00	350,00	,10	,05	4899450,00
20	100,00	5,00	100000,00	,45	,416	,423	250,00	350,00	,10	,05	264450,00
21	100,00	5,00	100000,00	,45	,416	,416	250,00	350,00	,10	,05	-60000,00
Total N	21	21	21	21	21	21	21	21	21	21	21

Stellenbosch University http://scholar.sun.ac.za

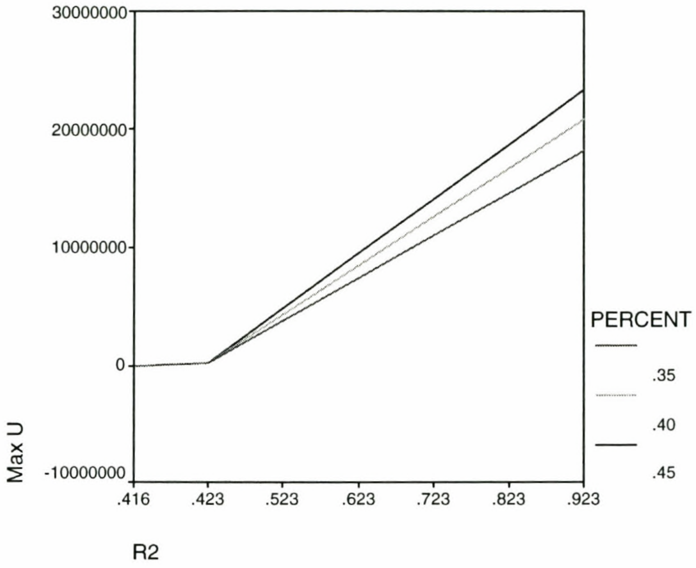

Figure 4.7. Incremental Utility as a Function of R(Y, E[Y|X$_1$,X$_2$] and Sd$_y$

Stellenbosch University http://scholar.sun.ac.za

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

5.1. Reviewing the Necessity and Objectives of the Research

Personnel selection is necessitated by the combined effect of inter-individual differences amongst applicants on those attributes that would determine their eventual job performance and the selecting organisation's desire to maximise performance. Personnel selection is, however, complicated by the obvious fact that information on the ultimate institutional criterion can never be available at the time of the selection decision. The only solution to this dilemma, apart from reducing selection to random assignment, is to base the decision on relevant substitute information that is assessable prior to the selection decision (Ghiselli et al., 1981; Theron, 1999). Substitute information can be considered relevant to the extent to which it correlates with a valid operationalization of the ultimate criterion. Relevant/valid substitute data, once obtained, is translated into decisions in accordance to some strategy for decision-making (Cronbach, 1960). A decision strategy describes how scores from tests are to be combined with non-test information, and what decision will be made for any given combination of facts. It is this selection decision strategy which should be evaluated in terms of its predictive validity - in other words in terms of the correspondence that exists between the criterion referenced inferences made via the decision rule from the available predictor information and the actual criterion performance achieved. The validity coefficients typically encountered in such validation studies are however quite often disappointingly low.

Numerous possibilities have been considered on how to affect an increase in the magnitude of the validity coefficient of selection prediction models (Campbell, 1991; Ghiselli et al., 1981, Guion, 1991). An in-depth examination of the literature surrounding personnel selection and measurement exposed the need for further exploration of this topic. Therefore, this research was, initiated by and based on an original idea proposed by Ghiselli (1956, 1960a, 1960b) on the use of a predictability index to improve prediction accuracy. The problem with Ghiselli's original proposal, however, was that

Stellenbosch University http://scholar.sun.ac.za

his predictability index only served the purpose of isolating a subset of individuals for whom the model provides relatively accurate criterion estimates. This research is therefore specifically dedicated to investigating the possibility that the differentiation between subjects on the basis of the predictability of their criterion performance could be used to increase the accuracy of the criterion estimates for the total applicant sample.

More specifically, the objectives of the study were:

- To propose modification to the Ghiselli procedure that would solve the problem experienced by Ghiselli (1956, 1960a, 1960b) in his original studies;
- To corroborate the earlier finding of Ghiselli (1956, 1960a, 1960b) that the development of a predictability index that significantly explains variance in the criterion residual is practically possible;
- To examine the factor structure of the predictability index to establish whether substantive theoretical meaning could be attached to the predictability index;
- To examine the incremental validity resulting from the inclusion of the predictability index in the prediction model; and
- To examine the impact of the inclusion of the predictability index in the prediction model on selection utility.

5.2. Research Hypotheses

These objectives were pursued by investigating the following substantive research hypotheses in the study.

1. Average MBA performance (η) is significantly influenced by learning potential (ξ_1).

2. A predictability index can be developed from the items of a personality measure that shows a strong and significant correlation with the real, algebraic residuals ($Y - E[Y|X_1]$) computed from the regression of the criterion on a learning potential predictor.

Stellenbosch University http://scholar.sun.ac.za

3. The addition of the predictability index (based on the real, algebraic values of the residuals) to the regression model will significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor.

4. A predictability index can be developed from the items of a personality measure that shows a strong and significant correlation with the absolute residuals $|(Y - E[Y|X])|$ computed from the regression of the criterion on a learning potential predictor.

5. The addition of the predictability index (based on the absolute values of the residuals) to the regression model will not significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor.

6. The predictability index, developed on the derivation sample will correlate significantly with the real, algebraic residuals obtained from fitting a new basic regression model on a representative holdout sample taken from the same population.

7. The addition of the predictability index, based on the real, algebraic values of the residuals, to the holdout regression model will significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor.[1]

8. The factor structure underlying the items comprising the predictability index provides evidence that a clear substantive theoretical interpretation could be attached to the predictability index.

[1] The further cross validation question as to whether the expanded regression model (including the predictability index) developed on the derivation sample would succeed in accurately predicting the criterion scores of the holdout sample with little shrinkage, has not been addressed.

Stellenbosch University http://scholar.sun.ac.za

9. The addition of the predictability index, based on the real, algebraic values of the residuals, to the regression model will significantly explain unique variance in the criterion measure that is not explained by the learning potential predictor, will increase the predictive validity of the selection procedure and thereby increase selection utility.

5.3. Summary of Results

5.3.1. The Relationship between Learning Potential and Average MBA Performance

A substantial linear relationship was found between the Apil-B ability test (X_1) and MBA performance (Y). The moderate (0,416) and significant ($p<0,05$) correlation between the Apil-B and MBA performance, confirmed that the learning potential measure can be used as the primary predictor of the criterion. Approximately 17% of the variance in the criterion can be explained in terms of the linear regression of the MBA average on learning potential. The substantial relationship which exists between learning potential and MBA performance could thus be used as a platform to empirically investigate the proposed modifications to the original Ghiselli procedure.

5.3.2. The Feasibility of Developing a Predictability Index that Shows a Strong and Significant Correlation with the Real, Algebraic Residuals ($Y - E[Y|X_1]$) Computed from the Regression of the Criterion on a Predictor.

Nine items from the OPP correlated significantly ($p<0,05$) with the real residuals derived from regressing the MBA averages on the Apil-B ability predictor. An unweighted linear composite, formed by taking the mean of the qualifying items, correlated moderately (0,509) and significantly ($p<0,05$) with the real residuals. The statistical results thus indicate that it is indeed possible to develop a predictability index from a personality measurement that shows a strong and significant correlation with the real, algebraic residuals computed from the regression of the criterion on the ability predictor.

Stellenbosch University http://scholar.sun.ac.za

5.3.3. *The Effect of the Addition of the Predictability Index, Based on the Real, Algebraic Values of the Residuals, to a Regression Model.*

The addition of the predictability index, based on the real, algebraic values of the residuals (X_2), to the basic regression model significantly ($p<0,05$) explains unique variance in the criterion measure that is not explained by the learning potential predictor. The expanded regression model explained substantially more of the variance in the criterion than the basic model. The developed predictability index thus positively impacted on the predictive validity of the selection battery. The proposed solution to the problem experienced by the original Ghiselli procedure thus had been supported. This finding illustrates the general principle that the ability of a selection battery to explain variance in the criterion can be enhanced when a predictability index is added to the battery, provided the index takes into account the direction of the differences between actual performance and predicted performance.

5.3.4. *The Feasibility of Developing a Predictability Index that Shows a Strong and Significant Correlation with the Absolute Residuals $|(Y - E[Y|X])|$ Computed from the Regression of the Criterion on a Predictor.*

Only a single OPP item presented itself as a significant predictor of the absolute prediction errors made by the fitted regression model. The possibility of harvesting items from the Critical Reasoning Test Battery (CRTB2) was consequently examined. The items of the CRTB2 subtests were correlated with the absolute residuals in a similar fashion to the OPP items. Again the yield was rather disappointing. Only three CRTB2 items correlated significantly with the absolute residuals at the .05 level. The results of this study therefore seem to suggest that, although it is possible to find items to construct a predictability index based on absolute residuals, the yield is much lower than in the case of a predictability index based on real, algebraic residuals. The absolute residual predictability index (X_3) correlated moderately (0,508) and significantly ($p<0,05$) with the absolute residuals derived from regressing the MBA averages on the Apil-B ability predictor. It is possible to develop a predictability index (X_3) from the items of a critical

Stellenbosch University http://scholar.sun.ac.za

reasoning measure that shows a strong and significant correlation with the real, algebraic residuals $|(Y - E[Y|X_1])|$ computed from the regression of the criterion on a learning potential predictor.

5.3.5. The Effect of the Addition of the Predictability Index, Based on the Absolute Values of the Residuals, to a Regression Model.

The addition of the predictability index, based on the absolute values of the residuals (X_3), to the basic regression model does not significantly ($p>0,05$) explain unique variance in the criterion measure that is not explained by the learning potential predictor. This finding is consistent with the earlier research by Ghiselli (1956, 1960a, 1960b). The ability of a predictability index to significantly explain variance in the criterion is definitely affected by the way in which it has been developed.

5.3.6. The Factor Structure Underlying the Items Comprising the Predictability Index.

The study also investigated the factor structure of the predictability index to determine if any substantive theoretical meaning could be attached to the index scores. The objective was to determine if the predictability index possibly measured one or more main constructs within the personality domain that could relate to the criterion. The results of the analysis provided no clear-cut evidence on the nature of the underlying common construct(s). Four principle components emerged and tentative interpretations of the components could be made. These interpretations are, however, at best tenuous. The indications emerging from this research is that the predictability index is more than an incoherent, meaningless collection of items that have nothing more in common than their correlation with the regression residuals. It would, however, be premature to conclude that the items included in the predictability index are indicators of one or more underlying latent variables that conceptually explain variance in the criterion.

Stellenbosch University http://scholar.sun.ac.za

5.3.7. The Effect of the Addition of the Predictability Index, Based on the Real, Algebraic Values of the Residuals, to the Regression Model on Selection Utility.

The addition of the predictability index resulted in an increase in predictive validity from 0,416 to 0,623. Since utility is a function of, amongst other things, the correlation between the selection battery and the criterion, this increase in correlation implies a subsequent increase in selection utility. However, to translate this increase in predictive validity to increases in decision quality in terms of the Taylor-Russell (Cascio, 1991), Naylor-Shine (Cascio, 1991) and Brogden-Cronbach-Gleser (Brogden, 1949; Cascio, 1991; Cronbach & Gleser, 1965) utility models, specific additional assumptions on the other selection parameters characterizing the three models had to be made.

The addition of the predictability index (X_2) to the basic regression model resulted in an approximate 12% increase in the percentage selected applicants who are successful, assuming a selection ratio of 0,05 and a base rate of 0,50.

Selecting the best 5% of applicants from an applicant pool with the expanded regression model instead of the basic prediction model resulted in an increase in average performance of approximately 0,43 standard deviation units.

Selecting the best 5% of applicants from an applicant pool in which an increase of one standard deviation in performance is worth R40 000 with the expanded regression model instead of the basic prediction model at a per applicant cost of C_1+C_2, resulted in an increase in average performance worth R8 468400-00 over the average tenure of 5 years. This is a somewhat overoptimistic estimate in as far as it fails to reflect the time value of future earnings and the tax liability higher performance earnings would imply.

The descriptive utility analyses illustrated that the increase in the predictive validity of a selection battery brought about by the addition of a predictability index to the battery, can produce substantial and useful increases in the selection decision quality.

Stellenbosch University http://scholar.sun.ac.za

5.3.8. Conclusion

The main accomplishments of this study regarding the development of a predictability index are threefold: (1) it is possible to develop a predictability index which correlates with the real, algebraic residuals derived from the regression of a criterion on one or more predictors, (2) the addition of such a predictability index to the original regression model can produce a significant increase in the correlation between the selection battery and the criterion, and (c) this increase can trigger a substantial and useful increase in the utility of the selection battery. The potential benefits especially apply to companies selecting large numbers of employees per year at small selection ratios from even larger applicant pools.

5.4. Limitations And Recommendations

To be able to convincingly demonstrate the feasibility of enhancing selection utility through the use of predictability indices would require the cross validation of the results obtained on a derivation sample on a holdout sample selected from the same population. The following two vital issues are at stake. The predictability index, developed on the derivation sample should still correlate significantly with the real, algebraic residuals obtained from fitting a new basic regression model on a representative holdout sample taken from the same population. Furthermore, the addition of the predictability index, developed on the derivation sample, to the holdout regression model should still significantly explain unique variance in the criterion measure that is not explained by the predictor(s) in the basic model. The first aspect is probably the Achilles heel of the proposed procedure. If the predictability index developed on the derivation sample would succeed in predicting the real prediction errors made by a newly fitted regression model on a second sample taken from the same population, then the second issue most likely will not present a problem. This study failed to investigate these two rather crucial aspects due to the limited size of the data set it had at its disposal.

Stellenbosch University http://scholar.sun.ac.za

There is, moreover, a related question which this study also failed to investigate. More in line with traditional cross validation of regression equations the question also arises to what extent the expanded regression model developed on the derivation sample would accurately predict the criterion when applied on the holdout sample data. In terms of the eventual regular use of predictability indices in selection research this clearly is an important issue.

The possibility of using bootstrapping to solve the problem of finding large enough initial samples to allow the division into derivation and holdout samples, should be considered. The term bootstrap is derived from the expression to pull yourself up by your own bootstraps generally believed to originate from one of Rudolph Raspe's Adventures of Baron von Münchhausen [Efron & Tibshirani, 1993]. The term appears to be appropriate since the bootstrap procedure in essence represents a seemingly impossible attempt to simulate the behaviour of a sample statistic across a large number of independent samples taken from a single parent population from data available only in a single sample (Diaconis & Efron, 1983; Efron, 1982; Efron & Tibshirani, 1993). Bootstrapping would imply a random sample Ψ of n observations drawn independently from a population Π. Should a statistic θ^ corresponding to the parameter θ in Π be calculated, an estimate of θ would be obtained. A succession of m [bootstrap] samples Ψ_{bi} of size n are subsequently drawn randomly with replacement from the original sample Ψ. From each bootstrap sample Ψ_{bi}, a bootstrap estimate $\theta\hat{}_{bi}$ is obtained. The fundamental bootstrap proposition is that the distribution of the bootstrap estimates $\theta\hat{}_{bi}$ [i.e. the sampling distribution of $\theta\hat{}_{b}$] will provide a sufficient approximation of the [true] sampling distribution derived empirically through the classical Monte Carlo generation of m independent random samples Ψ_i of size n from Π (Diaconis & Efron, 1983; Efron, 1982; Efron & Tibshirani, 1993). This procedure therefore seems to present a feasible way of investigating the first two issues mentioned above. Whether it presents a solution to the more traditional cross validation problem seems somewhat more debatable.

Stellenbosch University http://scholar.sun.ac.za

Predictability indices most likely are highly situation specific. Each prediction model would most likely require the development of a unique predictability index. The fact that it was possible to develop a predictability index for one prediction model does not necessarily mean it would practically be possible to do so for another. The question, therefore, arises how common the occurrence of a successful predictability index development actually is.

Stellenbosch University http://scholar.sun.ac.za

REFERENCES

Abdi, H., Valentin, D. & Edelman, B. (1999). Neural Networks. *Sage University Papers Series on Quantitative Applications in the Social Sciences*, *No. 124*. Thousand Oaks, CA: Sage.

Ackerman, P.L. & Humphreys, L.G. (1990). Judgement and Decision-Making Theory. In M.D. Dunnette & L.M. Hough (Eds), *Handbook of Industrial and Organizational Psychology* (pp.223–228). Palo Alto, CA: Consulting Psychologists Press.

American Psychological Association (APA) (1954). *Technical Recommendations for Psychological Tests and Diagnostic Techniques.* Washington, D.C.: American Psychological Association.

American Psychological Association (APA) (1966). *Standards for Educational and Psychological Tests and Manuals*. Washington, D.C.: American Psychological Association.

American Psychological Association (APA) (1974). *Standards for Educational & Psychological Tests*. Washington, D.C.: American Psychological Association.

Anastasi, A. & Urbina, S. (Eds) (1997). *Psychological Testing* (7th ed.). Upper Saddle River, NJ: Prentice Hall.

Anderson, J. A. (1995). *An Introduction to Neural Networks*. Cambridge, MA: MIT Press

Berenson, M.L., Levine, D.M. & Goldstein, M. (1983). *Intermediate Statistical Methods and Applications*. Englewood Cliffs, NJ: Prentice-Hall, Inc.

Stellenbosch University http://scholar.sun.ac.za

Binning, J.F. & Barrett, G.V. (1989). Validity of Personnel Decisions: a Conceptual Analysis of the Inferential and Evidential Bases. *Journal of Applied Psychology*, *74*(3), 478-494.

Bobko, P. (2001). *Correlation and Regression: Application for Industrial Organizational Psychology and Management* (2nd ed.). Thousand Oaks, CA: Sage Publications.

Boudreau, J. W. (1991). Utility Analysis for Decisions in Human Resource Management. In M. D. Dunnette & L. M. Hough (Eds), *Handbook of Industrial and Organizational Psychology* (2nd ed.) (pp. 621-745). Palo Alto, CA: Consulting Psychologists Press,

Breakwell, G. M., Hammond, S. & Fife-Schaw, C. (2000). *Research Methods in Psychology* (2nd ed.). Thousand Oaks, CA: Sage Publications.

Brogden, H.E. (1946). On the Interpretation of the Correlation Coefficient as a Measure of Predictive Efficiency. *Journal of Education and Psychology, 37*, 65-76.

Brogden, H.E. (1949a). When Testing Pays Off. *Personnel Psychology, 2*, 171-185.

Brogden, H.E. (1949b). A New Coefficient: Application to Biserial Correlation and to Estimation of Selective Efficiency. *Psychometrika, 14*, 169-182.

Campbell, J.P. (1991). Modelling the Performance Prediction Problem in Industrial and Organisational Psychology. In M.D. Dunnette & L.M. Hough (Eds), *Handbook of Industrial and Organizational Psychology* (pp.39-74). Palo Alto, CA: Consulting Psychologists Press.

Cascio, W.F. (1991). *Costing Human Resources: The Financial Impact of Behavior in Organizations* (3rd ed.). Boston, MA: PWS-Kent.

