Identifying Quantitative Relationships between Key Performance Indicators in Support of Physical Asset Management Decision-Making Processes

by

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December 2015

Declaration

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Date: 01/09/2015 ....

Abstract

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September 2015

Physical Asset Management (PAM) is increasingly being acknowledged by industry as an important contributor to the financial success of organisations, especially those who are dependent on their physical assets for organisational value creation. Amongst the PAM improvement opportunities identified by researchers and organisations is the derivation of additional, meaningful and innovative information from Key Performance Indicators (KPIs) for improved PAM decision-making process.

The Quantitative Relationships at the Performance Measurement System (QRPMS) methodology is an existing methodology which objectively identifies and quantifies the relationships between a set of KPIs, and presents these relationships as additional information for PAM decision-making processes. QRPMS employs two mathematical techniques, Principal Components Analysis and Partial Least Squares regression, to identify and quantify inter-KPI relationships, respectively. The Guttman-Kaiser criteria (K1) is employed by QRPMS to determine the number of principal components (PCs) to retain for further assessment. However, the K1 criterion is found to be one of the least reliable and most inaccurate selection criteria available, with some publications using it without reservation. Therefore, the K1 criterion severely compromises the reliability and mathematical accuracy of the results obtained from QRPMS.

This study proposes an improved methodology for the objective identification and quantification of inter-KPI relationships, called the Quantitative Identification of Inter-Performance Measure Relationships (QIIPMR) methodology. A comprehensive literature study is conducted, investigating the realms of PAM, Performance Management (PM), Performance Management Systems (PMS) and performance measures. Existing frameworks and methodologies which aim to identify relationships between performance elements are investigated, and their flaws identified. The literature study concludes with an investigation of PCA, PLS and selection criteria. The proposed QIIPMR methodology employs QRPMS as a foundational framework. Accurate and reliable alternatives to the K1 criterion are compared, and the most appropriate of these is incorporated into QIIPMR.

A case study is conducted, comparing the results of QRPMS and QIIPMR using real-world KPI data from an open-pit, thermal coal mine in South Africa. The case study results substantiate the improvement made to QRPMS methodology. This study concludes with recommendations for future research.

Uittreksel

Identifiseering van Gekwantifiseerde Verhoudinge tussen Sleutel Prestasiewysers in Ondersteuning van Besluit-Maakende Prosesse in Fisiese Bate Bestuur

("Identifying Quantitative Relationships between Key Performance Indicators in Support of Physical Asset Management Decision-Making Processes")

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Fisiese Batebestuur (FB) word toenemend deur die industrie erken as 'n belangrike bydraer tot die finansiële sukses van organisasies, veral diegene wat afhanklik is van hul fisiese bates vir organisatoriese waarde skepping. Van die FB verbetering geleenthede wat geïdentifiseer is deur navorsers en organisasies, is die toepassing van bykomende, betekenisvolle en innoverende inligting van Sleutel Prestasieaanwysers (SP) vir verbeterde FB besluitnemingsprosesse.

Die Kwantitatiewe Verwantskappe in die Prestasiemeting Sisteem (KVPS) metodologie is 'n bestaande metodologie wat die verhoudinge tussen 'n stel SP objektief identifiseer en kwantifiseer, en bied hierdie verhoudinge aan as bykomende inligting vir FB besluitnemingsprosesse. KVPS gebruik twee wiskundige tegnieke, Hoof Komponente Analise (HKA) en Parsiële Kleinste Kwadraat (PKK) regressie, om die identifisering en kwantifisering van SP verhoudings onderskeidelik the bereken. KVPS neem die Guttman-Kaiser kriteria (K1) in diens om die aantal hoofkomponente (HKe) te bepaal wat behou moet word vir verdere assessering. Die K1 kriteria was egter gevind as een van die minste betroubaarste en mees onakkurate keuringskriteria beskikbaar, met 'n paar publikasies wat dit gebruik sonder voorbehoud. Dus, die K1 kriteria stel die betroubaarheid en wiskundige akkuraatheid van die KVPS metodologie in groot gevaar.

Hierdie studie stel ’n verbeterde metodologie voor vir die identifisering en kwantifisering van SP verhoudings, genaamd die Kwantitatiewe Identifisering van Tussen-Prestasiemaatstaf Verhoudings (KITPV) metodologie. ’n Omvattende literatuurstudie is voltooi, en die areas van FB, Prestasiebestuur (PB), Prestasiebestuurstelsels (PBS) en prestasiemaatreëls is ondersoek. Bestaande raamwerke en metodologieë wat daarop gemik is om die verhoudinge tussen prestasie elemente te identifiseer is ook ondersoek, en hul foute is geïdentifiseer. Die literatuurstudie word afgesluit met ’n ondersoek van HKA, PKK en seleksie kriteria. Die voorgestelde KITPV metodologie neem KVPS in diens as ’n fundamentele raamwerk. Akkurate en betroubare alternatiewe vir die K1 kriteria word vergelyk, en die mees geskikte van hierdie kriteria is opgeneem in hierdie KITPV.

’n Gevallestudie is onderneem, en die resultate van KITPV en KVPS is vergelyk met die hulp van werklike wêreld SP data van ’n oop-put, termiese steenkool myn in Suid-Afrika. Hierdie gevallestudie resultate staaf die verbetering aan die QRPMS metodologie. Hierdie studie sluit af met aanbevelings vir toekomstige navorsing wat geloots kan word.

Acknowledgements

This thesis would not have been completed without the aid, guidance and support of multiple individuals. I would like to express my sincerest gratitude and appreciation to the following people and organisations.

- To my supervisor, Dr JL Jooste of the Department of Industrial Engineering at the University of Stellenbosch, for his continuous and dedicated support, time and effort expended in this thesis.
- To my good friends, Patrick O'Connell, Luke Potgieter and Genevieve Potgieter, for their effort and time expended in the pursuit of editing this thesis.
- To my fellow Masters colleagues, and good friends, for making the office and Masters experience a positive and entertaining one.
- To my friends outside of the University of Stellenbosch for supporting and encouraging me through the last months of my thesis.
- To my family, especially my parents, for their unwavering support, encouragement, love and belief in me. Without their continuous motivation, this thesis would not have been completed.
- And finally, my Lord and Saviour, Jesus Christ, for providing me with all the countless blessings I needed to complete this thesis (Joshua 24:15).

The Author
September, 2015

Dedications

This thesis is dedicated to my grandfather, Louis J Botha Senior, who passed away on the 4 August, 2015. May you rest in peace, oupa. You will be sorely missed.

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Nomenclature

PCA variables

p	Number of original variables used in PCA.
n	Number of samples, or observations, of each original variable in PCA.
x_{p}	pth original variable assessed in PCA.
z_{p}	pth principal component, see Equation B.1.8 and Equation B.1.9.
$\mathbf{S}$	Covariance matrix used in PCA, see Equation B.1.1.
$\mathbf{U}$	Orthonormal matrix, see Equation B.1.3.
$\mathbf{L}$	Diagonal matrix, see Equation B.1.4.
$\mathbf{I}$	Identity matrix, see Equation B.1.5.
$\mathbf{u}_i$	ith eigenvector, see Equation B.1.6.
$\mathbf{FV}$	Feature vector, see Equation B.1.10 and Equation B.1.11.

PLS variables

m	Number of predictors variables.
n	Number of sample values or observations.
p	Number of observable variables.
$\mathbf{X}$	Matrix containing the predictor variables, see Equation B.2.1.
$\mathbf{Y}$	Matrix containing the observable variables, see Equation B.2.2.
$\mathbf{T}$	Projection matrix of $\mathbf{X}$, see Equation B.2.1.
$\mathbf{U}$	Projection matrix of $\mathbf{Y}$, see Equation B.2.2.
$\mathbf{P}$	Orthogonal loading matrix, see Equation B.2.1.
$\mathbf{Q}$	Orthogonal loading matrix, see Equation B.2.2.
$\mathbf{E}$	Matrix containing error terms, see Equation B.2.1.
$\mathbf{F}$	Matrix containing error terms, see Equation B.2.2.

KPI variables and units

BCM	Basic Cubic Meter	[m^3]
CV	Calorific Value	[C]
DOH	Direct Operating Hours	[hours]

ROM	Run of Mine	[tons]
TCM	Total Cubic Meters	[m^3]

Acronyms and Abbreviations

AHP	Analytical Hierarchy Process
AM	Asset Management
AMDM	Asset Management Decision-Making
AMS	Asset Management System
ANOVA	Analysis of Variance
BCM	Basic Cubic Meter
BDKPI	Business Driver Key Performance Indicator
BDKPIs	Business Driver Key Performance Indicators
BPR	Business Process Re-engineering
BSC	Balance Scorecard
BSI	British Standards Institute
CBDKPIs	Causal Business Driver Key Performance Indicators
CV	Calorific Value
DOH	Direct Operating Hours
EA	Equipment Availability
FA	Factor Analysis
FME	Total Monthly Employees
GFMAM	Global Forum on Maintenance and Asset Management
HPI	High Potential Incidents
IAM	Institute of Asset Management
ISO	International Organisation for Standardisation

K1	Guttman-Kaiser criterion
KPI	Key Performance Indicator
KPIs	Key Performance Indicators
LTI	Lost Time Injury
MAP	Minimum Average Partial
MANOVA	Multivariate Analysis of Variance
MAUT	Multi-Attribute Utility Theory
MCDA	Multi-Criteria Decision Analysis
PA	Parallel Analysis
PAM	Physical Asset Management
PAS 55	Publicly Available Specification 55
PC	principal component
PCs	principal components
PCA	Principal Component Analysis
PLS	Partial Least Squares
PM	Performance Measurement
PMa	Performance Management
PMaS	Performance Management System(s)
PMS	Performance Measurement System(s)
PMF	Performance Measurement Framework(s)
QIIPMR	Quantitative Identification of Inter-Performance Measure Relationships
QMPMS	Quantitative Model for Performance Measurement System
QRPMS	Quantitative Relationships at the Performance Measurement System
ROM	Run of Mine
SCM	Supply Chain Management

SEM	Structural Equation Model
SPSS	Statistical Package for the Social Sciences
TCM	Total Cubic Meters

Chapter 1

Introduction

Chapter Aims:

Chapter 1 aims to introduce the reader to this study's field of research, as well as the fundamental elements it is comprised of. This chapter formulates the research question and accompanying research objectives.

Chapter Outcomes:

⇒ Introduction to the research domain
⇒ Research problem statement
⇒ Research objectives
⇒ Study delimitations
⇒ Research design and methodology

1.1 Introduction

Recent years have proved to be a time of significant progress and development for Physical Asset Management (PAM), an Asset Management (AM) field specifically focused on the optimal management of physical assets. In 2004, a standard specification for PAM was developed through a collaboration between the institutes, British Standards Institute (BSI) and Institute of Asset Management (IAM). The standard was called the Publicly Available Specification 55 (PAS 55); this was the first standard published in support of PAM.

In 2008, PAS 55 was revised to reflect the growing international consensus for good practices in PAM. However, even after this review, PAS 55 provided guidelines on what should be done in PAM, but lacked details on how to complete such tasks (van den Honert *et al.*, 2013). In early 2014, the International Organisation for Standardisation (ISO) published the ISO 55000 series of standards; a family of international standards for PAM. van den Honert *et al.* (2013) assert that the ISO 55000 series uses the content and primary concepts of PAS 55 as its foundation with the intent of providing a more user-friendly and instructive standard for PAM.

The ISO 55000 series was complimented with an additional document from the Global Forum on Maintenance and Asset Management (GFMAM); a specification called the ISO 55001 Auditor/Assessor Specification. This specification aims to help organisations identify individuals who are able to help the organisation realise the value of PAM. In light of these publications, IAM (2014) published a document that provides an overview of PAM, defines its scope, and describes its fundamental concepts and philosophies. The conceptual model of PAM used by IAM (2014) is depicted in Figure 1.1.