Stellenbosch University http://scholar.sun.ac.za

Cascio, W.F. & Ramos, R.A. (1986). Development and Application of a New Method for Assessing Job Performance in Behavioral/Economic Terms. *Journal of Applied Psychology, 71*, 20-28.

Cochran, W.G. (1951). Improvement By Means of Selection. In J. Neyman (Ed.), *Proceedings of the Second Berkeley Symposium on Mathematical Statistics and Probability* (pp.449-470). Berkeley, CA: University of California Press.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Cook, M. (1998). *Personnel Selection: Adding Value through People* (3rd ed.). New York: Wiley

Copi, I. M. & Cohen, C. (1990). *Introduction to Logic* (8th ed). New York: Macmillan.

Crocker, L. & Algina, J. (1986). *Introduction to Classical and Modern Test Theory.* Belmont, CA: Wadsworth.

Cronbach, L.J. (1960). *Essentials of Psychological Testing* (2nd ed.). New York: Harper & Row.

Cronbach, L. J. & Gleser, G. C. (1965). *Psychological Tests and Personnel Decisions* (2nd ed.). Urbana, IL: University of Illinois Press.

Dawes, R.M. (1971). A Case Study of Graduate Admissions: Application of Three Principles of Human Decision Making. *American Psychologist, 26*, 180-188.

Dawes, R.M. & Corrigan, B. (1974). Linear Models in Decision Making. *Psychological Bulletin, 81*, 95-106.

Diaconis, P.M. & Efron, B.S. (1983). Computer-Intensive Methods in Statistics. *Scientific American*, 116-130.

Stellenbosch University http://scholar.sun.ac.za

Diamantopoulos, A. and Sigauw, J. (2000). *Introducing LISREL. A Guide for the Uninitiated.* Thousand Oaks, CA: Sage Publications.

Dunnette, M.D. & Borman, W.C. (1979). Personnel Selection and Classification Systems. *Annual Review of Psychology, 30*, 477-525.

Efron, B.S. (1982). *The Jackknife, the Bootstrap and Other Resampling Plans.* Philadelphia: Society for Industrial and Applied Mathematics.

Efron, B.S. & Tibshirani, R.J. (1993). *An Introduction to the Bootstrap*. New York: Chapman and Hall.

Ellis, M. V. & Blustein, D. L. (1991). Developing and Using Educational and Psychological Tests and Measures: The Unificationist Perspective. *Journal of Counseling and Developmen*t, *69*, 550-555.

Frederiksen, N. & and Melville, S. D. (1954). Differential Predictability in the Use of Test Scores. *Educational and Psychological Measurement, 14*, 647-656.

Gatewood, R.B. & Feild, H.S. (1994). *Human Resource Selection* (3rd ed.). Fort Worth: Dryden.

Ghiselli, E. E. (1956). Differentiation of Individuals in Terms of their Predictability. *Journal of Applied Psychology, 4*0, 374–377.

Ghiselli, E. E. (1960a). The Prediction of Predictability. *Educational and Psychological Measurement, 20*, 3-8.

Ghiselli, E. E. (1960b). Differentiation of Tests in terms of the Accuracy with which they Predict for a Given Individual. *Educational and Psychological Measurement, 20*, 675-84.

Stellenbosch University http://scholar.sun.ac.za

Ghiselli, E.E. (1963). Moderating Effects and Differential Reliability and Validity. *Journal of Applied Psychology, 47*, 81-86

Ghiselli, E.E., Campbell, J.P. & Zedeck, S. (1981). *Measurement Theory for the Behavioral Sciences*. San Francisco: Freeman & Company.

Goldberg, L. R. (1970). Man versus Model of Man: A Rationale plus Evidence for a Method of Improving on Clinical Inferences. *Psychological Bulletin*, 73, 422-432.

Goodwin, B.C. (1995). *How the Leopard Changed its Spots*. London: Orion.

Guion, R.M. (1980). On Trinitarian Doctrines of Validity. *Professional Psychology, 11*, 385-398.

Guion, R. M. (1991). Personnel Assessment, Selection and Placement. In M. D. Dunnette & L. M. Hough (Eds), *Handbook of Industrial and Organizational Psychology* (2nd ed.) (pp. 327-398). Palo Alto, CA: Consulting Psychologists Press.

Hair, J.F., Anderson, R.E., Tatham, R.L. & Black, W.C. (1995). *Multivariate Data Analysis with Readings* (3rd ed.). Englewood Cliffs, NJ: Prentice-Hall.

Horst, P. (1941). The Prediction of Personal Adjustment: A Survey of Logical Problems and Research Techniques, with Illustrative Application to Problems of Vocational Selection, School Success, Marriage, and Crime. *Social Sciences Research Council Bulletin, 14*.

Howell, D. (1992). *Statistical Methods for Psychology* (3rd ed.). Belmont, CA: Duxbury Press.

Hull, C. L. (1928). *Aptitude testing*. New York: World Book Co.

Stellenbosch University http://scholar.sun.ac.za

Jaccard, J. (2001). *Interaction Effects in Logistical Regression*. Thousand Oaks: Sage Publications.

Jooste, M.J.L. (2001). *Introduction to Psychological Testing*. Johannesburg: RAU PERS

Kaplan, R. M. & Saccuzzo, D. P. (2001). *Psychological Testing: Principles, Applications, and Issues* (5th ed.). Belmont, CA: Wadsworth.

Kerlinger, F. N. & Lee, H. B. (2000). *Foundations of Behavioural Research* (4th ed.). Fort Worth: Harcourt College.

Kleinmutz, B. (1990). Why We Still Use Our Heads Instead of Formulas: Towards an Integrative Approach. *Psychological Bulletin, 107* (3), 296-310.

Landy, F. J. (1986). Stamp Collecting versus Science: Validation as Hypothesis Testing. *American Psychologis*t, *4*1, 1183-1192.

Lord, F. M. & Novick, M. R. (1968). *Statistical Theories of Mental Test Scores*. Reading, MA: Addison-Wesley

March, J. G. & Simon, H. A. (1958). *Organizations*. New York: Wiley

Meehl, P. E. (1954). *Clinical vs. Statistical Prediction: A Theoretical Analysis and a Review of the Evidenc*e. Minneapolis: University of Minnesota Press.

Meehl, P. E. (1957). When shall we use our Heads instead of the Formula? *Journal of Counseling Psychology, 4,* 268-273.

Messick, S. (1989). Validity. In RL Linn (Ed.), *Educational Measurement* (3rd ed.) (pp.13-103). New York: Macmillan.

Stellenbosch University http://scholar.sun.ac.za

Milkovich, G.T. & Boudreau, J.W. (1988). *Personnel/Human Resources Management: A Diagnostic Approach* (5th ed.). Homewood, IL: Richard Irwin Inc.

Mouton, J. & Marais, H.C. (1985). *Metodologie van die Geesteswetenskappe*. Pretoria: Raad vir Geesteswetenskaplike Navorsing,

Muchinsky, P.M. (1993). *Psychology Applied to Work* (4th ed.). Pacific Grove, CA: Brooks/Cole Publishing Company.

Muchinsky, P.M., Kriek, H.J. & Schreuder, A.M.G. (1998). *Personnel Psychology*. Johannesburg: International Thomson Publishing (Southern Africa).

Murphy, K.R. and Davidshofer, C.O. (1988). *Psychological Testing: Principles and Applications*. Englewood Cliffs, NJ: Prentice Hall.

Myers, R.H., Montgomery, D.C. & Vining, G.G. (2002). *Generalised Linear Models with Applications in Engineering and the Sciences.* New York: Wiley

Naylor, J.C. & Shine, L.C. (1965). A Table for Determining the Increase in Mean Criterion Score obtained by using a Selection Device. *Journal of Industrial Psychology, 3*, 33-42.

Nunnally, J.C. & Bernstein, I.H. (1994). *Psychometric Theory* (3rd ed.). New York: McGraw-Hill.

Osborne, J. & Waters, E. (2002). *Four Assumptions of Multiple Regression that Researchers Should Always Test*. World Wide Web (http://edresearch.org/pare/getvn.asp): *Practical Assessment, Research & Evaluation*.

Owen, K. & Taljaard, J.J. (1998). *Manual for the Use of Psychological and Scholastic Tests of the HSRC: Revised Version*. Pretoria: HSRC

Stellenbosch University http://scholar.sun.ac.za

Pedhazur, E. J. (1982). *Multiple Regression in Behavioral Research*. New York: Holt, Rinehart and Winston.

Popper, K. R. (1972). *Objective Knowledge*. Oxford: Clarendon Press.

Psytech (2003). *Instruments*. World Wide Web (http://www.psytech.co.za). Psytech SA (Pty) Ltd.

Saunders, D.R. (1956). Moderator Variables in Prediction. *Educational and Psychological Measurement, 16*, 209-222.

Schepers, J.M. (1996). The Development of a Statistical Procedure to Correct the Effects of Restriction of Range on Validity Coefficients. *SA Journal of Industrial Psychology, 22*(1), 19-28.

Schmidt, F.L. & Hunter, J.E. (1983). Individual Differences in Productivity: An Empirical Test of Estimates Derived from Studies of Selection Procedure Utility. *Journal of Applied Psychology, 68*, 407-414.

Schmitt, N. & Landy, F. J. (1993). The Concept of Validity. In N. Schmitt, W. C. Borman, & Associates (Eds), *Personnel Selection in Organizations* (pp. 275-340). San Francisco, CA: Jossey-Bass.

Schuler, H. & Guldin, A. (1991). Methodological Issues in Personnel Selection Research. In C.L. Cooper & I.T. Robertson (Eds), *International Review of Industrial and Organizational Psychology* (Vol. 6) (pp. 213-264). Chichester: Wiley.

Smith, M. (1993). *Neural Networks for Statistical Modelling*. New York: Van Nostrand Reinhold.

Stellenbosch University http://scholar.sun.ac.za

Stockburger, D.W. (2001). *Multivariate Statistics: Concepts, Models and Applications – WWWVersion 2.* World Wide Web (http://www. psychstat.smsu.edu): Southwest Missouri State University.

Tabachnick, B. G. & Fidell, L. S. (1989). *Using Multivariate Statistics* (2nd ed.). New York: Harper Collins.

Taylor, H.C. & Russel, J.T. (1939). The Relationship of Validity Coefficients to the Practical Effectiveness of Tests in Selection: Discussion and Tables. *Journal of Applied Psychology, 23*, 565-578

Taylor, T. (1994). A Review of Three Approaches to Cognitive Assessment, and a Proposed Integrated Approach based on a Unifying Theoretical Framework. *South African Journal of Psychology, 24*(4), 184 -193.

Theron, C.C. (1999). *Psychometric Implications of Corrections for Attenuation and Restriction of Range for Selection Validation Research.* Unpublished doctoral thesis, University of Stellenbosch.

Theron, C.C. (2001). *The Effect of a Joint Correction for the Attenuating Effect of Criterion Unreliability and Case 1 Restriction of Range on the Expected Criterion Performance and the Conditional Probability of Success*. Paper presented at The 6th Conference of the European Association of Psychological Assessment, Aachen.

Thorndike, R.L. (1982). *Applied Psychometrics*. Boston, MA: Houghton- Mifflin Co.

Tredoux, C.G. & Durrheim, K.L. (2002). *Numbers, Hypotheses and Conclusions.* Cape Town: Juta.

Wiggins, J.S. (1973). *Personality and Prediction: Principles of Personality Assessment*. Reading, MA: Addison-Wesley.

Stellenbosch University http://scholar.sun.ac.za

APPENDIX A
DATASET USED FOR ANALYSIS
(OBTAINED FROM PSYTECH SA)

Stellenbosch University http://scholar.sun.ac.za

Variable View:

Variable: RACE	Type: Number	Width: 4	Dec: 0
Variable: GENDER	Type: Number	Width: 8	Dec: 3
Variable: AGE	Type: Number	Width: 4	Dec: 0
Variable: LANG	Type: Number	Width: 4	Dec: 0
Variable: APIL	Type: Number	Width: 8	Dec: 3
Variable: VCR2	Type: Number	Width: 8	Dec: 3
Variable: NCR2	Type: Number	Width: 8	Dec: 3
Variable: ASSERT	Type: Number	Width: 6	Dec: 0
Variable: FLEX	Type: Number	Width: 4	Dec: 0
Variable: TRUST	Type: Number	Width: 5	Dec: 0
Variable: PHLEG	Type: Number	Width: 5	Dec: 0
Variable: GREGAR	Type: Number	Width: 6	Dec: 0
Variable: PERS	Type: Number	Width: 4	Dec: 0
Variable: CONTEST	Type: Number	Width: 7	Dec: 0
Variable: PESS	Type: Number	Width: 4	Dec: 0
Variable: PRAG	Type: Number	Width: 4	Dec: 0
Variable: CONF	Type: Number	Width: 4	Dec: 0
Variable: MID	Type: Number	Width: 4	Dec: 0
Variable: MBAAV	Type: Number	Width: 8	Dec: 3
Variable: CRTB2V_Q	Type: Number	Width: 8	Dec: 0
Variable: VAR43	Type: Number	Width: 5	Dec: 0
Variable: VAR44	Type: Number	Width: 5	Dec: 0
Variable: VAR45	Type: Number	Width: 5	Dec: 0
Variable: VAR46	Type: Number	Width: 5	Dec: 0
Variable: VAR47	Type: Number	Width: 5	Dec: 0
Variable: VAR48	Type: Number	Width: 5	Dec: 0
Variable: VAR49	Type: Number	Width: 5	Dec: 0
Variable: VAR50	Type: Number	Width: 5	Dec: 0
Variable: VAR51	Type: Number	Width: 5	Dec: 0
Variable: VAR52	Type: Number	Width: 5	Dec: 0
Variable: VAR53	Type: Number	Width: 5	Dec: 0
Variable: VAR54	Type: Number	Width: 5	Dec: 0
Variable: VAR55	Type: Number	Width: 5	Dec: 0
Variable: VAR56	Type: Number	Width: 5	Dec: 0
Variable: VAR57	Type: Number	Width: 5	Dec: 0
Variable: VAR58	Type: Number	Width: 5	Dec: 0
Variable: VAR59	Type: Number	Width: 5	Dec: 0
Variable: VAR60	Type: Number	Width: 5	Dec: 0
Variable: VAR61	Type: Number	Width: 5	Dec: 0
Variable: VAR62	Type: Number	Width: 5	Dec: 0
Variable: VAR63	Type: Number	Width: 5	Dec: 0
Variable: VAR64	Type: Number	Width: 5	Dec: 0
Variable: VAR65	Type: Number	Width: 5	Dec: 0
Variable: VAR66	Type: Number	Width: 5	Dec: 0
Variable: VAR67	Type: Number	Width: 5	Dec: 0
Variable: VAR68	Type: Number	Width: 5	Dec: 0
Variable: VAR69	Type: Number	Width: 5	Dec: 0
Variable: VAR70	Type: Number	Width: 5	Dec: 0
Variable: VAR71	Type: Number	Width: 5	Dec: 0
Variable: VAR72	Type: Number	Width: 5	Dec: 0
Variable: VAR73	Type: Number	Width: 5	Dec: 0
Variable: VAR74	Type: Number	Width: 5	Dec: 0
Variable: VAR75	Type: Number	Width: 5	Dec: 0
Variable: VAR76	Type: Number	Width: 5	Dec: 0

Stellenbosch University http://scholar.sun.ac.za

Variable: VAR77	Type: Number	Width: 5	Dec: 0
Variable: VAR78	Type: Number	Width: 5	Dec: 0
Variable: VAR79	Type: Number	Width: 5	Dec: 0
Variable: VAR80	Type: Number	Width: 5	Dec: 0
Variable: VAR81	Type: Number	Width: 5	Dec: 0
Variable: CRTB2N_Q	Type: Number	Width: 8	Dec: 0
Variable: VAR83	Type: Number	Width: 5	Dec: 0
Variable: VAR84	Type: Number	Width: 5	Dec: 0
Variable: VAR85	Type: Number	Width: 5	Dec: 0
Variable: VAR86	Type: Number	Width: 5	Dec: 0
Variable: VAR87	Type: Number	Width: 5	Dec: 0
Variable: VAR88	Type: Number	Width: 5	Dec: 0
Variable: VAR89	Type: Number	Width: 5	Dec: 0
Variable: VAR90	Type: Number	Width: 5	Dec: 0
Variable: VAR91	Type: Number	Width: 5	Dec: 0
Variable: VAR92	Type: Number	Width: 5	Dec: 0
Variable: VAR93	Type: Number	Width: 5	Dec: 0
Variable: VAR94	Type: Number	Width: 5	Dec: 0
Variable: VAR95	Type: Number	Width: 5	Dec: 0
Variable: VAR96	Type: Number	Width: 5	Dec: 0
Variable: VAR97	Type: Number	Width: 5	Dec: 0
Variable: VAR98	Type: Number	Width: 5	Dec: 0
Variable: VAR99	Type: Number	Width: 5	Dec: 0
Variable: VAR100	Type: Number	Width: 6	Dec: 0
Variable: VAR101	Type: Number	Width: 6	Dec: 0
Variable: VAR102	Type: Number	Width: 6	Dec: 0
Variable: VAR103	Type: Number	Width: 6	Dec: 0
Variable: VAR104	Type: Number	Width: 6	Dec: 0
Variable: VAR105	Type: Number	Width: 6	Dec: 0
Variable: VAR106	Type: Number	Width: 6	Dec: 0
Variable: OPP_Q1	Type: Number	Width: 6	Dec: 0
Variable: OPP_Q2	Type: Number	Width: 6	Dec: 0
Variable: OPP_Q3	Type: Number	Width: 6	Dec: 0
Variable: OPP_Q4	Type: Number	Width: 6	Dec: 0
Variable: OPP_Q5	Type: Number	Width: 6	Dec: 0
Variable: OPP_Q6	Type: Number	Width: 6	Dec: 0
Variable: OPP_Q7	Type: Number	Width: 6	Dec: 0
Variable: OPP_Q8	Type: Number	Width: 6	Dec: 0
Variable: OPP_Q9	Type: Number	Width: 6	Dec: 0
Variable: OPP_Q10	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q11	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q12	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q13	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q14	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q15	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q16	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q17	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q18	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q19	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q20	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q21	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q22	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q23	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q24	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q25	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q26	Type: Number	Width: 7	Dec: 0

Stellenbosch University http://scholar.sun.ac.za

Variable: OPP_Q27	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q28	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q29	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q30	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q31	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q32	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q33	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q34	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q35	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q36	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q37	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q38	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q39	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q40	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q41	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q42	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q43	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q44	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q45	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q46	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q47	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q48	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q49	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q50	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q51	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q52	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q53	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q54	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q55	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q56	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q57	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q58	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q59	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q60	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q61	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q62	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q63	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q64	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q65	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q66	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q67	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q68	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q69	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q70	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q71	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q72	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q73	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q74	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q75	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q76	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q77	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q78	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q79	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q80	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q81	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q82	Type: Number	Width: 7	Dec: 0