IAM (2014) created this model to represent the global scope of PAM and its high-level groups of activities. As can be seen in Figure 1.1, a diverse collection of elements constitutes the working parts of PAM, each consisting of numerous sub-activities. This clear description of PAM allows researchers and organisations to better identify improvement opportunities in PAM. Of particular interest to this study is the high-level PAM activity: Asset Management Decision-Making.

IAM (2014) states a key contributing factor to effective and good PAM decision-making, is the provision and employment of appropriate information. Arguably the most common type of information involved in the management of physical assets is asset performance information; information that sheds light on how well a physical asset is performing and being utilised by an organisation. The activities enabling organisations to quantify and manage the

Figure 1.1: The scope of PAM

Adapted from IAM (2014)

effectiveness and efficiency of their actions and physical assets are Performance Measurement (PM) and Performance Management (PMa). These two activities employ Performance Measurement System(s) (PMS), which according to Amaratunga and Baldry (2002), are systems which monitor and maintain organisational control.

In order to quantify asset performance, PMS employ *performance measures*; measurements designed to provide specific information of a process, asset or entity for their effective management. Performance measures can provide a variety of information, from how well an objective is being accomplished by an organisation, to the impact a physical asset has on the profitability of an organisation (Chenhall and Langfield-Smith, 2007). The two prominent classifications of performance measures are financial and non-financial performance measures. Financial performance measures were the first to be developed, and emerged during the Industrial Revolution as a method of justifying (in financial terms) the massive financial investments made into physical assets during that time (Jooste and Page, 2004).

However, as the years passed, it became apparent to organisations that financial measures were inadequate to fully represent the performance characteristics that were important to financial success (Kaplan *et al.*, 1998; Neely, 1999). Organisations started employing non-financial performance measures to yield information on the performance characteristics that could not be represented in monetary terms, such as customer satisfaction, responsiveness, quality and flexibility (Kaplan and Norton, 1992; van Veen-Dirks, 2010). Although the limitations of financial measures were identified by numerous publications, including Ghalayini and Noble (1996), PM consultants still encourage their continued employment (Chenhall and Langfield-Smith, 2007). A mixture of financial and non-financial performance measures overcomes the limitations of employing a single class of performance measure (Stivers *et al.*, 1998; van Veen-Dirks, 2010).

There are hundreds, possibly thousands, of established performance measures which organisations can choose from. The effective employment and monitoring of all performance measures available to an organisation is not a feasible solution (Atkinson *et al.*, 1997). As a result, organisations choose specific performance measures; measures which they believe deliver information on the most critical performance elements or characteristics of the respective organisation. These specifically selected performance measures are referred to as Key Performance Indicators (KPIs). A Key Performance Indicator (KPI) is a quantifiable measure which represents an organisation's performance in achieving its strategic goals and objectives (Bauer, 2004*b*; Liu *et al.*, 2015).

Amongst the PAM improvement opportunities identified by researchers and organisations is the derivation of additional, meaningful information from the KPIs employed by an organisation, according to Ittner and Larcker (2003), Jagdev *et al.* (2004), Merchant (2006), and Harmon and Wolf (2008). This additional information can be found through investigating the relationships that exist between a set of KPIs (Rodríguez *et al.*, 2010). This information may thus prove useful to PAM and PM if the knowledge of these inter-KPI relationships are employed in decision-making processes.

The cause-effect relationships between the KPIs found in Supply Chain Management (SCM) were investigated by Cai *et al.* (2009). Cai *et al.* (2009) sought to utilise this source of additional information in order to prioritise KPIs for their iterative accomplishment. The difficulty of identifying these cause-effect relationships was acknowledged, but they also state that it is important for organisations to be able to describe the relationships between its KPIs for improved strategic and managerial decision-making.

To date, very little research has been conducted on the intricate relationships which exist between KPIs (Patel *et al.*, 2008). Audits revealed that inter-KPI relationships in a PMS are not adequately understood, and therefore improperly accounted for (Bititci *et al.*, 2001). The limited research however did not discourage the development of methodologies and frameworks, albeit few, which aim to uncover and employ the additional information of these inter-KPI relationships.

Suwignjo *et al.* (2000), Youngblood and Collins (2003), Bauer (2005), and Cardona Siado and García (2005) developed frameworks and methodologies employing the concept of relationships between performance elements to achieve their respective objectives. However, it was only the Quantitative Relationships at the Performance Measurement System (QRPMS) methodology, proposed by Rodriguez *et al.* (2009), which aimed to objectively identify and quantify relationships between a set of KPIs, and present these relationships as additional information for PM and PMa decision-making processes. Rodriguez *et al.* (2009) argued that subjective analytical techniques, as well as piece-wise correlation analysis, were inadequate to complete a truly objective and all-considering analysis of inter-KPI relationships. These analytical techniques were employed by the methodologies and frameworks developed by the aforementioned publications.

The QRPMS methodology is, to the knowledge of this study, the only available methodology that objectively identifies and quantifies inter-KPI relationships, as well as actively projects the collected information upstream of a PMS for improved decision-making processes (Rodriguez *et al.*, 2009). Considering this, and the aforementioned lack of research completed on inter-KPI relationships, it is evident that the QRPMS methodology is of critical importance to PM, and by relation, PAM. It is therefore imperative to investigate opportunities for its improvement or further development.

1.2 Problem Statement And Research Question

Rodriguez *et al.* (2009) assessed the frameworks and methodologies proposed by Suwignjo *et al.* (2000), Youngblood and Collins (2003), Bauer (2005), and Cardona Siado and García (2005). These frameworks and methodologies proposed methods of identifying and quantifying relationships between various performance elements. Rodriguez *et al.* (2009) found these to be inadequate for the objective identification and quantification of relationships between a set of KPIs due to the subjective analysis and pair-wise correlation analysis techniques they employed.

In response to the inadequacies identified in the aforementioned frameworks and methodologies, Rodriguez *et al.* (2009) proposed the Quantitative Relationships at the Performance Measurement System (QRPMS) methodology. QRPMS is a methodology which actively avoids the use of any subjective analytical and pair-wise correlation techniques. The QRPMS methodology employs two mathematical techniques to complete the objective identification and quantification of inter-KPI relationships. Principal Component Analysis (PCA) is employed to identify the relationships, and Partial Least Squares (PLS) analysis is utilized to quantify these relationships; two techniques that, according to Rodriguez *et al.* (2009), are completely objective analytical techniques due to the exclusion of biased interference. Further investigation of the constituents of the QRPMS methodology revealed a critical step in the final stages of PCA.

PCA is a multivariate statistical technique through which the important information found in a multivariate dataset can be reproduced, with minimal loss of information, by new and fewer variables called principal components (PCs). Tabachnick *et al.* (2001) describe principal components (PCs) as linear combinations of the original variables; linear combinations that are uncorrelated to each other. PCA computes a number of PCs that are equal to the total number of variables (KPIs, within this context) being assessed by PCA (Tabachnick *et al.*, 2001). The total information captured by all of the PCs is equal to the total information found in the aforementioned multivariate dataset (the set of KPIs). The critical step is thus how to select the appropriate number of PCs to retain for further analysis, whilst suffering minimum loss of information from the original dataset.

The selection of the appropriate number of PCs in PCA is carried out using rules or techniques referred to as selection criteria. The QRPMS methodology employs the Guttman-Kaiser criterion (K1), which has found to be a very popular selection criterion among researchers (Yeomans and Golder, 1982; Lance and Vandenberg, 2009). However, Yeomans and Golder (1982) and Lance and Vandenberg (2009) found K1 to be one of the least reliable and most inaccurate selection criteria available, with some publications using it without reservation. This claim is supported by Zwick and Velicer (1986), Velicer *et al.* (2000) and Cortina (2002), stating in unison that K1 can not be recommended for use in PCA and should be discarded from the list of acceptable selection criteria.

The problem is the employment of Guttman-Kaiser criterion (K1), in the QRPMS methodology, severely compromises the reliability and mathematical accuracy of the results obtained from QRPMS. Considering this, and the critical importance of the QRPMS methodology to PM and PAM as stated in Section 1.1, it is of utmost importance to seek a solution to the research question of this study; a question formulated from the aforementioned problem stated. The research question is stated as follows:

> *Can the Quantitative Relationships at the Performance Measurement System (*QRPMS*) methodology be modified and improved through the incorporation of a more accurate and reliable selection*

*criteria to ensure true and dependable information of the relationships between Key Performance Indicators (*KPIs*) is delivered?*

This study will aim to disprove the null hypothesis (H_0) derived from the research question stated above, which is specified in Table 1.1.

Table 1.1: Study null hypothesis (H_0)

H_0:	*The Quantitative Relationships at the Performance Measurement System (*QRPMS*) methodology cannot be improved and modified to yield more accurate and reliable results through the employment of an alternative selection criteria used in the execution of Principal Component Analysis (*PCA*).*

1.3 Research Objectives

This aim of this study is to answer the research question stated in Section 1.2. The answer is systematically developed through completing a sequence of research objectives. The research objectives of this study are listed in Table 1.2.

Table 1.2: Summary of research objectives

Chapter	*#*	*Research objective*
2	1.	Establish the fundamentals of PAM, PM, PMS and KPIs.
	2.	Investigate the academic literature of, and methodologies founded on, inter-KPI relationships.
	3.	Investigate the mathematical techniques employed by QRPMS to identify and quantify inter-KPI relationships.
3	4.	Describe the phases of QRPMS.
	5.	Compare and select an alternative selection criteria to the K1 criterion.
	6.	Develop an improved methodology founded on the QRPMS methodology.
4	7.	Determine the number of PCs to retain using the QRPMS methodology, and the methodology developed by this study.
	8.	Validate the developed methodology through a comparison and analysis of results.
5	9.	Draw conclusions from the results analysis.
	10.	Reject or do not reject the null hypothesis.

The first three research objectives listed in Table 1.2 entail the establishment of the fundamental key concepts upon which this study is founded, forming the research domain of this study. In Chapter 2, these objectives are achieved by completing a thorough literature study on specific literature topics. Clear and logical relationships between the literature topics are provided to improve the comprehension and accumulation of the required knowledge to complete the remaining research objectives.

In Chapter 3, the next three research objectives listed in Table 1.2 are completed. Although the QRPMS methodology is introduced in Chapter 2, Chapter 3 carries out the detailing of its executable phases. A comparison of alternative selection criteria is performed, resulting in the selection of an adequate alternative selection criteria. Finally, an improved methodology is developed for the objective identification and quantification of inter-KPI relationships.

In Chapter 4, the seventh and eighth research objectives of this study are completed by means of a case study. The case study employs data collected from a thermal coal mine located in South Africa. The seventh research objective entails the computation of the appropriate number of PCs to retain for further analysis using both QRPMS and the methodology developed in Chapter 3. The following research objective constitutes the validation of the new methodology developed in Chapter 3.

The remaining research objectives are completed in Chapter 5. Conclusions are drawn from the results in Chapter 4, determining the applicability and effectiveness of the developed methodology. These conclusions answer the research question stated in Section 1.2, allowing the stated null hypothesis to be either rejected or not.

1.4 Delimitation

Leedy and Ormrod (2005) state it is important to clarify the delimitations of a study prior to its presentation of research. Delimitations enable a study to better remain within the boundaries of its research scope. It also aids the reader in maintaining focus on what the study's aim is. The focus of this study is on developing an improved methodology for the objective identification and quantification of inter-KPI relationships. The following boundaries apply to this study:

- This study is bound to the field of PM and PMa, contributing to the ongoing research being conducted in the optimisation of the decision-making activity within the scope of PAM.