Stellenbosch University http://scholar.sun.ac.za

Variable: OPP_Q83	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q84	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q85	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q86	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q87	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q88	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q89	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q90	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q91	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q92	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q93	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q94	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q95	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q96	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q97	Type: Number	Width: 7	Dec: 0
Variable: OPP_Q98	Type: Number	Width: 7	Dec: 0
Variable: RES_1	Type: Number	Width: 11	Dec: 5
Variable: PRE_1	Type: Number	Width: 11	Dec: 5
Variable: ABRES_1	Type: Number	Width: 8	Dec: 5
Variable: INDEX	Type: Number	Width: 8	Dec: 2
Variable: INDEX_2	Type: Number	Width: 8	Dec: 2

Stellenbosch University http://scholar.sun.ac.za

Dataview:

RACE	GENDER	AGE	LANG	APIL	VCR2	NCR2	ASSERT	FLEX	TRUST	PHLEG	GREGAR	PERS	CONTEST	PESS	PRAG	CONF	MID
100	100.000	38	113	61.410	18.000	-9999.000	41	26	45	53	27	27	26	14	29	26	74
100	101.000	41	-9999	52.900	22.000	-9999.000	32	30	38	42	32	31	33	12	32	17	87
102	100.000	28	100	61.980	15.000	-9999.000	35	31	40	35	34	19	23	19	21	16	91
100	101.000	43	109	44.320	18.000	-9999.000	38	30	31	47	39	32	29	18	24	22	100
101	101.000	32	101	62.000	28.000	13.000	32	31	32	36	34	28	27	12	34	20	114
101	100.000	42	100	55.000	29.000	10.000	28	29	43	46	35	21	24	16	26	19	95
100	101.000	31	110	43.000	11.000	14.000	34	28	34	34	38	31	25	22	21	23	108
100	101.000	36	110	37.000	27.000	16.000	35	32	38	37	37	37	32	16	31	23	86
100	101.000	29	107	48.450	22.000	10.000	31	27	37	37	31	23	26	19	31	21	89
102	101.000	25	100	63.000	25.000	15.000	26	36	40	32	27	41	16	33	18	94	83
101	100.000	30	100	81.830	19.000	-9999.000	34	25	38	42	36	23	33	15	28	21	82
100	100.000	29	105	57.000	27.000	17.000	37	38	44	40	27	21	20	15	24	21	89
100	100.000	34	107	68.430	24.000	-9999.000	37	31	33	42	31	27	30	15	23	24	69
101	101.000	49	100	73.500	30.000	-9999.000	27	26	28	45	28	23	28	15	33	19	96
100	101.000	38	114	58.310	19.000	10.000	24	33	32	21	20	36	9	26	16	41	98
100	101.000	36	105	40.000	16.000	7.000	31	26	40	38	28	21	21	14	27	22	96
-9999	100.000	37	-9999	55.570	20.000	-9999.000	34	22	30	31	32	23	36	25	31	25	77
101	101.000	33	101	57.940	23.000	-9999.000	32	25	26	39	33	24	28	21	27	22	99
101	101.000	27	100	68.280	31.000	-9999.000	25	23	35	29	27	24	34	21	32	22	100
101	101.000	32	-9999	58.090	27.000	-9999.000	25	30	38	36	48	29	34	20	29	19	64
101	101.000	31	101	57.610	19.000	-9999.000	34	28	34	34	41	21	32	15	43	23	89
-9999	100.000	35	100	63.520	30.000	-9999.000	41	27	38	41	39	29	37	12	31	21	96
101	101.000	29	100	68.970	24.000	-9999.000	33	21	38	48	35	34	22	14	28	15	86
100	101.000	40	104	57.000	27.000	11.000	35	25	33	49	38	27	30	14	22	24	91
102	100.000	29	100	51.000	13.000	10.000	19	26	33	39	32	25	31	23	31	22	87
101	101.000	30	100	72.000	28.000	17.000	34	26	44	42	36	23	23	22	36	33	75
101	101.000	29	100	68.270	31.000	-9999.000	25	25	39	51	31	26	28	12	39	22	56
101	100.000	42	101	76.180	22.000	-9999.000	35	26	33	49	28	27	31	13	22	22	110
-9999	101.000	36	-9999	53.370	25.000	-9999.000	28	26	33	28	24	20	27	17	23	22	96
100	101.000	30	114	60.420	26.000	-9999.000	37	28	31	43	34	35	28	17	20	18	87
100	101.000	28	109	43.000	24.000	13.000	44	38	47	53	41	39	15	8	23	20	30
101	101.000	38	100	64.430	28.000	-9999.000	36	33	38	39	37	39	24	9	35	21	81
101	101.000	31	101	80.630	22.000	-9999.000	32	24	27	43	29	31	31	10	31	19	85
101	101.000	32	101	72.070	20.000	-9999.000	28	21	26	34	21	18	36	21	30	22	99
102	101.000	33	100	56.840	32.000	13.000	37	22	44	37	34	27	27	15	26	24	87
100	101.000	25	113	52.000	22.000	7.000	34	33	48	33	30	29	22	24	16	83	80
101	101.000	33	100	65.000	26.000	15.000	33	28	30	44	39	22	32	17	25	23	83
101	100.000	34	101	69.670	21.000	-9999.000	34	29	40	41	40	24	35	14	29	27	85
101	101.000	40	101	74.360	26.000	-9999.000	41	43	41	53	35	29	20	10	18	24	56
100	101.000	30	105	50.000	27.000	20.000	32	23	19	38	26	20	34	24	28	20	84
100	101.000	31	103	48.000	14.000	13.000	28	31	42	32	26	22	16	22	26	115	115
101	100.000	35	100	75.510	30.000	-9999.000	36	30	31	45	31	33	30	13	21	25	85
100	101.000	41	100	50.000	27.000	12.000	41	22	42	48	37	29	14	12	16	21	58

Stellenbosch University http://scholar.sun.ac.za

101	101.000	30	100	53.000	28.000	15.000	40	34	41	50	37	35	25	11	28	20	79
101	101.000	36	101	44.000	29.000	15.000	34	25	41	41	30	22	24	20	27	23	83
101	101.000	25	100	63.300	25.000	-9999.000	39	34	36	41	43	37	25	11	26	16	86
100	100.000	25	107	50.550	13.000	13.000	29	26	35	44	27	19	15	10	32	26	65
102	101.000	27	100	68.000	29.000	15.000	32	30	32	43	38	36	24	12	28	19	90
101	101.000	34	100	74.070	25.000	-9999.000	30	36	42	49	34	31	36	15	33	20	96
100	100.000	28	107	64.000	22.000	12.000	35	22	33	38	41	25	26	22	37	27	64
101	101.000	35	100	58.000	33.000	6.000	35	32	39	42	28	23	29	15	31	24	88
101	101.000	27	106	45.000	27.000	14.000	44	26	35	49	38	35	30	10	29	16	72
101	101.000	35	100	61.000	33.000	14.000	39	39	39	41	39	25	14	22	24	73	73
101	101.000	36	100	54.250	17.000	14.000	33	25	35	30	27	25	21	16	27	21	102
101	100.000	32	100	71.150	33.000	6.000	38	42	43	51	26	24	32	10	18	22	84
101	101.000	35	133	73.870	29.000	-9999.000	30	31	39	44	23	17	27	14	29	23	87
101	100.000	49	100	55.800	24.000	15.000	28	34	46	32	24	32	14	22	28	83	89
101	100.000	34	100	42.000	18.000	10.000	36	34	47	41	34	26	21	9	27	18	75
101	101.000	34	101	74.230	28.000	-9999.000	33	29	26	51	31	29	29	17	26	19	112
101	101.000	36	100	52.000	32.000	21.000	26	33	39	42	36	33	38	15	27	22	97
101	101.000	37	100	69.650	30.000	13.000	28	31	36	39	32	32	27	11	22	22	92
101	101.000	34	101	69.540	25.000	-9999.000	31	30	40	43	29	27	23	16	26	21	124
101	101.000	39	101	71.000	27.000	16.000	33	31	33	40	31	26	38	14	19	25	78
101	101.000	31	100	48.000	30.000	13.000	50	27	16	40	39	38	39	9	30	10	44
102	100.000	36	100	54.280	21.000	-9999.000	33	21	42	40	35	21	28	18	30	25	87
101	100.000	39	101	75.000	18.000	3.000	37	27	30	31	28	24	36	11	24	21	77
101	100.000	28	100	71.190	30.000	-9999.000	28	36	50	41	28	22	15	11	23	18	70
101	101.000	34	100	61.000	28.000	22.000	27	33	41	24	35	27	17	17	28	17	74
101	101.000	36	101	73.000	36.000	18.000	34	32	44	44	30	24	32	15	35	24	90
101	101.000	24	100	78.240	35.000	-9999.000	38	32	36	51	30	24	31	18	32	24	82
101	101.000	28	100	70.920	27.000	14.000	40	37	24	42	36	36	32	11	21	22	63
102	101.000	27	100	68.980	22.000	-9999.000	33	22	36	45	37	29	37	14	35	26	90
101	100.000	39	100	61.530	30.000	-9999.000	37	38	40	37	28	33	23	14	15	16	103
100	101.000	26	-9999	61.820	31.000	14.000	30	30	39	47	38	36	27	11	28	25	75
101	101.000	29	100	61.490	29.000	-9999.000	26	28	37	27	30	34	29	21	30	17	111
101	100.000	31	100	54.000	25.000	11.000	33	27	35	46	36	30	31	17	23	25	111
101	101.000	35	101	80.000	32.000	18.000	36	35	31	45	33	19	21	17	32	17	100
101	101.000	36	100	65.000	28.000	10.000	42	28	37	56	21	21	24	16	38	24	75
101	101.000	39	100	70.610	32.000	-9999.000	38	30	33	40	31	27	33	18	29	19	102
101	100.000	-9999	101	71.030	32.000	-9999.000	32	36	38	42	23	18	21	17	35	19	127
101	100.000	35	100	61.110	24.000	-9999.000	36	33	36	46	40	24	30	17	29	23	112
101	101.000	28	100	63.180	32.000	16.000	36	22	25	53	29	25	29	11	35	20	59
101	101.000	27	100	65.000	28.000	5.000	35	29	29	31	21	36	35	16	28	17	77
101	101.000	40	100	67.620	37.000	-9999.000	32	29	42	47	32	29	23	13	26	25	100
101	101.000	34	-9999	63.340	34.000	-9999.000	31	29	35	42	44	26	30	12	21	25	85
101	101.000	27	100	69.000	25.000	17.000	35	32	40	54	40	28	23	12	29	25	90
101	100.000	39	134	70.570	25.000	9.000	31	24	40	37	31	24	24	19	15	27	80
101	101.000	26	100	67.460	30.000	-9999.000	39	33	25	39	34	29	28	18	38	19	94
101	101.000	40	101	83.000	35.000	15.000	30	31	37	46	37	26	24	16	25	20	106

Stellenbosch University http://scholar.sun.ac.za

101	100.000	38	101	79.320	31.000	18.000	33	31	26	40	25	21	33	17	19	23	74
101	101.000	35	100	73.860	21.000	-9999.000	30	22	29	36	30	22	36	19	34	20	110
101	100.000	27	100	75.860	31.000	-9999.000	29	36	32	40	32	33	27	13	24	17	73
102	101.000	28	100	63.470	24.000	-9999.000	34	30	38	40	44	20	14	12	34	16	24
100	101.000	30	114	55.000	23.000	12.000	27	40	40	37	27	28	14	30	22	123	92
101	101.000	31	101	61.930	27.000	15.000	28	35	39	40	28	29	28	14	21	23	99
101	100.000	30	100	76.460	36.000	-9999.000	41	40	42	43	32	23	26	14	27	22	64
101	101.000	28	100	72.520	28.000	-9999.000	42	31	27	47	30	37	27	17	35	17	102
102	100.000	37	100	76.760	24.000	-9999.000	20	31	40	37	24	27	21	21	24	17	84
101	100.000	34	100	75.000	30.000	1.000	36	30	49	40	40	26	36	16	14	23	78
101	101.000	32	101	65.000	31.000	17.000	39	31	34	42	31	27	32	12	32	23	111
101	101.000	29	101	75.540	29.000	-9999.000	34	23	32	48	29	25	26	13	20	26	82

Stellenbosch University http://scholar.sun.ac.za

MBAAV	CRTB2V_Q	VAR43	VAR44	VAR45	VAR46	VAR47	VAR48	VAR49	VAR50	VAR51	VAR52	VAR53	VAR54	VAR55	VAR56	VAR57	VAR58
58.750	2	3	3	3	3	3	1	1	2	2	1	1	3	1	3	1	-9999
59.333	3	3	3	3	1	1	1	1	1	2	2	1	2	2	2	1	1
60.500	3	1	1	3	3	2	3	1	2	3	3	2	3	1	3	1	3
60.500	1	2	3	2	2	1	1	1	1	1	2	1	3	2	2	1	2
60.938	2	1	3	2	1	2	2	1	1	2	2	1	1	2	2	2	2
61.063	2	2	3	3	1	1	3	2	2	2	1	2	2	1	2	1	2
61.214	2	3	2	3	1	1	1	3	1	2	2	1	2	1	1	1	3
61.375	2	1	3	3	1	1	2	1	2	2	3	2	2	2	2	1	3
61.688	1	2	2	1	1	1	3	1	1	3	2	1	1	2	2	1	2
61.929	3	2	3	3	2	1	3	1	1	2	2	1	2	2	2	1	3
62.250	3	1	3	3	1	3	3	1	2	-9999	1	1	3	3	1	1	3
62.400	2	1	3	2	1	1	3	1	2	2	1	3	2	3	3	1	2
63.250	2	1	3	3	2	1	3	1	1	2	1	1	2	1	2	1	2
63.250	2	1	3	3	1	2	3	1	1	1	1	1	3	2	3	1	3
63.375	2	2	3	3	3	1	2	2	1	3	1	1	3	2	2	1	1
63.563	3	1	2	3	1	3	3	2	1	1	3	2	3	3	3	1	2
63.750	3	1	3	3	1	1	1	1	1	1	1	1	2	2	1	1	1
64.000	1	2	3	1	1	1	3	1	1	1	1	1	2	2	1	3	2
64.000	2	2	3	3	1	3	3	1	1	1	1	1	2	1	2	1	2
64.000	2	1	3	3	2	1	2	1	2	2	1	2	3	2	2	2	2
64.000	2	2	2	3	2	1	1	2	1	2	1	1	1	1	3	1	1
64.250	2	1	3	3	1	1	3	1	2	3	1	3	2	2	2	1	3
64.250	3	2	3	3	2	1	3	1	1	1	3	1	2	3	2	1	2
64.313	2	1	3	3	1	1	3	1	1	2	1	1	2	2	3	1	3
64.438	2	1	3	3	2	2	3	1	1	1	3	2	2	2	3	1	2
64.500	2	1	3	3	1	1	3	1	2	2	3	2	2	1	2	1	3
64.500	2	2	2	3	1	1	3	1	2	2	1	1	2	2	2	1	2
64.750	2	1	3	2	1	3	3	1	2	3	1	-9999	2	2	1	1	3
65.000	3	1	2	3	2	1	3	1	1	1	1	3	1	2	2	1	3
65.000	2	3	3	3	1	1	2	1	2	2	3	1	3	2	2	1	3
65.125	3	1	3	2	1	3	3	1	1	2	1	2	3	3	2	1	3
65.250	2	1	3	3	1	1	3	1	1	2	3	2	1	3	2	1	2
65.500	1	1	3	3	1	1	3	1	1	2	3	1	3	3	3	2	3
65.500	3	1	3	3	1	3	3	1	3	3	3	1	3	3	3	1	3
65.625	2	1	3	3	1	2	3	1	2	2	1	1	2	3	2	1	2
65.688	2	1	2	3	1	3	3	1	2	2	2	3	1	-9999	2	1	2
65.938	2	1	3	3	1	1	3	1	1	2	1	1	2	2	2	1	3
66.000	2	1	3	2	1	3	3	1	1	2	1	1	1	2	2	2	2
66.000	3	3	3	3	1	1	3	1	1	1	3	1	3	2	2	1	2
66.063	2	2	3	2	1	1	3	1	2	2	1	2	3	2	2	1	2
66.125	2	1	3	3	1	2	3	1	2	2	2	3	2	3	2	1	1
66.250	2	1	3	3	1	3	3	1	2	2	1	1	2	3	2	1	2
66.500	2	1	3	3	2	1	2	1	2	2	1	1	2	2	2	1	2

Stellenbosch University http://scholar.sun.ac.za

66.500	3	1	1	2	1	3	3	1	2	2	1	3	3	2	2	1	2
66.688	2	2	2	2	1	1	3	2	2	2	2	1	2	1	2	1	2
67.000	2	1	3	3	1	1	1	2	1	3	1	1	3	3	2	1	2
67.125	3	1	3	3	1	1	2	1	2	2	1	1	3	3	2	1	3
67.250	2	1	3	2	2	1	3	1	2	2	1	1	2	2	2	1	2
67.250	2	1	3	3	1	1	3	1	2	2	2	1	3	2	3	1	2
67.375	2	1	1	2	2	1	3	1	1	2	1	1	2	2	2	1	2
67.438	2	1	3	3	1	3	3	1	2	2	1	2	2	2	2	1	2
67.688	3	1	3	3	1	2	3	1	2	3	1	1	2	3	2	1	3
67.688	2	1	2	3	1	1	2	2	2	2	1	3	2	2	2	1	2
67.813	1	2	2	3	1	1	2	2	2	2	1	1	2	2	2	2	3
67.875	2	3	3	2	1	3	2	1	1	2	1	1	2	2	2	1	2
68.000	2	1	3	3	1	2	3	2	2	3	1	2	2	2	2	1	2
68.000	2	1	3	2	2	2	2	1	1	2	2	1	2	2	3	1	3
68.067	3	2	3	3	2	3	3	1	2	2	1	2	2	3	2	3	3
68.250	3	2	3	3	1	1	3	1	1	2	1	1	3	2	3	1	2
68.438	2	1	3	3	1	3	3	1	1	2	1	1	2	2	2	1	2
68.438	2	3	3	3	1	2	3	1	1	3	1	1	2	2	2	1	3
68.750	3	3	3	3	1	1	3	1	1	2	2	1	2	2	3	1	2
69.188	2	1	2	3	1	1	3	1	1	1	1	1	2	3	2	1	2
69.313	2	1	3	3	1	1	3	1	1	2	1	1	2	2	2	1	2
69.500	3	3	1	3	1	1	3	1	1	1	1	1	1	1	2	1	2
69.563	2	1	3	3	1	2	3	1	3	2	1	2	2	2	1	2	1
69.750	2	1	2	3	1	1	3	1	1	2	1	1	2	3	2	1	2
69.875	2	2	3	3	1	2	3	1	2	2	1	1	3	1	2	1	2
70.125	2	1	3	3	1	3	3	1	2	2	1	1	2	2	2	1	2
70.250	2	2	3	3	1	1	3	1	2	2	1	1	2	2	2	2	2
70.313	2	1	3	3	1	1	3	1	1	1	1	1	1	2	2	1	3
70.500	2	1	1	2	2	1	3	1	1	1	1	1	3	2	2	1	2
71.000	2	2	3	3	1	1	3	1	1	2	1	1	2	2	1	1	2
71.063	2	1	3	3	1	1	3	3	2	2	2	1	2	2	3	1	2
71.250	2	3	3	3	1	1	2	1	1	2	1	1	2	2	2	1	2
71.250	3	1	3	3	1	1	3	1	2	1	1	3	2	2	3	1	1
71.313	2	1	2	3	1	2	3	2	2	2	1	3	2	2	2	1	2
71.375	2	1	3	1	1	1	3	2	1	2	1	1	3	2	2	1	2
71.750	2	2	3	3	1	1	3	1	1	2	1	1	2	2	2	1	2
71.750	2	1	2	3	1	3	3	1	1	2	2	1	2	2	2	1	2
71.750	3	1	3	3	1	1	3	3	1	2	1	1	1	2	2	1	3
71.938	3	2	3	3	1	2	3	1	2	2	1	1	3	2	3	1	2
71.938	3	1	3	3	1	2	3	1	1	2	1	1	2	1	2	1	2
72.250	2	1	3	3	1	2	2	1	2	2	1	1	2	2	2	1	2
72.250	2	1	1	1	1	-9999	3	1	2	2	1	1	2	2	2	1	2
72.313	2	1	3	2	1	1	3	1	2	2	3	2	2	2	2	1	2
72.375	2	1	3	3	1	1	3	1	2	2	1	1	2	2	2	1	2
72.500	2	2	3	3	1	1	3	1	1	2	1	2	2	3	2	1	2
72.563	2	1	3	3	1	2	3	1	2	2	1	1	2	3	2	1	2