- This study is bound to the identification and quantification of relationships between KPIs only; it does not aim to assess relationships between other performance elements.
- This study focuses solely on the improvement of the QRPMS methodology through the identification and employment of more accurate, alternative selection criteria.
- The case study conducted will only employ KPI data from a single thermal coal mine in South Africa.
- The case study conducted will only focus on the validation of the alterations made to the QRPMS methodology. A complete execution of the QIIPMR methodology will not be carried out.

The above listed statements concludes the delimitations for this study.

1.5 Research Design And Methodology

The plan, or guide, of an intended research process is referred to as the research design. Creswell (2002) assert that the research design entails the overlapping and intersection of three elements: *specific research methods, philosophical world-views* and *strategies of enquiry*. These three elements and their interactions are depicted in Figure 1.2 and are detailed in Table 1.3.

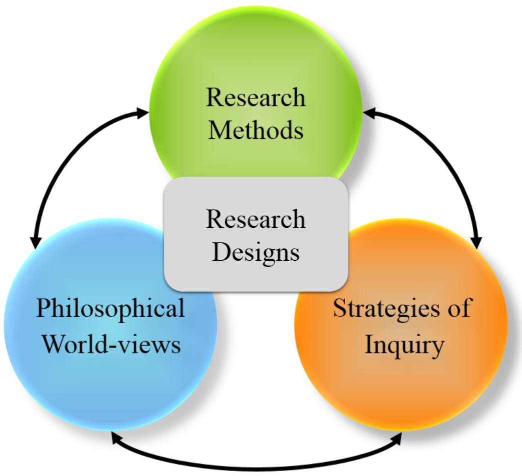


Figure 1.2: Research design framework

Adapted from Creswell (2002)

There exist three categories of research design: *qualitative, quantitative* and *mixed-methods* (Mouton, 2001; Edmonds and Kennedy, 2012). Qualitative and quantitative research are the two common distinctions between types

Table 1.3: Research design constituents

Constituents	*Description and content*
Research Designs:	Qualitative, quantitative or mixed methods.
	An overlapping of research methods, philosophical world-views and strategies of inquiry.
Research Methods:	Data collection and statistical-based analysis.
	Instrument-based questions and validation.
	Interpretation and write-up.
Philosophical World-views:	Post-positivism.
	Pragmatic.
	Social construct.
	Advocacy / participatory
Strategies of Inquiry:	Qualitative strategies.
	Quantitative strategies.
	Mixed-methods strategies.

of research. However, Newman and Benz (1998) and Baum (2012) state that it should not be viewed as two distinct classes of research, but rather two ends of a continuum. According to Newman and Benz (1998) and Mouton (2001), research either leans towards a more qualitative approach than quantitative, or vice versa. Furthermore, the mixed-methods category describes a research design that falls in between the other two categories.

The aforementioned qualitative approach to research, according to Creswell (2002), can be advantageous because of its exploratory nature. It allows many fields of research to be investigated and considered, while carrying out little, in-depth research in each field. Qualitative research includes the collection and assessment of *subjective data* generated from processes such as interviews and interpretations, and employs open-ended questions and subjective arguments (Creswell, 2002).

Quantitative research, however, involves the collection and assessment of *objective data* generated from methods or techniques that use mathematical principles or experimental procedures (Welman *et al.*, 2005). It employs close-ended questions or hypothesis and numerical and factual information. The mixed-methods approach to research design is therefore a study that involves the characteristics of both qualitative and quantitative approaches.

With regard to this study, the quantitative approach to research is employed due to the objective nature of the mathematical concepts investigated and the respective data delivered from each. Although multiple topics are investigated in this study, they are studied in-depth and follow a logical progression that leads to a comprehensive, objective answer to the research question stated in Section 1.2.

In addition to the clarification of which research design approach is to be followed by this study, Creswell (2002) states a philosophical world-view is adopted by the researcher, and must therefore be stated as well. The philosophical world-views are: *post-positivism*, *pragmatism*, *social constructivism* and *advocacy*, as first introduced in Table 1.3. These are fully detailed by Creswell (2002) and will thus not be repeated here.

The philosophical world-view of post-positivism best characterises the research completed in this study. Creswell (2002) states that research carried out in a post-positivism manner entails the sequential completion of the following elements: introductory theory, literature review, methodology development and a results assessment which refutes or does not refute the introductory theory.

The research design of this study therefore, in conclusion, employs a quantitative approach that is based on a post-positivism philosophical world-view. This research design is summarised in Table 1.4.

Table 1.4: Summary of present study's research design

Constituents	*Description and content*
Research Design:	Quantitative approach.
Research Methods:	Predetermined approaches, instrument-generated numerical data collection, statistical-based analysis and empirical validation.
Philosophical World-view:	Post-positivism.
Strategies of Inquiry:	Experimental and objective research including a case study.
Practices of research:	Employment of statistical procedures and unbiased approaches and the verification of theories.

1.6 Document Structure

This section describes the structural layout of this study; a structure specifically aligned with the research objectives listed in Table 1.2. Included in Section 1.3 is a brief discussion of the research objectives to be achieved by each chapter in this study. This discussion includes information, albeit incomplete, detailing the content of each chapter. A brief summary of each chapter's complete content is therefore provided in the following sections. Figure 1.3 depicts the chapter layout and the core topics of discussion.