Stellenbosch University http://scholar.sun.ac.za

72.688	2	1	3	3	1	1	3	1	1	2	1	1	2	2	2	1	2
72.750	2	1	3	3	1	1	3	2	2	2	2	1	2	2	2	2	1
72.750	2	1	3	3	1	1	3	1	2	2	1	1	2	1	3	1	2
73.000	2	1	3	2	1	3	3	1	1	2	1	2	2	3	3	1	2
73.125	2	1	3	3	1	1	3	1	1	2	2	1	2	2	2	1	2
74.688	2	1	3	3	1	1	3	2	1	2	1	1	1	2	2	2	2
75.750	2	1	2	3	1	2	3	1	2	2	1	1	2	2	2	1	2
77.250	2	1	3	3	1	3	3	1	2	2	1	1	1	3	3	1	2
77.500	3	1	2	3	2	3	2	1	1	1	1	1	2	2	2	1	2
78.250	2	1	3	3	1	1	3	1	1	2	1	1	2	1	2	1	3
78.938	2	1	3	3	1	2	2	1	2	2	1	1	2	2	2	3	2
81.000	3	1	3	3	1	1	3	1	2	2	1	3	1	2	3	1	2

Stellenbosch University http://scholar.sun.ac.za

VAR59	VAR60	VAR61	VAR62	VAR63	VAR64	VAR65	VAR66	VAR67	VAR68	VAR69	VAR70	VAR71	VAR72	VAR73	VAR74	VAR75	VAR76	VAR77	VAR78	VAR79	VAR80	VAR81
-9999	-9999	3	1	3	1	1	1	3	1	3	1	1	3	1	1	2	-9999	-9999	-9999	-9999	-9999	-9999
1	2	3	1	3	1	1	2	3	1	2	1	2	2	1	1	2	-9999	-9999	-9999	-9999	-9999	-9999
3	3	3	1	3	2	1	2	3	1	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
3	2	3	2	2	3	1	1	3	1	2	1	1	-9999	2	1	1	3	2	1	1	2	2
2	3	3	2	3	2	1	2	3	2	3	1	1	3	1	1	2	3	2	2	1	1	3
1	2	3	1	3	2	1	2	3	1	2	1	1	1	1	1	2	3	2	2	1	2	3
3	1	-9999	1	3	1	1	2	3	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
3	3	3	2	3	2	1	3	3	1	1	1	1	2	3	2	2	2	2	2	1	3	1
1	1	3	1	3	3	1	1	3	1	2	1	3	1	2	1	2	2	2	2	1	2	1
1	2	3	2	3	2	1	3	3	1	2	1	1	3	2	1	1	3	3	3	2	1	3
1	3	3	1	3	1	1	3	3	1	2	1	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
2	3	2	1	3	2	1	1	3	2	3	1	1	3	1	1	2	3	2	2	2	1	3
3	3	3	2	3	1	1	2	3	1	3	1	1	3	1	1	1	-9999	-9999	-9999	-9999	-9999	-9999
1	2	3	2	3	3	1	2	1	1	2	1	1	2	3	2	2	3	2	1	1	1	3
3	2	3	2	3	3	1	2	3	1	2	3	3	1	2	2	1	2	1	2	1	2	3
1	2	3	1	3	3	1	3	2	1	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
3	3	3	1	3	1	1	3	3	1	1	1	1	1	1	1	1	3	-9999	-9999	-9999	-9999	-9999
1	3	3	1	3	1	1	3	3	1	2	1	1	3	1	1	2	3	3	1	2	3	3
1	1	3	2	3	2	1	1	3	1	2	1	2	3	1	2	2	3	2	2	1	1	3
1	3	3	2	3	2	1	3	3	1	2	1	1	2	1	1	3	3	3	1	2	2	1
3	2	3	1	3	1	1	2	3	3	1	1	1	2	3	1	1	3	3	2	1	1	3
1	3	3	1	3	2	1	3	3	1	2	1	1	3	1	1	2	3	2	1	2	1	3
1	3	3	2	3	3	1	3	3	1	2	1	3	3	1	1	1	3	3	2	1	2	3
3	3	3	1	3	2	1	2	3	1	2	1	1	2	1	2	-9999	-9999	-9999	-9999	-9999	-9999	-9999
2	2	2	1	2	1	1	1	1	1	1	2	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
3	3	3	2	3	2	1	2	3	1	2	1	1	1	3	1	2	3	2	1	2	-9999	1
3	3	3	2	3	2	1	3	3	1	2	1	1	3	1	2	2	3	2	3	2	1	1
1	3	3	1	3	2	1	2	3	1	2	2	1	3	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
3	2	3	2	3	1	1	2	3	1	2	1	1	2	3	1	2	3	2	1	1	1	3
1	3	3	2	3	3	1	2	3	1	2	1	1	3	2	2	2	3	3	-9999	-9999	-9999	-9999
2	3	3	2	3	2	1	3	3	1	2	1	1	3	2	3	1	3	3	3	2	1	3
1	3	3	1	3	2	1	3	3	1	2	1	1	3	1	1	2	3	2	3	1	3	3
3	1	3	1	3	3	1	3	3	1	3	1	1	3	1	1	2	3	2	3	1	1	3
1	3	3	1	3	3	1	1	3	1	3	1	3	3	1	1	3	3	3	3	3	1	3
1	2	3	2	3	2	1	1	3	1	2	1	1	2	1	1	1	3	2	1	1	2	3
2	3	2	-9999	2	3	1	2	3	1	1	1	1	2	1	1	1	3	2	-9999	-9999	-9999	-9999
1	1	2	1	3	2	1	2	3	1	3	1	1	3	1	3	1	3	2	1	-9999	-9999	-9999
3	1	2	2	3	3	1	1	3	1	2	1	1	3	2	1	1	3	3	1	-9999	-9999	-9999
2	3	2	1	3	1	1	2	3	1	2	1	1	3	1	3	2	3	2	2	1	2	3
2	3	3	2	3	2	1	2	3	1	3	1	1	2	1	1	1	2	2	2	1	2	2
3	2	2	2	#NULL!	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
1	1	3	2	3	3	1	2	3	1	3	1	1	3	1	1	2	3	2	3	3	2	3
2	3	3	2	2	1	1	2	3	2	2	1	1	1	2	2	1	3	2	1	2	2	1
1	2	3	2	3	2	1	3	3	1	2	1	1	3	1	1	2	3	2	3	2	1	2

Stellenbosch University http://scholar.sun.ac.za

1	3	3	2	3	2	1	3	3	1	2	1	1	2	1	2	2	3	3	1	2	2	3
1	1	3	1	3	2	1	3	3	1	3	1	1	3	2	1	2	3	2	2	1	1	2
3	3	3	3	#NULL!	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
1	2	3	1	3	2	1	2	3	1	2	1	1	3	1	1	2	3	1	1	1	2	3
2	2	3	1	3	3	1	3	3	3	3	1	1	3	1	1	2	3	2	2	2	1	1
2	2	3	1	3	2	1	2	3	1	1	1	1	3	1	1	1	-9999	-9999	-9999	-9999	-9999	-9999
1	3	3	2	3	2	1	2	3	1	2	1	1	3	1	3	2	3	2	2	-9999	-9999	-9999
2	3	3	2	3	1	1	1	3	1	3	1	1	3	1	1	1	2	2	2	3	1	3
1	2	3	2	3	2	1	2	3	1	2	1	1	3	1	2	2	3	2	2	2	1	3
1	2	3	1	2	2	3	1	3	1	1	1	2	1	2	1	1	2	2	3	1	2	3
1	3	3	2	3	1	1	2	3	1	2	1	1	2	1	2	2	3	2	1	2	1	3
3	1	3	2	3	2	1	2	2	1	2	1	1	3	1	1	1	3	2	2	2	2	3
2	1	3	1	2	2	1	2	3	1	2	1	1	1	2	1	2	3	2	1	2	2	3
2	3	3	2	3	3	1	3	2	2	3	1	1	3	3	3	3	3	3	3	3	3	3
1	3	3	1	3	3	1	3	3	1	2	3	1	3	1	1	2	3	2	2	1	1	3
2	3	3	1	3	2	1	3	3	1	2	1	1	3	1	2	1	3	2	1	1	1	3
1	3	3	2	3	2	2	2	3	1	2	1	1	3	1	1	1	3	3	1	2	1	3
3	1	3	2	3	2	1	3	3	1	2	1	1	3	1	1	3	2	2	1	2	1	3
2	2	3	2	3	2	1	2	3	1	2	1	1	1	1	1	2	3	2	1	1	2	1
2	3	3	1	3	3	1	2	3	1	2	1	1	3	1	1	2	3	1	1	2	1	1
3	2	3	1	3	1	1	1	3	1	3	1	1	3	1	1	1	3	1	1	1	1	3
3	3	2	1	1	1	2	3	2	2	1	1	3	1	1	2	3	2	2	2	1	2	6
2	3	3	2	3	2	1	2	2	2	2	1	1	3	1	1	2	3	2	2	2	1	3
3	3	3	2	3	3	1	3	3	1	2	1	1	3	1	1	1	3	2	2	1	-9999	-9999
1	2	3	2	3	2	1	2	3	1	2	1	1	3	1	2	3	3	2	2	2	1	3
1	3	3	2	3	2	1	2	3	1	2	1	1	3	1	1	2	3	2	2	1	1	3
1	3	3	1	3	2	1	3	3	1	3	1	1	1	1	3	2	3	2	1	2	1	3
2	3	3	1	3	1	1	2	3	1	2	2	1	3	2	1	1	3	3	1	2	1	3
1	1	3	2	3	2	1	3	3	2	3	1	1	3	1	2	2	3	2	2	2	1	3
3	3	3	1	3	2	1	2	3	1	2	1	1	3	1	2	2	3	1	2	1	1	3
1	1	3	2	2	3	1	2	3	1	3	1	1	3	1	2	1	3	2	1	1	1	3
3	3	1	1	3	1	1	3	3	1	2	1	1	3	2	1	1	3	2	2	2	1	3
1	3	3	1	2	2	1	2	3	1	2	1	1	2	1	1	2	2	2	2	2	1	2
1	1	3	2	3	2	1	2	3	2	3	1	1	3	1	1	2	3	2	1	1	1	3
1	3	3	2	3	2	1	2	3	1	2	1	1	3	1	2	2	1	3	3	1	2	3
3	3	3	2	3	2	1	2	3	1	2	1	1	2	1	1	2	3	2	2	2	2	3
3	3	3	1	3	1	1	1	3	1	3	1	1	3	3	1	1	3	1	2	1	1	3
3	3	3	3	3	2	1	2	3	1	2	1	1	3	1	2	2	3	2	3	2	1	3
1	3	3	2	3	2	1	3	3	1	3	1	1	3	1	1	2	3	3	-9999	-9999	-9999	-9999
1	3	3	2	3	2	1	2	3	1	2	1	1	2	1	2	2	3	2	1	2	1	3
1	3	3	2	3	2	1	2	3	1	2	1	1	2	1	2	1	3	1	3	1	1	3
1	3	2	2	3	2	1	2	3	1	2	1	1	1	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
1	3	3	1	3	1	-9999	1	3	1	2	3	1	3	1	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
1	2	3	2	3	2	1	3	3	1	2	1	1	3	1	2	2	3	2	3	1	2	3
1	3	3	2	3	2	1	3	2	1	2	1	1	3	1	1	2	3	2	2	2	1	3
1	3	3	2	3	1	1	2	3	1	3	1	1	3	2	1	2	3	2	1	2	1	1

Stellenbosch University http://scholar.sun.ac.za

CRTB2N_Q	VAR83	VAR84	VAR85	VAR86	VAR87	VAR88	VAR89	VAR90	VAR91	VAR92	VAR93	VAR94	VAR95	VAR96	VAR97	VAR98	VAR99	VAR100	VAR101	VAR102	VAR103
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	2	1	1	3	6	6	6	1	4	6	3	1	3	3	1	2	-9999	-9999	-9999	-9999
6	3	2	6	1	6	6	3	6	1	5	4	-9999	6	6	2	1	6	5	5	5	2
6	3	4	1	1	3	5	6	6	5	4	2	3	3	3	3	6	6	4	6	6	4
6	3	4	1	1	3	2	4	6	1	4	2	3	1	3	3	1	4	5	-9999	5	4
6	4	6	6	1	2	6	4	6	1	4	2	3	3	2	3	6	3	4	4	3	4
6	3	2	1	1	3	6	4	2	1	-9999	2	3	3	3	3	1	6	4	5	3	4
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	-9999	2	1	2	2	6	5	6	1	3	2	3	3	3	3	1	3	3	-9999	4	3
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	2	1	1	5	2	4	3	4	4	3	6	3	3	3	1	3	1	6	3	-9999
6	2	3	6	1	3	6	5	4	1	4	2	3	3	3	3	6	6	3	6	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	2	6	1	6	3	5	5	3	1	5	2	6	-9999	-9999	-9999	-9999	-9999	-9999	-9999	5	4
6	2	-9999	6	1	3	6	5	6	1	5	2	4	6	2	-9999	1	3	-9999	-9999	-9999	-9999
6	3	-9999	6	1	3	3	5	4	1	4	2	3	3	3	3	1	3	6	-9999	-9999	4
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	1	1	1	6	6	5	2	1	4	2	3	1	3	3	6	2	1	6	3	2
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
2	6	-9999	5	5	3	-9999	1	1	3	2	2	3	3	3	3	1	2	3	4	5	4
6	3	1	3	6	6	4	5	3	1	4	1	6	5	6	3	2	3	1	5	1	3
6	3	3	1	1	3	5	5	6	1	4	2	3	3	3	3	1	4	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
5	3	2	6	1	3	6	5	6	1	4	2	3	3	3	3	1	6	3	4	6	4
5	3	2	6	4	3	6	5	6	6	4	2	3	3	3	6	1	6	3	4	6	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	6	6	6	1	3	6	5	6	1	4	2	6	3	3	3	6	6	-9999	-9999	4	-9999
6	3	2	6	3	3	6	6	6	1	4	2	3	3	3	3	6	6	3	4	3	1

Stellenbosch University http://scholar.sun.ac.za

6	4	6	6	1	3	6	5	6	3	4	2	3	3	3	3	1	3	4	2	6	2
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	3	1	1	3	5	5	6	1	4	2	3	3	3	-9999	-9999	-9999	-9999	-9999	-9999	-9999
1	3	2	6	2	5	4	5	6	1	4	2	3	1	3	3	1	6	3	2	5	4
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	-9999	6	1	3	6	5	6	1	4	2	3	4	2	3	5	5	5	-9999	-9999	-9999
6	3	3	6	2	1	5	5	4	1	2	1	3	3	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	4	1	2	2	6	5	6	1	4	2	2	3	2	3	1	2	3	-9999	-9999	-9999
6	6	-9999	6	1	4	5	4	6	4	4	2	3	3	6	3	1	3	3	4	5	4
6	1	6	1	1	3	6	5	6	1	4	2	3	2	6	2	6	6	5	1	5	4
5	3	4	5	6	3	2	1	4	3	5	2	3	3	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	6	6	1	3	1	5	6	4	4	2	3	3	2	3	1	3	3	4	6	-9999
6	3	6	1	2	5	2	2	6	1	4	2	6	4	3	4	3	4	3	4	3	3
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	3	1	1	3	6	5	6	1	4	2	3	3	3	3	1	1	3	5	-9999	-9999
6	2	2	3	1	3	6	1	6	1	4	2	3	5	3	3	1	-9999	3	1	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
5	6	2	3	1	3	6	5	6	1	4	2	3	3	3	3	1	3	4	4	5	2
6	2	2	1	1	3	6	5	6	1	5	2	3	2	5	3	6	6	3	2	4	3
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
3	4	6	2	2	-9999	5	4	1	4	2	3	3	3	-9999	-9999	-9999	-9999	-9999	-9999	5	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	2	1	1	3	6	5	6	1	4	2	3	3	2	3	1	2	3	4	5	4
6	3	2	6	1	3	6	5	6	1	3	2	3	-9999	3	3	1	3	3	4	3	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	5	5	1	6	3	4	6	4	4	2	6	3	2	3	5	3	3	4	3	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	2	1	6	1	3	2	5	6	1	1	4	3	3	3	3	1	6	3	4	3	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	2	2	6	1	2	6	5	4	1	5	3	3	3	2	6	1	4	4	6	6	4
6	4	3	1	1	3	4	5	4	1	4	2	3	3	5	3	2	6	3	4	5	4
5	-9999	2	6	1	3	6	5	6	1	4	2	3	1	-9999	1	6	3	4	-9999	-9999	1
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	3	1	1	3	6	5	6	1	4	2	3	3	3	3	6	2	4	4	-9999	-9999
6	3	-9999	1	3	3	5	4	1	-9999	2	-9999	3	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	2	1	2	3	6	5	6	1	4	2	3	3	3	3	1	2	3	2	5	-9999
5	4	-9999	6	2	2	4	5	6	-9999	4	2	3	3	-9999	3	6	3	5	4	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
1	2	2	1	1	2	6	5	3	1	4	2	3	3	3	3	1	4	3	4	5	-9999
6	5	2	1	1	3	6	5	6	1	5	2	3	3	3	3	1	6	4	6	5	2

Stellenbosch University http://scholar.sun.ac.za

-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
6	3	2	6	1	3	6	4	6	1	4	2	3	3	3	-9999	6	-9999	4	-9999	-9999	-9999
6	3	2	6	1	3	4	5	6	1	4	2	3	3	3	3	6	2	3	4	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
1	3	6	5	6	1	3	2	3	3	3	3	1	6	4	2	4	2	-9999	-9999	-9999	-9999
6	3	6	1	1	3	6	5	6	1	4	2	3	1	3	3	1	6	4	4	5	4
-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999

Stellenbosch University http://scholar.sun.ac.za

VAR104	VAR105	VAR106	OPP_Q1	OPP_Q2	OPP_Q3	OPP_Q4	OPP_Q5	OPP_Q6	OPP_Q7	OPP_Q8	OPP_Q9	OPP_Q10	OPP_Q11	OPP_Q12	OPP_Q13	OPP_Q14	OPP_Q15	OPP_Q16
-9999	-9999	-9999	2	4	2	3	5	4	4	4	2	2	4	4	2	4	5	4
-9999	-9999	-9999	2	4	4	4	5	5	4	2	4	1	4	4	2	4	3	2
-9999	-9999	-9999	2	4	2	4	4	4	4	4	2	4	4	4	2	4	4	4
-9999	-9999	-9999	2	2	4	1	4	4	3	5	4	4	5	3	1	1	4	3
-9999	-9999	-9999	2	3	2	4	5	4	4	4	4	4	4	3	3	4	4	2
1	4	-9999	2	4	4	4	4	4	5	4	4	2	4	4	2	4	2	4
-9999	-9999	-9999	2	3	2	3	4	4	4	3	2	3	4	4	3	4	4	3
4	3	2	3	2	2	5	5	5	4	4	2	3	4	5	2	1	4	3
4	4	3	2	4	4	2	5	4	5	4	1	4	5	4	2	4	2	4
-9999	4	6	1	3	2	2	1	4	5	4	3	1	4	4	2	4	2	4
-9999	-9999	-9999	1	2	2	4	5	4	5	4	2	1	4	4	2	4	4	4
1	4	4	4	4	4	5	4	4	4	4	2	4	4	4	4	4	4	4
-9999	-9999	-9999	2	4	4	3	5	4	4	4	4	2	3	4	4	4	2	3
-9999	-9999	-9999	1	4	4	2	5	4	5	4	2	2	4	2	4	4	4	4
3	3	3	1	4	5	5	5	3	5	2	5	1	1	4	1	5	4	5
-9999	-9999	-9999	2	4	4	4	4	2	4	4	2	4	3	4	2	4	1	2
-9999	-9999	-9999	2	4	4	2	5	4	4	3	2	2	4	2	4	4	2	4
-9999	-9999	-9999	2	4	4	2	5	4	4	3	4	2	2	2	2	4	4	4
-9999	-9999	-9999	2	3	4	2	4	2	4	2	5	2	4	4	2	2	1	4
-9999	-9999	-9999	1	2	1	2	5	4	4	2	4	5	5	4	2	4	1	3
-9999	-9999	-9999	2	4	2	4	4	4	4	2	2	2	4	2	2	2	4	4
-9999	-9999	-9999	2	4	2	4	5	4	1	4	4	2	4	4	2	2	4	2
-9999	-9999	-9999	1	2	2	4	5	3	4	5	4	4	2	4	1	4	5	4
1	4	4	2	3	2	2	4	4	2	4	4	2	4	3	2	4	4	4
-9999	-9999	-9999	2	4	4	2	5	4	5	4	4	4	2	4	2	2	1	2
1	4	-9999	1	4	4	4	5	4	4	5	4	4	5	5	2	1	4	4
-9999	-9999	-9999	1	4	4	1	5	5	4	2	5	2	1	4	2	2	2	5
-9999	-9999	-9999	1	4	5	3	5	4	5	4	4	1	3	2	2	2	4	4
-9999	-9999	-9999	2	4	4	2	4	2	4	2	2	4	2	4	2	4	4	2
-9999	-9999	-9999	2	4	4	3	5	4	2	5	1	4	5	2	3	4	4	4
1	5	2	1	2	5	5	5	5	2	4	5	4	5	5	3	1	4	5
-9999	-9999	-9999	2	2	2	2	5	4	1	2	2	2	4	2	4	2	5	3
-9999	-9999	-9999	2	4	5	1	5	4	4	4	2	2	3	2	2	4	4	4
-9999	-9999	-9999	1	4	4	2	4	4	5	4	4	2	2	4	1	2	2	4
1	4	2	2	4	4	5	1	2	4	2	2	4	4	5	1	2	4	4
2	5	6	3	4	3	2	5	4	2	4	4	4	4	4	2	4	3	4
-9999	-9999	-9999	2	4	2	4	5	4	5	4	2	2	4	2	4	2	4	5
-9999	-9999	-9999	2	3	2	3	5	4	5	4	4	1	4	4	2	1	4	4
-9999	-9999	-9999	5	4	4	4	5	4	2	5	1	4	5	2	5	2	5	5
1	4	4	2	4	5	1	5	2	4	4	4	2	4	1	1	4	2	4
-9999	-9999	-9999	2	3	3	2	4	4	4	4	2	4	3	3	1	3	4	4
-9999	-9999	-9999	1	4	4	4	5	4	4	2	4	1	4	2	3	1	4	4
-9999	-9999	-9999	2	2	4	1	5	5	3	5	2	5	5	4	1	4	5	5
1	5	2	4	2	1	2	5	4	2	4	1	4	2	4	4	4	4	5

Stellenbosch University http://scholar.sun.ac.za

1	5	-9999	2	4	4	5	2	5	5	4	2	4	4	5	2	4	4	4
-9999	-9999	-9999	2	2	2	2	5	4	3	4	2	4	4	3	2	2	4	4
-9999	-9999	-9999	1	1	1	2	5	2	5	5	2	5	2	5	2	2	1	4
1	4	5	2	2	2	2	5	4	2	4	4	4	4	2	2	2	4	4
-9999	-9999	-9999	2	1	4	4	5	4	2	4	4	2	4	4	4	4	4	4
-9999	-9999	-9999	1	4	2	1	4	2	5	4	2	1	5	4	1	1	2	5
-9999	-9999	-9999	1	4	4	2	5	4	5	4	2	3	2	2	3	2	4	4
-9999	-9999	-9999	1	1	4	4	5	5	2	4	2	2	4	4	2	4	5	5
-9999	-9999	-9999	4	2	1	4	5	5	2	4	2	3	4	4	2	4	2	4
6	4	6	2	4	5	4	5	3	5	4	4	4	3	4	2	2	4	2
-9999	-9999	-9999	2	2	5	3	5	4	4	5	2	2	4	5	5	2	5	3
-9999	-9999	-9999	2	4	4	4	5	4	5	4	4	2	2	4	2	4	2	4
2	6	2	1	4	2	4	5	4	5	4	3	2	4	5	1	2	2	5
3	3	3	1	4	2	5	5	5	5	2	2	4	5	5	4	4	4	4
-9999	-9999	-9999	2	3	4	2	5	4	4	4	2	2	2	2	2	4	2	4
-9999	-9999	-9999	2	3	4	2	5	4	2	4	5	1	4	4	2	4	4	3
-9999	-9999	-9999	2	3	4	3	5	5	4	4	5	2	4	2	4	4	2	2
-9999	-9999	-9999	2	3	4	4	5	3	4	4	2	3	3	4	2	4	4	3
4	-9999	-9999	2	4	4	4	5	5	4	4	2	2	4	2	2	2	4	1
2	4	3	1	2	2	2	5	4	2	4	1	4	5	1	1	4	5	4
-9999	-9999	-9999	1	4	5	4	4	4	5	5	2	2	4	4	1	2	2	5
-9999	-9999	-9999	2	4	2	2	5	5	4	2	1	1	4	4	2	4	4	4
-9999	-9999	-9999	1	4	4	4	5	5	5	2	5	4	2	5	4	4	2	4
1	4	4	2	4	2	1	5	4	4	2	2	4	4	5	2	4	2	2
1	4	2	2	4	4	4	5	4	5	4	4	2	3	4	4	4	4	3
-9999	-9999	-9999	2	4	4	4	5	5	4	4	2	2	2	3	4	2	4	4
-9999	-9999	-9999	2	4	1	1	5	5	2	4	2	1	4	2	5	4	5	2
-9999	-9999	-9999	1	3	2	2	5	4	4	4	4	2	4	4	1	1	2	5
-9999	-9999	-9999	2	2	3	3	4	4	5	4	2	5	4	5	4	5	2	3
1	-9999	-9999	2	2	3	3	5	3	4	3	2	2	4	4	3	4	4	4
-9999	-9999	-9999	2	2	3	4	5	4	3	4	2	2	3	4	2	4	2	2
2	4	4	2	3	3	2	4	4	4	4	4	3	4	4	2	2	4	4
1	4	4	4	4	2	4	4	3	5	4	2	4	4	2	2	4	4	5
-9999	-9999	-9999	2	5	5	1	4	4	5	5	1	2	3	4	3	2	4	5
-9999	-9999	-9999	2	4	4	2	5	4	2	2	4	4	1	2	5	4	2	4
-9999	-9999	-9999	4	5	4	3	5	4	5	3	4	4	2	4	3	4	3	3
-9999	-9999	-9999	2	4	2	4	4	4	4	4	2	3	4	4	4	3	4	4
-9999	-9999	-9999	1	4	5	1	5	4	5	5	2	1	4	2	2	4	2	5
-9999	-9999	-9999	2	2	4	2	5	4	2	2	2	1	1	2	2	4	2	2
-9999	-9999	-9999	2	4	4	2	5	4	5	4	4	3	4	4	2	2	4	4
-9999	-9999	-9999	2	4	4	2	5	5	4	4	2	2	4	4	2	4	4	4
-9999	-9999	-9999	2	2	4	4	5	4	4	4	3	3	4	4	4	2	4	5
-9999	-9999	-9999	1	4	4	4	4	4	4	1	4	4	4	4	1	2	4	5
-9999	-9999	-9999	2	3	3	2	4	2	4	3	2	4	3	2	4	4	4	2
-9999	-9999	-9999	1	2	4	1	5	1	2	5	4	2	1	2	2	4	4	4
1	4	4	1	4	5	2	5	4	5	5	2	4	4	4	4	2	4	5

Stellenbosch University http://scholar.sun.ac.za

-9999	-9999	-9999	2	4	2	1	5	4	5	4	4	3	2	4	1	4	4	4
-9999	-9999	-9999	4	2	2	2	5	2	4	4	2	4	1	2	4	4	1	4
-9999	-9999	-9999	1	5	2	5	5	5	5	5	2	5	5	5	1	5	1	5
-9999	-9999	-9999	2	4	2	4	5	4	4	2	2	3	4	4	2	4	3	4
-9999	-9999	-9999	2	4	4	3	5	4	4	4	4	2	4	4	2	4	4	3
-9999	-9999	-9999	4	5	2	5	5	4	5	4	1	2	4	5	4	4	2	5
-9999	-9999	-9999	2	2	4	2	4	2	2	4	2	4	3	2	4	4	4	4
-9999	-9999	-9999	1	4	4	4	4	5	5	2	5	2	4	2	2	4	2	4
-9999	-9999	-9999	2	2	2	4	5	4	4	4	4	4	5	5	2	2	2	5
1	4	4	2	3	5	2	5	4	5	4	2	2	3	3	2	3	5	3
-9999	-9999	-9999	2	4	4	1	5	4	5	4	4	4	4	3	2	1	4	4

Stellenbosch University http://scholar.sun.ac.za

OPP_Q17	OPP_Q18	OPP_Q19	OPP_Q20	OPP_Q21	OPP_Q22	OPP_Q23	OPP_Q24	OPP_Q25	OPP_Q26	OPP_Q27	OPP_Q28	OPP_Q29	OPP_Q30	OPP_Q31	OPP_Q32	OPP_Q33
3	2	4	2	4	5	3	1	2	2	4	2	4	2	2	4	2
5	2	2	3	4	5	5	1	2	3	4	4	4	2	2	4	1
2	2	4	2	5	2	4	3	2	2	4	3	4	5	4	4	1
2	1	4	2	3	5	4	2	3	1	5	2	2	3	2	4	2
4	3	3	4	2	4	3	2	3	2	4	2	4	4	4	4	2
4	2	4	2	4	4	4	4	4	4	4	4	4	4	2	4	4
2	3	2	2	4	4	4	2	2	2	3	4	4	2	3	2	4
3	1	4	1	1	3	5	2	3	2	4	2	5	2	3	5	2
4	2	1	4	2	5	4	2	2	2	2	2	5	5	2	2	1
5	2	2	2	4	4	4	1	4	4	4	5	5	3	4	4	1
5	2	2	2	2	4	4	5	2	4	4	-9999	5	5	4	4	1
2	4	4	4	4	4	4	4	4	4	4	4	5	5	4	4	3
2	2	2	2	4	4	4	1	3	2	2	5	4	5	4	4	1
5	2	4	3	4	4	4	2	4	2	4	2	1	2	4	4	2
4	1	1	1	5	5	1	2	2	1	2	5	5	5	2	5	1
2	2	2	4	4	4	4	4	2	2	2	2	4	5	2	2	2
4	2	2	2	1	3	3	2	2	2	2	2	2	5	4	3	2
4	2	2	2	4	4	2	4	4	2	4	4	4	4	4	4	2
5	4	2	3	4	5	4	4	4	2	2	2	4	5	3	4	2
4	4	5	1	2	2	4	1	2	2	4	2	4	5	4	4	2
5	4	2	2	2	4	4	4	2	4	4	2	4	5	2	4	2
2	2	2	2	4	4	4	2	4	4	4	4	4	4	2	4	2
2	1	4	3	5	5	4	2	3	2	4	3	4	2	2	4	4
1	2	4	2	4	5	4	4	2	2	4	2	5	4	4	4	2
4	1	4	2	4	4	4	4	2	1	2	2	4	4	5	4	4
4	1	4	2	2	5	5	4	2	4	4	1	5	5	4	2	2
5	1	4	4	2	5	4	5	2	4	4	2	5	2	4	5	4
3	2	3	4	4	4	4	3	3	2	4	4	4	3	4	5	3
2	2	2	4	4	2	2	4	4	4	4	4	2	4	4	4	2
2	2	1	2	5	5	4	1	2	2	4	2	5	4	3	4	4
5	1	5	2	5	5	5	1	3	4	4	5	5	1	2	5	5
5	2	4	2	4	5	5	1	4	4	5	1	5	2	4	4	4
2	1	2	2	2	4	4	2	4	4	4	2	5	2	4	4	2
3	4	2	4	2	4	2	4	2	2	2	4	3	4	4	2	2
4	2	2	2	3	4	4	1	2	4	4	2	4	2	2	5	2
4	1	2	3	4	5	3	2	4	2	4	4	3	5	1	4	1
4	1	2	2	4	4	2	4	2	2	4	4	4	4	4	4	2
3	2	3	1	2	4	4	4	2	4	4	4	4	5	3	5	1
1	2	5	2	5	5	4	5	5	4	5	5	5	2	2	5	1
2	2	2	2	1	1	2	4	2	2	4	2	4	4	4	4	4
3	4	2	2	5	5	4	3	3	3	4	3	4	3	3	5	4
4	2	3	4	5	4	2	1	4	3	4	4	5	1	4	5	2
1	1	4	2	5	5	5	3	2	2	4	5	5	2	1	5	5
4	2	5	4	1	4	4	4	4	2	4	4	5	1	2	5	2

5	2	5	4	4	4	4	2	1	2	4	4	4	4	5	4	2
2	1	4	1	4	5	4	1	4	4	4	2	5	1	3	4	5
5	1	2	5	2	5	2	4	2	4	5	5	4	5	4	5	4
4	1	2	2	4	4	4	4	4	2	4	2	5	1	4	2	2
4	2	4	4	4	5	4	4	4	4	4	2	4	4	4	4	4
5	3	2	2	5	5	4	2	1	3	2	3	5	5	2	5	2
5	2	4	4	4	5	5	4	4	4	4	3	4	5	3	4	2
4	1	2	3	4	5	5	2	3	2	5	5	5	4	4	5	2
5	5	4	2	4	4	5	1	4	2	4	3	5	2	2	5	2
4	5	3	5	1	5	4	3	5	2	4	5	5	3	2	3	4
3	2	5	4	4	5	4	3	5	4	4	5	5	5	4	3	3
5	2	4	4	4	5	4	5	4	4	3	2	4	5	4	2	1
4	1	2	5	5	5	3	2	4	4	4	5	5	4	4	5	1
5	2	4	2	4	5	4	4	4	4	4	4	5	4	2	4	4
3	1	2	2	4	5	3	2	2	2	4	3	5	2	4	5	4
2	4	4	2	4	5	4	2	4	4	4	2	4	2	4	4	2
5	2	4	4	5	4	4	1	4	3	4	3	5	3	4	2	2
4	2	4	4	4	3	4	2	3	4	4	4	2	4	3	4	3
1	2	2	2	4	5	4	2	4	2	3	2	4	2	2	4	2
5	1	1	4	4	5	2	1	1	2	5	4	5	2	5	5	2
4	2	4	2	4	4	4	4	2	4	2	4	4	4	2	4	1
2	5	2	2	4	4	4	2	2	2	4	2	4	4	4	4	2
5	2	4	5	4	5	4	4	5	5	4	3	5	2	2	5	4
1	5	5	4	4	2	5	4	5	2	2	1	2	2	2	4	4
4	2	5	3	4	5	4	2	5	4	4	2	5	5	2	5	2
5	1	4	2	4	4	2	2	2	2	4	1	4	4	4	4	4
2	2	2	2	4	4	4	1	2	2	4	2	2	2	5	4	2
4	2	4	2	2	4	4	4	3	3	4	2	5	1	2	5	1
2	3	4	4	4	2	3	2	4	4	3	4	5	2	3	4	4
5	1	1	2	5	5	4	1	4	3	4	4	5	1	2	4	2
2	4	2	3	3	2	4	2	4	3	2	4	2	3	4	3	3
3	2	3	2	2	4	4	1	3	4	4	4	5	4	3	5	4
4	2	4	4	4	4	2	4	4	2	4	1	4	5	4	4	4
5	1	3	4	1	5	4	5	3	2	5	1	4	5	3	5	4
5	2	4	2	5	5	4	2	2	2	4	2	5	2	2	4	4
4	3	4	4	3	5	4	3	5	3	3	2	4	5	3	4	3
4	2	2	2	2	5	4	4	4	3	4	4	4	4	4	4	2
5	1	2	4	4	4	4	5	2	2	5	1	5	2	5	5	4
5	1	2	2	4	1	5	1	2	2	4	5	4	2	4	4	1
4	2	4	4	4	5	5	1	4	4	4	2	4	2	3	4	4
2	1	4	3	5	5	5	2	5	2	4	2	4	4	4	4	3
4	1	4	2	2	5	4	2	4	4	5	1	5	4	3	5	4
1	2	4	4	4	4	4	5	2	4	4	3	4	5	4	5	4
5	4	2	4	2	5	4	2	4	2	4	4	5	4	4	4	4
1	1	1	2	1	5	4	2	2	2	4	1	4	1	4	5	2
3	4	2	4	5	4	2	2	4	2	4	4	4	5	4	5	1