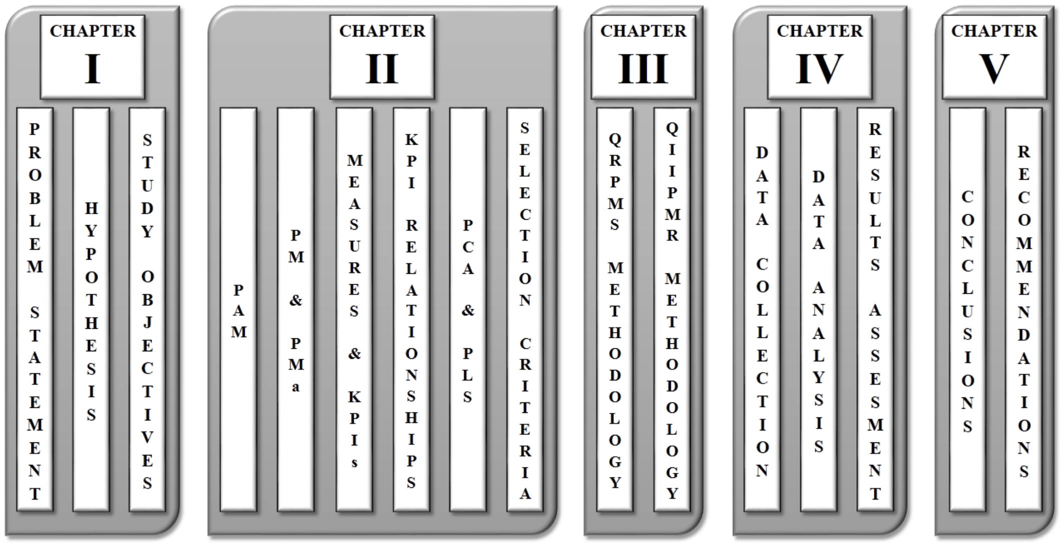


Figure 1.3: Document structure

The structural layout depicted by Figure 1.3 corresponds to the research methodology and design stated in Section 1.5. As a result, this structure allows the reader to follow and comprehend the laminated knowledge contained in each chapter.

Chapter 1: Introduction

Chapter 1 introduces the reader to the research undertaken in this study through a description of the research domain and core concepts of this study. A problem statement is presented which is translated piecewise into research objectives. Following the progression of the research objectives, the delimitations of this study can be defined, allowing a research design and methodology to be developed. A description of the study structure is finally provided as a conclusion to this chapter.

Chapter 2: Literature Study

Chapter 2 begins the logical progression for finding an answer to the research question stated in Section 1.2 by first describing the PAM landscape.

Stemming from this landscape, the literature review covers the concepts of PM, PMa, PMS, KPIs and inter-KPI relationships. Existing frameworks and methodologies that employ the concept of inter-KPI relationships are investigated, as well as the mathematical techniques and rules employed. Through the investigation of these topics and concepts, the chapter collates the necessary information for the development of the methodology in Chapter 3.

Chapter 3: The Quantitative Identification of Inter-Performance Measure Relationships Methodology

Chapter 3 develops an improved methodology for the objective identification and quantification of relationships between a set of KPIs. This methodology, called the Quantitative Identification of Inter-Performance Measure Relationships (QIIPMR) methodology, is this study's proposed solution to the problem stated in Section 1.2. The QIIPMR methodology is discussed and all of its constituents are detailed.

Chapter 4: Case Study

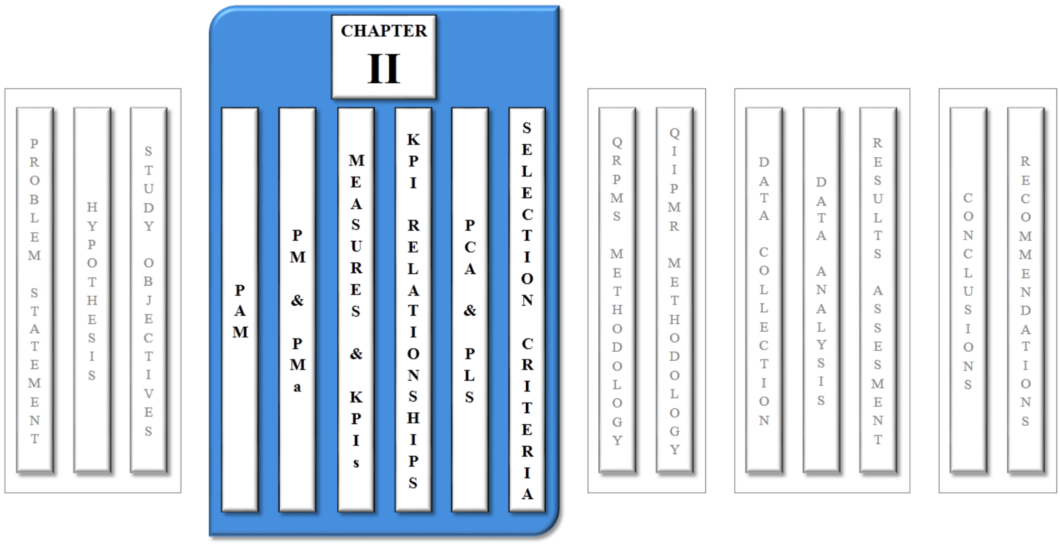
The QIIPMR methodology (which is developed in Chapter 3) is validated as the solution methodology to a real world problem. The deliverables of the QIIPMR methodology are compared to those of its predecessor, the QRPMS methodology. A comparison study is completed and an assessment of the results presented. The validation of the QIIPMR methodology results are provided as the conclusion to this chapter.

Chapter 5: Conclusion and Recommendations

A reflection of the research is presented in Chapter 5, along with a discussion of the limitations of the study. Final conclusions are formulated which provide an answer to the research question presented in Section 1.2. In addition, the null hypothesis is tested and either rejected or not rejected. Chapter 5 concludes the study by providing recommendations and opportunities for future research.

Chapter 2

Literature Study



Chapter Aims:

This chapter aims to introduce and investigate the primary research topics of this study, as well as their accompanying peripherals, in a logical sequence to aid in the conceptualisation and comprehension of this study's research question. The information gathered through this research is intended to facilitate the laminated development of the knowledge required to answer to the aforementioned research question.

Chapter Outcomes:

⇒ Familiarisation with, and understanding of, the topics relevant to this study.

⇒ Comprehension of the links between the fundamental research topics.

⇒ Comprehension of the elements which constitutes the research question.