4	2	3	4	4	4	4	4	2	2	4	3	4	4	4	4	2
5	2	4	4	4	4	1	1	4	2	4	4	5	2	4	4	4
5	1	1	2	1	1	5	5	3	1	5	5	5	5	4	5	5
3	3	4	2	2	5	4	4	2	3	4	3	5	3	2	4	4
2	2	4	4	4	3	4	1	4	4	2	4	5	4	3	4	2
4	5	4	4	5	4	2	2	5	2	5	2	5	3	4	5	4
4	4	2	2	2	4	2	2	4	2	4	3	4	2	3	4	4
2	4	4	5	5	4	4	2	4	4	2	2	2	4	4	4	2
2	3	5	2	5	4	4	2	4	4	4	4	4	5	2	5	2
5	4	3	2	4	4	4	2	4	4	4	2	4	3	3	4	4
5	4	4	4	5	5	4	1	4	2	2	4	5	4	4	5	2

Stellenbosch University http://scholar.sun.ac.za

OPP_Q34	OPP_Q35	OPP_Q36	OPP_Q37	OPP_Q38	OPP_Q39	OPP_Q40	OPP_Q41	OPP_Q42	OPP_Q43	OPP_Q44	OPP_Q45	OPP_Q46	OPP_Q47	OPP_Q48	OPP_Q49	OPP_Q50
4	4	3	4	1	5	2	4	2	5	3	2	2	4	4	2	5
5	5	4	4	1	4	2	2	4	3	2	4	4	4	2	4	5
4	2	2	4	4	5	2	4	4	2	4	4	4	4	4	4	5
4	4	2	4	2	4	2	3	4	4	2	4	4	5	2	4	5
4	5	4	4	1	4	3	3	4	4	3	4	1	4	3	2	5
4	4	2	4	2	4	4	2	4	4	2	4	4	4	4	2	4
4	3	2	4	2	5	4	4	4	2	2	3	2	4	3	2	5
4	5	4	4	1	5	3	2	1	4	2	4	4	4	4	2	5
4	3	3	4	2	5	4	4	4	5	4	4	1	3	4	2	5
4	4	5	4	2	5	2	2	4	4	3	2	2	4	2	2	5
4	4	4	5	4	5	2	2	4	4	4	2	2	4	2	2	5
5	4	4	4	4	5	3	2	4	1	4	4	4	4	4	4	5
4	5	1	4	1	5	2	4	5	4	4	4	2	4	2	2	4
4	4	2	4	1	4	3	2	4	4	2	4	3	4	3	4	4
5	5	2	5	1	5	2	5	3	2	1	4	1	5	4	1	5
4	4	2	2	4	4	4	4	3	5	3	5	3	5	5	3	5
4	4	2	2	2	5	1	4	2	2	2	3	2	5	2	2	4
4	4	2	3	4	2	4	2	4	4	4	4	2	2	2	2	4
4	3	2	2	2	2	2	2	4	3	4	4	2	2	4	1	5
5	2	2	5	4	4	4	2	5	5	5	4	2	2	2	2	5
4	4	5	4	2	4	2	4	2	5	2	2	2	4	2	2	5
4	5	2	4	4	4	2	4	4	2	2	4	4	4	4	4	5
5	4	4	5	5	5	2	2	4	5	2	4	3	4	4	1	4
4	4	1	4	4	4	2	4	2	2	2	4	4	4	2	2	5
1	5	4	4	4	4	4	2	4	4	4	2	4	2	4	2	1
2	2	4	5	4	4	2	4	2	4	2	5	4	2	4	2	4
5	5	4	5	4	5	2	1	5	5	4	4	1	5	4	2	5
4	5	2	3	4	3	2	4	4	4	4	4	3	4	3	2	5
4	4	2	4	2	4	4	4	4	4	2	4	2	4	4	2	5
5	2	1	4	4	5	2	2	2	4	3	2	2	4	1	2	5
5	5	2	5	5	5	1	4	5	5	1	4	5	5	4	4	5
5	5	5	1	4	5	2	2	3	5	3	4	2	5	4	2	5
4	5	2	5	2	2	4	2	1	2	2	4	2	5	2	1	5
4	2	2	3	2	4	4	4	2	2	2	2	2	4	2	2	4
4	4	1	1	4	5	2	3	4	4	5	1	2	5	4	2	5
5	5	2	5	2	5	1	3	5	1	3	4	2	3	2	4	5
4	5	2	4	2	4	4	4	5	4	2	2	2	4	4	2	5
4	5	2	5	1	4	2	3	1	5	3	4	2	4	4	4	5
4	5	2	5	5	5	2	2	5	4	4	4	4	5	2	4	5
4	4	2	4	2	5	4	4	3	2	2	2	4	2	2	2	4
4	5	2	3	4	4	1	3	3	2	2	4	2	5	3	2	5
4	4	2	5	5	4	2	2	5	4	2	4	2	4	3	4	5
5	5	2	5	5	5	2	4	3	4	5	5	1	4	3	1	5
5	5	3	5	4	4	1	2	4	4	4	4	4	5	4	4	5

Stellenbosch University http://scholar.sun.ac.za

4	2	2	4	2	4	2	4	2	3	5	4	2	4	4	2	4
5	5	4	5	4	4	2	1	2	5	4	3	2	5	2	4	5
5	5	2	2	5	5	4	5	5	5	5	5	2	5	2	4	5
4	4	2	5	4	4	2	2	2	4	4	4	4	4	2	4	4
4	4	4	4	2	4	4	2	2	4	4	2	4	4	4	4	4
5	3	5	5	2	4	2	4	1	5	1	5	1	2	2	1	5
4	4	2	5	2	4	1	3	2	4	4	4	1	2	4	3	5
5	4	5	5	4	4	1	2	5	5	1	4	4	5	3	2	5
4	4	2	4	4	5	1	3	5	5	2	4	4	4	2	4	5
5	4	3	3	4	4	3	2	5	3	3	4	2	5	2	1	5
5	5	2	4	2	5	2	4	4	2	4	2	5	5	4	5	5
5	5	4	2	4	4	1	2	4	3	2	4	4	4	3	2	4
3	4	4	2	4	4	2	4	4	5	2	2	1	5	3	2	5
4	5	2	5	4	5	2	2	4	4	5	4	4	5	4	2	5
4	4	3	4	4	4	3	2	4	4	2	2	4	4	3	3	4
4	5	2	5	2	5	4	3	2	4	4	1	3	4	3	4	5
4	5	3	4	4	5	3	2	5	4	4	5	4	4	3	1	5
5	4	3	4	4	4	4	4	3	3	3	4	3	4	3	4	5
1	4	1	5	2	5	4	4	1	2	1	2	5	4	4	2	4
5	5	4	5	2	5	1	2	5	5	1	2	5	5	2	2	5
4	4	2	4	1	4	2	4	4	4	2	4	2	4	4	2	4
4	4	2	2	1	4	2	4	2	2	2	2	2	4	2	2	5
4	5	1	5	5	5	2	2	5	2	5	5	3	5	5	4	5
4	5	2	4	4	5	2	4	2	4	2	4	2	5	4	4	4
4	4	3	2	2	4	1	2	4	2	2	4	2	2	4	3	5
4	1	4	4	4	5	2	4	5	4	5	2	4	5	2	4	5
4	5	1	5	4	5	1	2	4	4	2	4	5	5	2	5	5
5	4	4	4	1	4	3	2	1	3	4	2	2	5	4	1	4
5	5	1	3	4	5	2	3	4	2	4	4	3	4	4	4	4
4	5	3	5	3	5	3	2	5	4	5	4	4	5	4	4	5
5	4	4	2	4	5	4	2	2	4	3	4	2	2	3	2	4
4	4	2	4	4	4	3	2	3	4	2	4	3	2	3	2	5
5	5	3	4	4	4	2	2	4	2	2	4	2	4	4	4	4
5	4	3	2	5	5	2	3	1	3	5	5	2	5	3	2	5
5	4	1	4	1	5	4	3	2	5	2	4	5	5	2	5	5
4	3	3	2	4	5	3	5	4	2	3	4	4	4	3	4	4
4	4	4	4	4	4	3	3	4	4	2	4	3	4	4	4	5
5	5	5	5	1	2	2	2	2	5	2	5	5	5	5	1	5
5	5	4	1	2	4	2	2	4	2	2	5	3	5	2	2	4
4	5	2	4	4	4	1	2	3	4	5	4	4	4	4	2	5
5	5	2	4	4	4	2	2	2	4	4	4	4	5	3	4	4
4	4	3	5	4	5	3	4	4	5	3	2	4	4	4	3	5
4	4	1	4	4	5	4	4	5	4	4	4	2	2	4	1	5
4	4	5	4	4	4	2	2	5	4	2	2	2	4	2	4	4
5	5	2	5	4	2	2	1	2	2	2	4	2	2	2	2	5
4	2	2	2	2	4	2	4	5	1	2	4	2	4	2	2	5

Stellenbosch University http://scholar.sun.ac.za

4	4	4	4	2	2	4	2	3	4	2	3	2	2	2	1	4
5	5	5	4	2	5	4	2	5	4	4	2	1	2	4	4	5
5	4	5	5	5	5	5	1	5	5	2	5	1	2	3	1	5
4	3	3	4	3	5	3	3	3	4	2	4	4	4	3	2	5
5	5	3	4	2	5	2	2	4	2	4	5	4	2	3	2	5
4	5	2	2	4	5	1	4	3	4	5	2	2	5	4	4	4
4	4	4	3	4	4	2	2	2	4	2	2	4	3	2	4	4
4	1	2	4	4	5	2	2	2	2	4	4	1	4	4	4	4
4	4	2	5	1	5	1	4	5	3	4	2	2	4	5	2	4
4	5	3	4	3	5	2	3	3	3	2	3	4	5	3	3	5
4	4	2	4	4	5	2	1	4	4	4	4	2	4	4	2	4

Stellenbosch University http://scholar.sun.ac.za

OPP_Q51	OPP_Q52	OPP_Q53	OPP_Q54	OPP_Q55	OPP_Q56	OPP_Q57	OPP_Q58	OPP_Q59	OPP_Q60	OPP_Q61	OPP_Q62	OPP_Q63	OPP_Q64	OPP_Q65	OPP_Q66	OPP_Q67	OPP_Q68
2	2	4	1	3	2	3	2	2	4	2	5	2	3	3	4	2	3
3	4	4	1	5	2	4	3	4	5	2	5	2	1	2	4	3	2
4	5	2	2	1	4	4	1	4	4	2	4	4	2	2	4	4	4
4	4	1	3	5	1	3	1	4	4	4	3	4	2	3	4	4	2
3	3	4	2	2	4	4	2	4	3	2	4	2	2	2	2	3	3
4	4	4	2	2	4	5	4	4	2	4	4	4	2	2	4	4	4
4	3	4	2	2	4	3	2	3	4	2	2	4	4	1	4	4	4
2	2	2	1	2	2	3	4	4	4	2	4	2	3	1	1	2	3
4	4	2	2	2	4	4	2	3	3	2	1	4	2	3	4	2	2
2	5	4	2	2	1	5	2	2	2	2	5	2	2	3	4	2	3
2	5	2	1	4	2	4	2	4	4	2	2	1	2	2	4	2	4
2	4	2	1	2	4	4	2	4	4	2	3	5	4	3	5	2	1
2	4	1	2	2	1	4	2	2	3	2	4	2	4	1	4	5	2
3	4	4	2	2	3	4	2	3	4	2	4	2	2	2	4	4	3
4	5	5	1	2	1	2	1	4	1	1	4	1	2	4	5	1	4
2	4	4	2	4	4	4	2	4	2	2	4	4	4	2	4	2	2
4	4	4	2	2	4	4	2	4	5	2	2	3	2	2	4	2	4
2	4	3	2	2	4	4	2	2	4	2	2	4	2	2	2	2	4
4	3	5	2	2	3	2	1	2	1	2	2	2	3	2	4	2	5
2	4	5	2	4	1	3	2	2	5	1	4	1	2	2	4	5	4
1	4	5	2	2	2	4	2	4	4	2	4	2	2	2	4	4	4
2	4	2	1	2	1	4	2	4	2	4	5	4	4	2	2	2	2
4	2	5	5	4	4	4	1	4	2	4	4	1	2	2	2	4	4
2	4	2	2	4	2	4	1	2	4	5	4	2	2	2	4	4	2
5	2	5	4	2	1	2	4	2	2	2	2	2	2	2	4	4	4
2	4	4	2	1	2	5	2	5	2	2	2	2	4	4	5	2	4
1	4	5	2	5	4	4	4	1	1	5	5	1	2	2	4	5	5
3	2	3	2	4	3	3	2	3	3	4	4	1	4	3	4	5	3
4	4	2	2	2	4	5	4	4	2	2	4	2	2	2	4	2	4
2	2	2	4	1	2	5	2	3	3	4	5	2	2	1	3	4	2
4	2	4	1	1	2	5	1	5	5	4	5	5	1	1	5	5	1
4	2	4	2	5	4	4	4	4	5	2	5	2	4	2	4	3	4
2	3	4	2	4	4	2	2	2	2	2	4	1	1	1	2	2	4
2	4	4	2	2	4	4	2	2	2	2	4	2	2	2	2	2	4
2	4	2	2	2	2	4	2	5	4	2	5	3	2	2	4	4	2
4	3	1	1	5	4	5	1	3	3	5	1	2	2	3	2	5	3
2	4	2	2	2	4	4	2	4	4	2	2	2	2	2	2	2	5
2	5	5	3	1	2	4	2	4	2	3	4	3	4	1	3	4	2
5	2	4	1	2	4	4	1	4	2	5	4	4	2	1	4	2	4
4	4	2	2	4	4	2	2	1	1	1	2	4	2	2	1	2	4
2	5	2	2	4	4	4	4	4	4	3	3	3	4	2	3	2	3
2	4	1	2	4	2	4	2	4	2	4	3	2	2	1	3	2	4
2	4	2	1	4	5	5	1	5	3	4	5	4	4	2	4	5	2
2	4	2	1	4	1	4	1	4	2	4	4	4	4	1	4	4	4

Stellenbosch University http://scholar.sun.ac.za

1	5	2	1	4	4	4	5	4	3	4	4	4	4	2	5	2	2
3	3	4	2	1	2	4	1	4	4	4	3	2	1	1	2	4	3
2	5	3	2	1	4	4	2	4	2	4	4	4	4	4	4	2	4
3	2	2	2	4	2	4	2	4	2	2	4	4	2	2	4	4	2
2	4	4	4	4	2	4	2	2	4	4	4	2	4	2	4	4	4
3	5	4	1	4	4	4	1	4	1	2	2	4	5	3	4	5	4
2	4	3	2	4	1	4	2	4	1	2	4	3	4	4	2	4	4
3	2	4	1	4	2	4	1	4	4	4	5	1	2	4	4	5	4
1	1	1	1	4	2	4	4	5	4	2	4	2	5	1	4	2	2
2	4	3	2	2	4	3	2	4	4	3	2	3	2	2	2	3	3
3	4	1	3	5	2	4	2	4	4	4	5	2	3	2	4	1	3
2	5	4	2	5	4	4	2	3	4	2	4	2	5	1	4	1	5
2	5	2	1	5	2	2	4	4	4	3	4	1	3	3	3	3	2
4	4	2	2	2	4	4	2	4	2	2	5	2	2	2	4	2	4
4	4	3	4	3	2	3	2	4	3	4	3	4	2	3	2	2	4
2	3	4	1	2	1	4	4	4	3	2	2	1	4	2	4	3	4
3	4	2	2	4	2	4	4	4	2	2	4	1	2	1	4	4	3
3	4	3	2	3	4	4	4	4	3	4	4	3	4	2	4	4	4
2	4	2	1	5	2	4	4	2	2	2	4	2	4	1	2	2	2
4	4	2	1	2	2	1	1	1	4	1	5	2	1	2	1	2	1
1	2	2	1	2	4	4	2	4	4	2	2	4	4	4	4	4	2
1	5	2	2	1	2	4	2	4	2	1	5	1	2	2	4	1	2
2	5	1	4	5	4	5	3	5	4	2	4	4	2	2	5	4	3
4	2	2	2	1	4	4	4	5	2	1	4	4	2	2	5	2	4
2	4	5	4	4	2	4	1	4	4	2	3	2	4	4	5	2	4
2	4	5	1	5	2	4	2	2	4	4	4	1	4	2	4	2	4
2	4	4	1	5	1	4	4	5	2	4	5	1	2	1	2	4	2
2	5	2	2	4	1	1	2	4	3	3	3	1	5	2	2	4	3
3	2	1	1	2	1	4	2	3	2	3	4	4	3	1	3	3	2
2	5	2	1	2	4	4	4	4	5	4	5	2	4	2	4	5	5
4	2	4	2	2	3	4	4	4	4	2	2	2	2	2	4	1	4
2	3	2	2	2	1	3	1	4	4	4	4	1	4	1	4	4	3
4	4	4	2	4	4	2	2	3	3	2	2	4	2	3	4	2	2
1	4	3	1	5	5	4	1	3	2	5	2	1	2	1	3	1	2
2	3	2	1	2	1	3	4	4	2	2	5	2	4	3	2	3	5
3	3	4	3	3	4	4	3	4	3	3	4	4	3	3	4	2	3
2	4	3	2	2	2	4	2	2	4	4	2	3	3	2	3	4	2
4	5	4	2	5	2	2	2	4	4	2	4	1	2	2	2	2	5
1	4	4	1	1	2	4	4	4	4	1	4	1	1	1	4	2	1
3	4	2	3	4	4	4	2	3	4	4	4	3	4	2	4	2	4
2	4	4	2	2	4	4	2	4	3	4	4	4	2	2	4	2	4
2	4	4	1	4	4	4	2	4	4	4	4	5	4	1	3	4	4
2	2	2	2	1	2	4	1	4	2	2	2	2	5	1	2	4	4
4	2	5	2	5	2	3	2	4	3	2	4	2	4	2	2	4	2
2	2	2	2	5	4	4	2	4	4	5	2	2	2	2	2	4	2
2	5	5	2	2	2	2	1	2	4	2	4	2	4	1	2	2	4

Stellenbosch University http://scholar.sun.ac.za

2	4	4	3	2	2	4	2	2	2	2	2	2	2	4	2	2	4
2	4	1	4	1	2	5	2	4	2	4	4	5	2	2	4	4	2
2	5	5	1	1	1	5	1	5	5	5	5	5	1	1	5	5	4
2	3	3	2	2	2	4	2	4	4	4	4	2	2	2	4	2	3
3	4	2	2	2	3	4	4	4	4	2	4	2	5	1	4	4	4
2	4	4	1	2	4	4	5	2	3	4	4	4	2	2	5	1	1
4	2	3	2	4	4	4	1	2	2	4	4	4	2	2	4	2	1
2	2	2	3	2	4	4	5	5	2	4	4	4	2	2	4	2	4
2	4	1	1	2	2	5	2	2	4	3	2	1	2	2	4	4	2
2	4	4	2	2	1	4	2	3	3	2	4	3	2	2	3	3	3
2	4	2	2	2	2	5	2	4	3	5	4	2	5	2	4	3	4

Stellenbosch University http://scholar.sun.ac.za

OPP_Q69	OPP_Q70	OPP_Q71	OPP_Q72	OPP_Q73	OPP_Q74	OPP_Q75	OPP_Q76	OPP_Q77	OPP_Q78	OPP_Q79	OPP_Q80	OPP_Q81	OPP_Q82	OPP_Q83	OPP_Q84	OPP_Q85	OPP_Q86
2	2	4	4	2	1	2	2	2	4	2	2	2	2	5	4	4	4
4	5	4	4	2	2	2	3	4	4	4	2	1	4	4	3	2	4
4	4	4	4	2	4	2	4	4	2	4	2	2	4	2	4	3	2
2	2	4	4	3	2	3	3	3	2	5	3	2	4	4	4	4	4
4	4	4	4	3	3	2	2	4	4	3	4	2	4	5	3	3	4
4	4	4	4	2	4	1	1	2	4	2	2	2	4	4	4	2	4
3	2	4	4	2	2	1	2	3	2	4	3	1	4	2	4	2	5
4	2	4	4	2	1	2	2	4	4	5	1	1	3	2	4	3	2
2	5	2	4	2	2	2	4	4	4	3	4	2	4	5	3	2	5
2	4	2	3	2	4	2	3	2	3	2	2	1	3	4	3	4	5
3	5	2	4	2	4	1	4	4	4	3	2	1	4	4	3	2	4
5	4	4	4	2	4	4	4	4	2	2	2	2	4	4	4	4	4
4	2	4	2	3	4	2	4	4	4	4	2	2	4	4	2	2	4
2	4	2	3	2	2	2	4	2	4	1	2	2	3	4	4	2	3
4	4	2	2	1	1	1	4	5	1	2	2	1	5	5	4	1	3
2	2	4	4	2	4	2	2	4	3	2	2	2	4	4	4	2	4
4	2	3	4	2	2	2	4	4	2	4	2	1	4	3	4	2	4
1	4	4	4	4	4	2	2	4	4	2	2	2	2	4	4	2	4
2	4	4	2	3	1	2	2	4	2	4	3	2	4	4	3	2	2
4	5	4	4	1	4	2	2	5	2	2	2	4	1	4	1	5	5
4	5	4	4	4	4	2	2	4	2	4	2	2	4	4	2	2	4
2	2	4	4	2	4	2	4	4	5	1	2	2	2	2	5	4	4
2	3	4	4	2	3	2	2	4	4	4	2	1	4	5	4	4	5
2	2	4	4	2	2	2	2	4	4	4	4	1	4	4	4	2	5
2	2	2	2	3	2	2	2	4	2	2	2	2	4	4	2	2	4
4	4	4	5	2	4	2	2	4	4	4	5	1	4	2	4	2	4
2	5	4	4	2	4	1	1	4	4	5	4	1	4	4	2	3	5
3	2	2	3	2	4	2	4	3	4	3	2	2	3	4	2	2	5
4	4	2	2	4	2	2	4	4	2	4	4	2	5	4	2	2	2
3	2	4	4	2	4	3	3	4	4	5	2	2	3	4	4	3	4
5	5	5	5	2	4	5	1	1	5	5	3	2	5	5	5	4	5
4	4	4	4	2	2	2	3	4	4	5	3	2	4	5	4	2	4
2	4	4	4	2	4	2	2	4	2	4	1	1	4	4	2	2	4
2	4	2	2	4	2	1	4	2	4	2	2	1	2	4	2	2	4
2	3	4	4	3	2	2	1	4	4	1	4	1	4	5	4	2	2
2	5	2	4	3	5	5	1	4	2	5	1	1	3	1	5	2	5
2	4	4	2	2	5	2	1	2	4	2	2	1	4	4	4	2	5
2	4	2	3	1	3	3	1	3	4	4	2	1	4	5	4	1	5
2	4	4	4	2	4	4	1	4	5	4	4	4	5	5	4	1	5
2	2	2	1	4	2	2	2	2	2	4	2	1	4	1	4	2	4
4	2	4	4	4	3	2	2	2	5	3	4	2	3	4	4	2	3
3	4	4	4	3	3	1	2	2	3	4	4	1	2	5	4	2	5
2	2	4	4	2	1	1	2	4	4	2	2	1	3	5	4	2	5
2	4	4	4	2	4	2	1	2	4	4	2	2	4	4	4	4	4

Stellenbosch University http://scholar.sun.ac.za

2	4	4	4	5	2	2	2	4	4	2	2	1	4	4	4	2	1
4	2	4	4	2	2	3	2	3	4	4	1	2	3	5	4	3	4
3	4	2	4	3	2	2	3	2	4	2	2	1	5	5	1	1	5
2	4	4	4	2	4	2	3	4	4	5	2	1	4	5	2	4	4
4	4	4	2	2	4	4	2	4	4	4	2	2	2	4	4	4	4
5	3	3	3	2	1	1	1	4	5	4	3	1	4	2	5	1	2
4	5	2	4	1	2	3	4	4	4	4	4	1	4	5	4	4	5
4	4	4	4	2	4	1	2	2	2	4	2	2	2	5	4	4	4
4	2	5	4	2	3	4	2	4	2	5	2	2	4	5	5	2	4
2	4	4	4	2	1	2	4	3	4	2	2	2	4	2	3	2	2
3	2	4	2	2	5	4	4	2	5	4	2	4	5	5	3	2	4
4	3	3	4	2	4	2	3	3	3	1	2	2	5	5	3	1	5
2	2	4	4	2	5	3	4	2	4	2	3	2	4	3	4	1	3
4	4	4	4	2	4	1	4	4	4	4	2	4	4	4	4	2	5
4	3	4	3	3	4	2	2	2	4	3	2	2	2	4	4	2	5
2	2	4	4	2	4	4	2	4	4	4	3	2	3	4	2	2	5
2	3	4	4	2	3	2	2	4	2	4	3	2	5	5	4	2	4
4	2	4	4	3	4	3	3	4	4	4	3	4	5	5	5	4	5
2	1	4	2	2	2	1	2	4	2	2	2	3	2	5	5	4	2
2	5	5	1	4	2	2	1	1	2	5	1	4	1	5	5	5	1
2	4	4	4	2	2	2	4	4	4	2	2	1	4	4	4	2	4
4	4	4	4	4	2	2	2	4	4	2	2	2	2	5	2	2	2
4	4	5	5	2	3	2	4	4	2	2	2	2	5	3	3	3	2
4	4	4	5	2	2	1	1	4	2	5	2	2	5	2	4	2	4
2	4	4	4	2	5	2	2	2	2	4	2	2	4	5	2	2	5
2	4	4	4	2	4	2	4	4	5	4	2	2	4	2	4	4	4
2	1	2	4	4	1	2	4	2	4	5	2	4	4	5	5	4	1
4	3	2	4	2	3	1	1	2	4	4	2	1	3	4	3	1	4
4	2	4	4	3	4	4	3	3	3	4	2	3	4	4	4	4	4
2	5	2	3	3	2	2	2	5	5	5	3	1	4	5	4	1	4
2	3	2	3	2	2	2	2	4	2	4	2	2	2	4	2	3	2
3	2	3	4	3	4	2	2	4	4	2	3	2	3	4	2	3	4
4	4	4	4	3	4	4	2	4	4	2	4	2	4	4	4	4	4
2	4	3	3	1	5	1	3	3	5	3	2	1	5	5	4	1	5
2	2	5	2	1	2	3	4	3	4	5	1	1	4	4	2	4	5
3	4	4	4	3	3	3	3	2	4	3	2	2	4	4	4	3	4
3	3	4	2	2	4	2	2	4	4	3	3	2	4	4	4	2	4
4	5	2	4	4	4	1	4	2	4	4	2	1	4	4	4	1	5
3	2	2	4	4	2	2	4	4	4	4	2	3	2	2	4	3	2
4	3	4	4	3	2	2	2	4	4	2	3	2	3	4	4	2	4
4	3	4	4	2	4	2	4	3	4	4	2	2	4	4	4	4	4
2	2	5	4	3	4	2	2	4	5	4	2	1	3	5	3	2	5
2	1	3	4	2	4	2	2	4	4	4	2	2	4	4	2	2	4
4	5	4	4	4	2	3	1	2	4	2	2	1	2	4	4	3	4
2	4	5	4	2	2	2	2	2	4	4	1	1	4	5	4	1	4
4	2	4	2	2	4	2	2	4	4	4	2	1	4	5	2	2	4

Stellenbosch University http://scholar.sun.ac.za

OPP_Q87	OPP_Q88	OPP_Q89	OPP_Q90	OPP_Q91	OPP_Q92	OPP_Q93	OPP_Q94	OPP_Q95	OPP_Q96	OPP_Q97	OPP_Q98
4	2	2	4	4	4	2	2	2	4	4	4
4	2	2	4	4	2	2	4	5	4	4	4
1	2	1	2	4	2	4	4	4	2	4	4
3	1	3	4	2	3	2	2	1	4	3	4
4	1	2	3	4	2	2	3	4	4	4	4
2	2	3	4	4	2	2	4	4	2	4	4
2	1	2	4	4	4	2	2	2	5	2	4
3	1	1	2	3	4	1	2	4	5	2	4
3	2	1	2	4	4	2	3	2	4	2	5
3	3	2	2	2	2	2	2	3	4	4	2
2	2	2	2	4	3	2	4	1	4	4	4
1	4	4	4	4	2	4	4	4	4	4	4
2	5	5	2	3	2	2	4	4	4	4	5
2	3	2	4	4	2	1	2	4	4	4	4
1	1	1	1	4	2	1	4	5	3	5	5
4	1	2	2	4	2	2	2	4	4	4	4
2	1	2	4	4	2	2	4	3	3	4	4
2	2	2	2	4	4	2	2	2	4	2	2
4	2	1	1	3	3	4	4	4	3	3	4
1	1	2	4	2	5	1	2	1	4	2	5
5	2	2	2	4	2	2	2	2	2	4	2
2	1	1	2	4	2	2	4	4	4	2	4
3	4	2	2	4	2	2	2	4	4	4	3
2	2	2	4	4	4	2	4	2	4	4	4
4	2	2	4	4	2	2	4	2	4	2	4
1	2	2	2	4	5	2	2	2	4	4	4
5	2	1	5	4	2	5	3	5	4	2	1
2	2	1	4	4	2	1	1	2	4	4	4
3	4	2	2	4	4	4	4	4	2	4	4
2	4	2	2	4	2	2	2	5	5	1	5
2	1	1	5	5	5	1	1	5	5	5	5
3	2	1	2	4	2	2	2	3	4	4	4
3	2	3	4	4	2	1	2	4	3	5	4
3	3	2	2	4	2	3	2	4	2	2	4
3	3	2	4	4	2	1	3	4	3	4	4
2	2	1	2	4	3	3	4	4	5	3	4
2	1	1	2	4	4	1	4	2	4	2	2
2	1	1	2	2	4	1	4	2	4	2	5
2	1	4	4	5	2	5	2	4	5	4	5
4	2	2	4	2	4	4	2	4	2	2	4
2	2	2	2	4	3	2	2	3	4	2	4
1	1	2	5	4	2	1	2	4	4	4	2
1	4	2	4	5	2	1	2	5	4	2	5
3	2	3	4	4	2	1	4	2	5	4	4

Stellenbosch University http://scholar.sun.ac.za

2	2	2	4	4	2	2	4	4	4	4	4
2	1	2	2	4	1	2	2	2	4	4	5
5	2	2	2	5	4	4	4	3	4	5	3
2	1	2	2	4	2	2	4	2	4	5	4
2	2	2	4	4	2	2	2	4	4	4	3
4	1	1	1	5	4	1	2	2	5	3	2
1	1	2	3	4	2	2	4	2	4	4	4
2	4	2	3	5	2	2	1	4	4	4	4
1	1	2	2	5	2	1	2	2	4	2	2
2	4	2	1	4	2	2	3	3	4	4	4
1	1	2	3	4	3	4	2	4	4	3	4
2	1	2	2	4	2	2	3	5	2	3	4
2	1	2	1	4	4	1	1	3	5	3	5
4	2	2	1	5	2	1	2	4	4	5	4
2	2	3	4	4	2	3	2	4	4	2	4
3	2	1	4	3	2	2	4	3	4	4	4
1	2	2	4	4	4	1	3	4	4	4	4
4	5	3	3	4	3	2	4	5	4	4	4
1	1	2	4	4	2	2	4	4	4	4	5
3	1	1	4	4	1	1	1	4	5	4	2
4	4	2	2	4	2	4	4	2	4	4	2
1	4	2	4	5	2	2	2	5	5	5	5
2	2	1	4	4	2	4	2	5	4	5	4
2	2	1	1	4	2	2	5	2	2	4	2
3	2	2	3	2	4	4	2	2	4	4	2
2	2	2	4	4	4	4	1	4	4	4	4
2	1	4	4	2	4	1	4	2	5	5	4
4	4	2	3	4	2	2	2	2	4	4	3
1	2	1	2	4	3	1	2	4	4	4	5
5	2	1	5	5	4	1	4	4	5	2	4
4	3	2	2	4	3	2	2	2	4	4	4
2	3	2	4	1	3	1	2	4	4	3	4
2	2	2	4	4	2	4	4	2	3	4	3
3	1	2	4	3	3	1	3	5	4	3	2
1	3	1	4	4	1	1	4	2	3	4	4
4	3	2	3	4	2	4	2	5	3	3	2
3	2	2	4	4	2	2	3	2	4	4	4
2	2	4	4	5	2	2	2	4	4	4	5
2	1	1	4	3	2	2	3	5	5	3	1
2	3	2	4	5	3	2	4	4	5	4	4
2	3	2	4	4	4	2	4	4	4	4	4
3	1	2	4	4	3	2	2	3	4	4	5
1	2	4	1	4	2	2	2	4	4	4	4
5	1	2	4	4	2	2	3	4	4	1	2
2	4	2	5	4	2	2	2	4	4	2	4
1	1	1	1	4	2	4	4	5	4	2	5

Stellenbosch University http://scholar.sun.ac.za

3	2	2	2	3	2	3	3	2	3	4	3
1	1	1	4	4	2	2	2	4	4	4	5
2	1	1	4	5	1	4	1	5	4	5	1
3	2	2	3	3	3	2	3	2	4	4	3
2	1	2	4	4	2	1	4	4	4	4	4
2	1	1	5	4	5	1	2	2	4	5	5
4	3	2	4	4	2	2	2	5	4	4	3
2	2	1	2	4	2	4	4	5	4	4	4
1	1	2	4	4	3	2	2	4	4	4	5
3	2	2	4	5	4	1	2	4	4	4	4
2	4	1	4	5	4	2	2	5	5	4	4

Stellenbosch University http://scholar.sun.ac.za

RES_1	PRE_1	ABRES_1	INDEX	INDEX_2
-8.80072	67.55072	8.80072	2.44	3.00
-6.70812	66.04146	6.70812	2.33	3.00
-7.15181	67.65181	7.15181	2.33	3.00
-4.01978	64.51978	4.01978	3.00	1.50
-6.71786	67.65536	6.71786	3.22	3.67
-5.35140	66.41390	5.35140	2.89	3.00
-3.07139	64.28567	3.07139	2.78	2.50
-1.84656	63.22156	1.84656	2.67	2.33
-3.56474	65.25224	3.56474	2.56	2.33
-5.90414	67.83271	5.90414	2.44	2.67
-8.92225	71.17225	8.92225	2.22	3.00
-4.36860	66.76860	4.36860	3.44	2.33
-5.54573	68.79573	5.54573	2.56	3.00
-6.44491	69.69491	6.44491	2.78	2.00
-3.62593	67.00093	3.62593	1.78	2.67
-.19112	63.75362	.19112	2.67	2.50
-2.76499	66.51499	2.76499	2.22	3.00
-2.93531	66.93531	2.93531	2.89	2.00
-4.76913	68.76913	4.76913	3.00	2.50
-2.96191	66.96191	2.96191	2.67	2.00
-2.87678	66.87678	2.87678	2.67	2.50
-3.67493	67.92493	3.67493	2.89	2.00
-4.64150	68.89150	4.64150	3.22	2.50
-2.45610	66.76860	2.45610	2.78	2.50
-1.26699	65.70449	1.26699	2.89	2.00
-4.92888	69.42888	4.92888	2.33	2.00
-4.26736	68.76736	4.26736	3.22	3.00
-5.42021	70.17021	5.42021	3.11	3.00
-1.12481	66.12481	1.12481	3.11	2.00
-2.37514	67.37514	2.37514	3.22	3.00
.83933	64.28567	.83933	3.44	2.67
-2.83632	68.08632	2.83632	2.89	3.00
-5.45943	70.95943	5.45943	2.44	3.00
-3.94129	69.44129	3.94129	2.67	3.00
-1.11522	66.74022	1.11522	2.78	2.00
-.19434	65.88184	.19434	3.33	1.50
-2.24992	68.18742	2.24992	2.33	2.00
-3.01565	69.01565	3.01565	2.22	2.00
-3.84743	69.84743	3.84743	3.44	2.50
.53536	65.52714	.53536	2.56	2.33
.95257	65.17243	.95257	3.67	2.00
-3.80138	70.05138	3.80138	3.22	3.00
.97286	65.52714	.97286	3.33	1.67
.44081	66.05919	.44081	3.56	2.67

Stellenbosch University http://scholar.sun.ac.za

2.22448	64.46302	2.22448	3.33	2.00
-.88592	67.88592	.88592	3.22	2.50
1.50032	65.62468	1.50032	3.67	2.00
-1.46947	68.71947	1.46947	2.56	2.00
-2.54600	69.79600	2.54600	3.33	2.50
-.63506	68.01006	.63506	2.56	2.50
.49155	66.94595	.49155	2.89	2.00
3.04712	64.64038	3.04712	2.89	2.33
.20949	67.47801	.20949	3.22	2.33
1.53162	66.28088	1.53162	3.89	2.33
-1.40313	69.27813	1.40313	3.22	2.00
-1.76053	69.76053	1.76053	2.33	2.50
1.44422	66.55578	1.44422	3.11	1.67
3.95835	64.10832	3.95835	3.11	2.67
-1.57437	69.82437	1.57437	3.00	2.50
2.55566	65.88184	2.55566	2.78	2.00
-.57460	69.01210	.57460	2.67	2.00
-.24259	68.99259	.24259	3.33	2.00
-.06403	69.25153	.06403	2.67	2.00
4.14007	65.17243	4.14007	3.00	2.00
3.21380	66.28620	3.21380	2.33	2.00
-.39843	69.96093	.39843	2.89	2.00
.46478	69.28522	.46478	3.67	2.50
2.39699	67.47801	2.39699	3.44	2.33
.51877	69.60623	.51877	3.00	2.33
-.28556	70.53556	.28556	2.78	2.50
1.07516	69.23734	1.07516	2.89	2.00
1.60672	68.89328	1.60672	2.67	2.00
3.42800	67.57200	3.42800	3.78	2.50
3.43906	67.62344	3.43906	3.00	3.00
3.68509	67.56491	3.68509	3.00	1.50
5.01346	66.23654	5.01346	3.33	2.67
.46481	70.84769	.46481	3.33	2.00
3.18758	68.18742	3.18758	3.22	2.00
2.56764	69.18236	2.56764	2.67	3.00
2.49315	69.25685	2.49315	3.56	2.50
4.25248	67.49752	4.25248	3.00	2.50
4.07286	67.86464	4.07286	3.00	2.67
3.75008	68.18742	3.75008	2.33	3.00
3.59792	68.65208	3.59792	3.67	2.00
4.35699	67.89301	4.35699	3.11	3.00
3.41568	68.89682	3.41568	3.33	2.50
3.19973	69.17527	3.19973	3.22	2.50
3.87630	68.62370	3.87630	3.78	3.00
1.18275	71.37975	1.18275	2.78	2.33
1.96040	70.72710	1.96040	3.33	2.00