2.1 Chapter Introduction

The literature topics required to conceptualise the research question stated in Section 1.2 are described and investigated in this chapter. The aforementioned literature topics are introduced in a sequential manner with relationships linking the topics. This flow pattern is depicted in Figure 2.1.

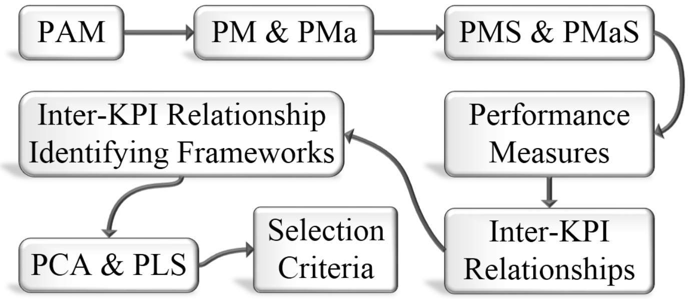


Figure 2.1: The flow between the investigated literature topics in Chapter 2

The concept of Physical Asset Management (PAM) is first introduced, describing it with respect to the common concept of Asset Management (AM). A brief overview of the international standards for PAM is provided, establishing the link between PAM and the fields of Performance Measurement (PM) and Performance Management (PMa). Following this is the introduction and description of PM and PMa. Upon completion, the respective systems employed by PM and PMa, Performance Measurement System(s) (PMS) and Performance Management System(s) (PMaS), are investigated as well as the elements employed by these systems, performance measures and Key Performance Indicators (KPIs).

The Quantitative Relationships at the Performance Measurement System (QRPMS) is the methodology on which this study aims to improve. Phase 1 of the QRPMS methodology requires the basic knowledge of how to design and implement, or adopt, a PMS. Therefore, the discussion of PMS and PMaS is orientated at a general overview of PMS development and includes relevant sources for more, in-depth guidance. Furthermore, performance measures and KPIs are also discussed in a manner similar to that of PMS and PMaS, facilitating the inclusion of recommendations and discussions of their problems, as well as the challenges met in their development and implementation. It is for this reason why Section 2.3 and Section 2.4 contributes to the majority of the literature in this chapter.

Following the discussion of PMS and KPIs, an investigation is carried out regarding frameworks which aim to identify relationships between performance elements. Following the guidance of Rodriguez *et al.* (2009), existing frameworks are introduced and their individual inadequacies are briefly discussed with respect to the assessment techniques they employ. The aforementioned QRPMS methodology is among these frameworks, and is singled out and described in more detail. The mathematical procedures employed by the QRPMS methodology, Principal Component Analysis (PCA) and Partial Least Squares (PLS) analysis, are briefly described. This description leads to the origin of the research question stated in Section 1.2.

The crux of the research problem this study aims to address constitutes the last topic discussed in this chapter. The selection criteria chosen by the QRPMS methodology for employment in PCA, the Guttman-Kaiser criterion (K1), is discussed. Multiple literature sources are consulted for the criterion analysis, and multiple alternative selection criteria to K1 are investigated; a task which concludes the literature review of this study.

2.2 Physical Asset Management: A Brief Discussion

Asset Management (AM) is a widely practised term in multiple industries. There are many adjectives to the term *asset management*, such as Strategy Asset Management, Integrated Asset Management and Enterprise Asset Management (IAM, 2014). Due to the synonymic use of AM, some ambiguous terminology joins it. Therefore, it is necessary to explain which understanding of AM this thesis will be built upon to avoid confusion between the other available terminologies.

The following section introduces the basic concept of AM with regard to the assets dealt with. Building on this concept, the specific understanding of AM which this thesis is based on, Physical Asset Management (PAM), is explained and defined. In conclusion, this section provides a discussion of PAM in sufficient depth to link PAM with the other topics introduced and investigated in this literature study.

2.2.1 Introducing Physical Asset Management

Arguably the most popular understanding of the term *asset management* would be the management of either financial or real estate investment portfolios. But apart from the financial and real estate industries, the term *asset management* is also used in the corporate management and information technology industries, amongst others (Woodhouse, 2006; Mitchell *et al.*, 2007).

AM has different definitions due to the various understandings of it; some of which are provided, with their respective supporting literature, by Mitchell *et al.* (2007), Hastings (2009) and Schneider *et al.* (2006). Although these definitions share similarities, it is best to first define AM in a broad and unspecific manner. Tywoniak *et al.* (2008) provides such a definition:

> *"Asset Management is the process or cycle in which assets are "put through" in order to create a product or provide a service at optimum level."* - (Tywoniak *et al.*, 2008)

AM generally refers to the actions taken by organisations to monitor and maintain their assets, ensuring that overall, value is created for the organisation and not destroyed. The type of asset dealt with in each industry is at the core of the respective industry's understanding of AM, and thus plays a critical role in their definition of AM. In the financial industries, the most common definitions of assets are fixed assets and current assets.

A fixed asset is defined as a physical item which retains value for a time period greater than one year (machinery and property), whereas current assets (inventory and cash) are assets that are to be turned into cash within a year (Hastings, 2009). It is more convenient, however, to define assets as either *intangible* assets or *tangible* assets.

AM may be applied to intangible assets, such as data, cash and intellectual property, and tangible assets, such as machinery, buildings and inventory. Inclusive to other industry specific contexts, AM has been increasingly used to describe the comprehensive management of tangible, or rather, physical assets, over their entire life cycle. Physical Asset Management (PAM) is based on this understanding of AM, which is more accurately defined by PAS (2008) as:

> *"(the) systematic and coordinated activities and practices through which an organisation optimally and sustainably manages its assets and asset systems, their associated performance, risks and expenditures over their life cycles for the purpose of achieving its organisational strategic plan..."* - (PAS, 2008)

where an organisational strategic plan is also defined by PAS (2008) as:

> *"(the) overall long-term plan for the organisation that is derived from, and embodies, its vision, mission, values, business policies, stakeholder requirements, objectives and management of its risks."* - (PAS, 2008)

A decision was made to use the above definition of AM for this thesis, and from henceforth to consistently use the term PAM when referring to AM to mitigate confusion between all its possible adjectives. PAM is, as mentioned above, the management of physical assets. Its primary objective is to increase the value of, and return from, physical assets over their life cycles (Mitchell *et al.*, 2007). More specifically, PAM focuses on the physical assets of an organisation that generates income within the different organisational silos.