Stellenbosch University http://scholar.sun.ac.za

APPENDIX B
OPP CORRELATION MATRIX

Stellenbosch University http://scholar.sun.ac.za

		Unstandardized Residual	Unstandardized absolute residual
Item1	Pearson Correlation Sig. (2-tailed) N	,040 ,692 101	-,120 ,233 101
Item2	Pearson Correlation Sig. (2-tailed) N	-,041 ,682 101	,060 ,553 101
Item3	Pearson Correlation Sig. (2-tailed) N	,053 ,600 101	,024 ,809 101
Item4	Pearson Correlation Sig. (2-tailed) N	-,085 ,397 101	,046 ,647 101
Item5	Pearson Correlation Sig. (2-tailed) N	,063 ,529 101	-,028 ,783 101
Item6	Pearson Correlation Sig. (2-tailed) N	-,006 ,953 101	,070 ,485 101
Item7	Pearson Correlation Sig. (2-tailed) N	,034 ,737 101	,184 ,066 101
Item8	Pearson Correlation Sig. (2-tailed) N	,011 ,916 101	-,028 ,781 101
Item9	Pearson Correlation Sig. (2-tailed) N	-,110 ,271 101	,078 ,440 101
Item10	Pearson Correlation Sig. (2-tailed) N	**,204** **,041** 101	-,115 ,251 101
Item11	Pearson Correlation Sig. (2-tailed) N	-,007 ,949 101	,167 ,096 101
Item12	Pearson Correlation Sig. (2-tailed) N	,051 ,613 101	,010 ,923 101
Item13	Pearson Correlation Sig. (2-tailed) N	,010 ,918 101	-,048 ,632 101
Item14	Pearson Correlation Sig. (2-tailed) N	,023 ,823 101	,078 ,439 101
Item15	Pearson Correlation Sig. (2-tailed) N	-,061 ,547 101	,083 ,411 101
Item16	Pearson Correlation Sig. (2-tailed) N	,090 ,369 101	,053 ,599 101
Item17	Pearson Correlation Sig. (2-tailed) N	,065 ,519 101	,054 ,589 101
Item18	Pearson Correlation Sig. (2-tailed) N	**,205** **,040** 101	,178 ,075 101

Stellenbosch University http://scholar.sun.ac.za

Item19	Pearson Correlation Sig. (2-tailed) N	,092 ,359 101	,015 ,881 101
Item20	Pearson Correlation Sig. (2-tailed) N	**,197** **,049** 101	-,048 ,636 101
Item21	Pearson Correlation Sig. (2-tailed) N	,048 ,635 101	-,006 ,949 101
Item22	Pearson Correlation Sig. (2-tailed) N	-,050 ,616 101	-,054 ,595 101
Item23	Pearson Correlation Sig. (2-tailed) N	,031 ,761 101	,035 ,731 101
Item24	Pearson Correlation Sig. (2-tailed) N	-,089 ,374 101	-,100 ,322 101
Item25	Pearson Correlation Sig. (2-tailed) N	**,216** **,030** 101	,040 ,689 101
Item26	Pearson Correlation Sig. (2-tailed) N	,050 ,621 101	,054 ,588 101
Item27	Pearson Correlation Sig. (2-tailed) N	,005 ,958 101	-,062 ,539 101
Item28	Pearson Correlation Sig. (2-tailed) N	,062 ,539 100	,085 ,399 100
Item29	Pearson Correlation Sig. (2-tailed) N	,079 ,435 101	-,001 ,992 101
Item30	Pearson Correlation Sig. (2-tailed) N	-,048 ,630 101	,065 ,517 101
Item31	Pearson Correlation Sig. (2-tailed) N	,005 ,963 101	,095 ,346 101
Item32	Pearson Correlation Sig. (2-tailed) N	**,229** **,021** 101	,029 ,770 101
Item33	Pearson Correlation Sig. (2-tailed) N	**,315** **,001** 101	-,094 ,347 101
Item34	Pearson Correlation Sig. (2-tailed) N	,106 ,290 101	-,032 ,748 101
Item35	Pearson Correlation Sig. (2-tailed) N	,063 ,532 101	-,074 ,462 101
Item36	Pearson Correlation Sig. (2-tailed) N	,013 ,895 101	,125 ,212 101
Item37	Pearson Correlation Sig. (2-tailed) N	-,061 ,545 101	,074 ,461 101

Stellenbosch University http://scholar.sun.ac.za

Item38	Pearson Correlation Sig. (2-tailed) N	,173 ,084 101	-,125 ,214 101
Item39	Pearson Correlation Sig. (2-tailed) N	,144 ,150 101	,079 ,431 101
Item40	Pearson Correlation Sig. (2-tailed) N	-,078 ,437 101	-,047 ,643 101
Item41	Pearson Correlation Sig. (2-tailed) N	-,105 ,297 101	-,164 ,100 101
Item42	Pearson Correlation Sig. (2-tailed) N	-,010 ,922 101	,035 ,726 101
Item43	Pearson Correlation Sig. (2-tailed) N	-,006 ,953 101	,056 ,580 101
Item44	Pearson Correlation Sig. (2-tailed) N	,052 ,607 101	,041 ,684 101
Item45	Pearson Correlation Sig. (2-tailed) N	,036 ,724 101	-,029 ,773 101
Item46	Pearson Correlation Sig. (2-tailed) N	,093 ,357 101	-,032 ,749 101
Item47	Pearson Correlation Sig. (2-tailed) N	-,008 ,936 101	-,026 ,799 101
Item48	Pearson Correlation Sig. (2-tailed) N	,129 ,198 101	,056 ,575 101
Item49	Pearson Correlation Sig. (2-tailed) N	,065 ,517 101	-,098 ,330 101
Item50	Pearson Correlation Sig. (2-tailed) N	-,106 ,290 101	-,057 ,572 101
Item51	Pearson Correlation Sig. (2-tailed) N	-,141 ,160 101	,013 ,900 101
Item52	Pearson Correlation Sig. (2-tailed) N	-,053 ,600 101	-,051 ,612 101
Item53	Pearson Correlation Sig. (2-tailed) N	-,157 ,116 101	,075 ,453 101
Item54	Pearson Correlation Sig. (2-tailed) N	-,085 ,398 101	-,067 ,505 101
Item55	Pearson Correlation Sig. (2-tailed) N	-,096 ,339 101	**-,262** **,008** 101
Item56	Pearson Correlation Sig. (2-tailed) N	-,044 ,664 101	-,062 ,540 101

Stellenbosch University http://scholar.sun.ac.za

Item57	Pearson Correlation Sig. (2-tailed) N	,057 ,569 101	,082 ,416 101
Item58	Pearson Correlation Sig. (2-tailed) N	,133 ,185 101	-,074 ,464 101
Item59	Pearson Correlation Sig. (2-tailed) N	,109 ,279 101	-,167 ,096 101
Item60	Pearson Correlation Sig. (2-tailed) N	,057 ,574 101	,091 ,364 101
Item61	Pearson Correlation Sig. (2-tailed) N	**,204** **,041** 101	,040 ,690 101
Item62	Pearson Correlation Sig. (2-tailed) N	,008 ,939 101	,088 ,380 101
Item63	Pearson Correlation Sig. (2-tailed) N	,102 ,312 101	-,093 ,356 101
Item64	Pearson Correlation Sig. (2-tailed) N	,122 ,225 101	-,150 ,135 101
Item65	Pearson Correlation Sig. (2-tailed) N	-,080 ,424 101	-,010 ,919 101
Item66	Pearson Correlation Sig. (2-tailed) N	-,017 ,869 101	,142 ,155 101
Item67	Pearson Correlation Sig. (2-tailed) N	-,024 ,812 101	-,042 ,675 101
Item68	Pearson Correlation Sig. (2-tailed) N	-,114 ,256 101	,033 ,740 101
Item69	Pearson Correlation Sig. (2-tailed) N	-,051 ,615 101	-,057 ,575 101
Item70	Pearson Correlation Sig. (2-tailed) N	-,119 ,234 101	,119 ,235 101
Item71	Pearson Correlation Sig. (2-tailed) N	,089 ,374 101	-,050 ,621 101
Item72	Pearson Correlation Sig. (2-tailed) N	-,070 ,490 101	-,074 ,460 101
Item73	Pearson Correlation Sig. (2-tailed) N	**,196** **,049** 101	-,007 ,945 101
Item74	Pearson Correlation Sig. (2-tailed) N	,040 ,690 101	,093 ,353 101
Item75	Pearson Correlation Sig. (2-tailed) N	,105 ,298 101	-,148 ,139 101

Stellenbosch University http://scholar.sun.ac.za

Item76	Pearson Correlation	-,143	,069
	Sig. (2-tailed)	,152	,490
	N	101	101
Item77	Pearson Correlation	-,095	-,018
	Sig. (2-tailed)	,343	,859
	N	101	101
Item78	Pearson Correlation	,135	,081
	Sig. (2-tailed)	,179	,419
	N	101	101
Item79	Pearson Correlation	,035	-,129
	Sig. (2-tailed)	,725	,197
	N	101	101
Item80	Pearson Correlation	-,027	,083
	Sig. (2-tailed)	,788	,408
	N	101	101
Item81	Pearson Correlation	,141	,000
	Sig. (2-tailed)	,159	,998
	N	101	101
Item82	Pearson Correlation	-,018	-,150
	Sig. (2-tailed)	,862	,136
	N	101	101
Item83	Pearson Correlation	,036	,026
	Sig. (2-tailed)	,719	,794
	N	101	101
Item84	Pearson Correlation	,083	-,096
	Sig. (2-tailed)	,411	,339
	N	101	101
Item85	Pearson Correlation	-,037	,005
	Sig. (2-tailed)	,716	,960
	N	101	101
Item86	Pearson Correlation	-,083	,060
	Sig. (2-tailed)	,408	,554
	N	101	101
Item87	Pearson Correlation	,006	,080
	Sig. (2-tailed)	,951	,426
	N	101	101
Item88	Pearson Correlation	,021	,056
	Sig. (2-tailed)	,838	,577
	N	101	101
Item89	Pearson Correlation	-,143	-,019
	Sig. (2-tailed)	,153	,850
	N	101	101
Item90	Pearson Correlation	,163	,116
	Sig. (2-tailed)	,104	,247
	N	101	101
Item91	Pearson Correlation	,156	,021
	Sig. (2-tailed)	,120	,833
	N	101	101
Item92	Pearson Correlation	,028	,014
	Sig. (2-tailed)	,782	,892
	N	101	101
Item93	Pearson Correlation	-,081	-,076
	Sig. (2-tailed)	,419	,448
	N	101	101
Item94	Pearson Correlation	-,092	-,037
	Sig. (2-tailed)	,359	,713
	N	101	101

Stellenbosch University http://scholar.sun.ac.za

Item95	Pearson Correlation Sig. (2-tailed) N	,184 ,066 101	,092 ,360 101
Item96	Pearson Correlation Sig. (2-tailed) N	**,212** **,033** 101	-,026 ,794 101
Item97	Pearson Correlation Sig. (2-tailed) N	,124 ,215 101	,171 ,087 101
Item98	Pearson Correlation Sig. (2-tailed) N	-,058 ,562 101	-,012 ,909 101

Stellenbosch University http://scholar.sun.ac.za

APPENDIX C

CRTB2 CORRELATION MATRIX

		Unstandardized Residual	Unstandardized absolute residual
ItemV1	Pearson Correlation	,076	,124
	Sig. (2-tailed)	,450	,218
	N	101	101
ItemV2	Pearson Correlation	**-,218**	,004
	Sig. (2-tailed)	**,028**	,967
	N	101	101
ItemV3	Pearson Correlation	-,036	,164
	Sig. (2-tailed)	,718	,101
	N	101	101
ItemV4	Pearson Correlation	,045	,070
	Sig. (2-tailed)	,658	,484
	N	101	101
ItemV5	Pearson Correlation	**-,279**	,135
	Sig. (2-tailed)	**,005**	,178
	N	101	101
ItemV6	Pearson Correlation	-,012	,061
	Sig. (2-tailed)	,906	,545
	N	100	100
ItemV7	Pearson Correlation	,192	-,087
	Sig. (2-tailed)	,055	,389
	N	101	101
ItemV8	Pearson Correlation	,064	-,081
	Sig. (2-tailed)	,522	,421
	N	101	101
ItemV9	Pearson Correlation	,037	-,005
	Sig. (2-tailed)	,714	,962
	N	101	101
ItemV10	Pearson Correlation	-,065	,025
	Sig. (2-tailed)	,523	,805
	N	100	100
ItemV11	Pearson Correlation	**-,292**	,029
	Sig. (2-tailed)	**,003**	,776
	N	101	101
ItemV12	Pearson Correlation	,018	-,127
	Sig. (2-tailed)	,858	,208
	N	100	100
ItemV13	Pearson Correlation	**-,256**	-,073
	Sig. (2-tailed)	**,010**	,468
	N	101	101
ItemV14	Pearson Correlation	,051	-,169
	Sig. (2-tailed)	,611	,093
	N	100	100
ItemV15	Pearson Correlation	,063	,118
	Sig. (2-tailed)	,533	,239
	N	101	101
ItemV16	Pearson Correlation	,092	,155
	Sig. (2-tailed)	,362	,121
	N	101	101
ItemV17	Pearson Correlation	-,154	,085
	Sig. (2-tailed)	,127	,400
	N	100	100
ItemV18	Pearson Correlation	-,119	-,087
	Sig. (2-tailed)	,239	,391
	N	100	100
ItemV19	Pearson Correlation	,085	,023
	Sig. (2-tailed)	,398	,820
	N	100	100
ItemV20	Pearson Correlation	-,071	,037
	Sig. (2-tailed)	,481	,713
	N	100	100
ItemV21	Pearson Correlation	**,254**	-,047
	Sig. (2-tailed)	**,011**	,646

Stellenbosch University http://scholar.sun.ac.za

	N	100	100
ItemV22	Pearson Correlation Sig. (2-tailed) N	-,054 ,593 99	**,208** **,039** 99
ItemV23	Pearson Correlation Sig. (2-tailed) N	-,009 ,927 99	-,028 ,787 99
ItemV24	Pearson Correlation Sig. (2-tailed) N	,024 ,818 98	-,163 ,108 98
ItemV25	Pearson Correlation Sig. (2-tailed) N	,159 ,115 99	,045 ,660 99
ItemV26	Pearson Correlation Sig. (2-tailed) N	,081 ,426 99	,118 ,244 99
ItemV27	Pearson Correlation Sig. (2-tailed) N	,049 ,629 98	,062 ,544 98
ItemV28	Pearson Correlation Sig. (2-tailed) N	-,019 ,854 95	,183 ,077 95
ItemV29	Pearson Correlation Sig. (2-tailed) N	,006 ,957 95	-,012 ,909 95
ItemV30	Pearson Correlation Sig. (2-tailed) N	-,246 ,018 92	,027 ,796 92
ItemV31	Pearson Correlation Sig. (2-tailed) N	,135 ,200 91	,176 ,096 91
ItemV32	Pearson Correlation Sig. (2-tailed) N	-,120 ,261 90	-,012 ,912 90
ItemV33	Pearson Correlation Sig. (2-tailed) N	**,362** **,000** 89	,203 ,056 89
ItemV34	Pearson Correlation Sig. (2-tailed) N	,049 ,653 88	,111 ,304 88
ItemV35	Pearson Correlation Sig. (2-tailed) N	,026 ,818 84	,203 ,064 84
ItemV36	Pearson Correlation Sig. (2-tailed) N	**-,245** **,026** **83**	-,101 ,362 83
ItemV37	Pearson Correlation Sig. (2-tailed) N	**,251** **,025** 80	**,390** **,000** 80
ItemV38	Pearson Correlation Sig. (2-tailed) N	,190 ,100 76	,082 ,482 76
ItemV39	Pearson Correlation Sig. (2-tailed) N	-,112 ,341 75	-,079 ,500 75
ItemV40	Pearson Correlation Sig. (2-tailed) N	,136 ,246 75	,064 ,585 75
ItemN1	Pearson Correlation Sig. (2-tailed) N	-,082 ,560 53	,036 ,800 53
ItemN2	Pearson Correlation Sig. (2-tailed) N	-,075 ,600 51	-,196 ,167 51

Stellenbosch University http://scholar.sun.ac.za

ItemN3	Pearson Correlation Sig. (2-tailed) N	,152 ,312 46	,103 ,497 46
ItemN4	Pearson Correlation Sig. (2-tailed) N	,046 ,741 53	-,138 ,324 53
ItemN5	Pearson Correlation Sig. (2-tailed) N	,024 ,863 53	-,041 ,771 53
ItemN6	Pearson Correlation Sig. (2-tailed) N	-,213 ,130 52	-,168 ,233 52
ItemN7	Pearson Correlation Sig. (2-tailed) N	,010 ,945 52	-,026 ,856 52
ItemN8	Pearson Correlation Sig. (2-tailed) N	,001 ,996 53	-,048 ,734 53
ItemN9	Pearson Correlation Sig. (2-tailed) N	,134 ,339 53	,048 ,733 53
ItemN10	Pearson Correlation Sig. (2-tailed) N	-,072 ,618 51	-,144 ,312 51
ItemN11	Pearson Correlation Sig. (2-tailed) N	-,095 ,505 52	,052 ,713 52
ItemN12	Pearson Correlation Sig. (2-tailed) N	-,216 ,123 52	**,388** **,004** 52
ItemN13	Pearson Correlation Sig. (2-tailed) N	-,197 ,162 52	-,194 ,168 52
ItemN14	Pearson Correlation Sig. (2-tailed) N	-,046 ,749 50	-,054 ,707 50
ItemN15	Pearson Correlation Sig. (2-tailed) N	-,046 ,763 46	-,035 ,817 46
ItemN16	Pearson Correlation Sig. (2-tailed) N	,079 ,608 45	-,065 ,670 45
ItemN17	Pearson Correlation Sig. (2-tailed) N	,253 ,086 47	,037 ,805 47
ItemN18	Pearson Correlation Sig. (2-tailed) N	-,090 ,558 45	-,101 ,509 45
ItemN19	Pearson Correlation Sig. (2-tailed) N	-,073 ,648 42	,294 ,058 42
ItemN20	Pearson Correlation Sig. (2-tailed) N	-,191 ,271 35	,090 ,609 35
ItemN21	Pearson Correlation Sig. (2-tailed) N	,156 ,379 34	,016 ,928 34
ItemN22	Pearson Correlation Sig. (2-tailed) N	-,116 ,573 26	,177 ,388 26
ItemN23	Pearson Correlation Sig. (2-tailed) N	-,057 ,784 26	-,102 ,618 26
ItemN24	Pearson Correlation	,126	-,297

Stellenbosch University http://scholar.sun.ac.za

	Sig. (2-tailed)	,550	,150
	N	25	25
ItemN25	Pearson Correlation	-,081	,189
	Sig. (2-tailed)	,721	,399
	N	22	22