PAM, however, accomplishes more than just its primary objective. PAM also incorporates the organisation's strategic plans and objectives into the acquisition, operation, management and decommissioning processes of physical assets in order to achieve the organisation's said plans and objectives. IAM (2014) provides the following characteristics of good PAM:

- Multi-disciplinary: PAM creates or increases asset *value* by crossing disciplinary or departmental boundaries.
- Systematic: employs an effective management system for consistent and sustainable application.
- Systems-orientated: views assets in their respective system environment to realise value.
- Risk-based: decision-making includes risk and liability consideration.
- Optimal: best compromise between conflicting objectives for the short- and long-term.
- Sustainable: strive for the optimal asset value delivery over the complete asset life-cycle.
- Integrated: PAM requires to be linked up with other components to operate effectively.

The above shows PAM to be an important and integral part of an organisation; successful PAM is a pillar of organisational success, rather than just good maintenance (Mitchell *et al.*, 2007). This is arguably the most innovative contribution of a PAM framework to an organisation.

Some organisations still view PAM as identical to maintenance, not realising the organisational benefits that it offers. PAM was not well defined in the past, as Hastings (2009) notes. This can be partially attributed to the lack of cross-functional integration between the disciplines encompassing PAM, and the difficulties involved in systems integration. Hastings (2009) states this "undefined era" of PAM may be one of the reasons why PAM was, and still is, equated to maintenance by some. Frolov *et al.* (2010) suggest this is changing; the recognition of PAM and its importance is increasing rapidly world wide.

With the growing acknowledgement of PAM internationally, a need from industry for a standard in PAM originated; a guideline to effectively construct and employ a PAM framework that will incorporate all the necessary organisational facets to meet the aforementioned PAM objectives. From this need, the Publicly Available Specification 55 (PAS 55) and the ISO 55000 series of standards were born.

2.2.2 PAM Standards

The British Standards Institute (BSI) and Institute of Asset Management (IAM), with the help of other multiple assisting organisations, published an international standard for the improved management of physical assets in 2004; a standard specification for PAM, called the PAS 55. It originated from the industry's request for an internationally accepted framework outlining good PAM practises. This standard is especially applicable to any organisation whose strategic plan's success is dependent on the organisation's physical assets.

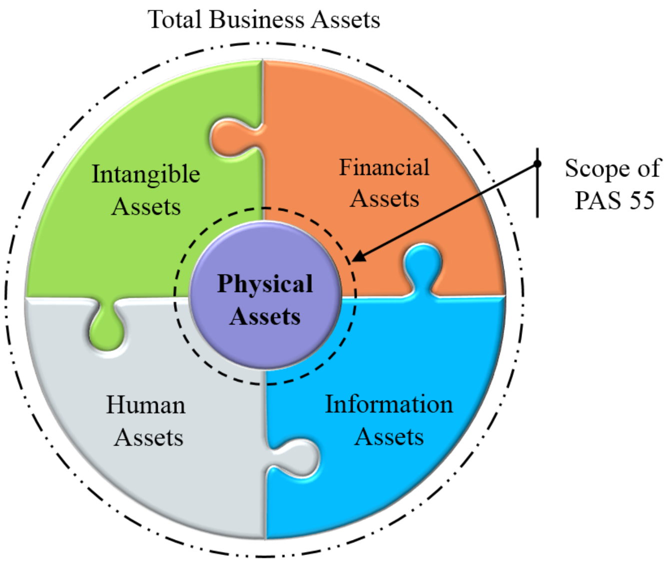


Figure 2.2: The asset scope of PAS 55

Adapted from PAS (2008)

Within a few short years since its introduction to industry, PAS 55 was revised to mirror the growing international consensus for required good practices in PAM. Even though the revision of PAS 55 only took place four years after its introduction, van den Honert *et al.* (2013) report that PAS 55 has been successfully implemented by organisations during its entire period of employment by industry. PAS 55 defines five asset classes, which if successfully incorporated into PAM according to the PAS 55 framework, would completely align an organisation's PAM with its strategic plan (PAS, 2008). These five asset classes are *human assets, information assets, financial assets, intangible* *assets* and *physical assets*. The asset scope of PAS 55 is depicted in Figure 2.2.

Although PAS 55 and PAM are primarily focused on physical assets, PAS (2008) acknowledges that the management of physical assets are coupled to the other four asset classes depicted in Figure 2.2. PAS 55 considers these asset classes when they have a direct impact on the optimised management of the physical assets (PAS, 2008). It is important to note that even though PAS 55 does not directly address human factors such as motivation and leadership, they play a crucial role in successful and sustainable PAM. It is for this reason why human assets are considered in the PAS 55 framework.

In addition to the aforementioned, Woodhouse (2006) states that PAS 55 encourages change from within the organisation through implementing a bottom up approach. This is specifically the case with individual activities regarding cost, risk and performance evaluation. According to Hastings (2009), PAS 55 can provide:

- Effective relationships between top management, asset management, asset maintenance, and cross-functional communications.
- Improvements in asset management organisations.
- Safety and regulatory benefits.
- Improvements in training and development.

PAS 55 provides a flexible, yet robust, PAM framework that encourages a continuous improvement attitude (Botha and Vlok, 2014). However, PAS 55 lacks details according to van den Honert *et al.* (2013); it provides guidelines on what needs to be done, but does not address how it should be done.

In January 2014, the International Organisation for Standardisation (ISO) produced the ISO 55000 series; a family of international standards for PAM. The ISO 55000 series bases its content on the primary concepts of PAS 55, and aims to make this PAM standard more applicable and user friendly than PAS 55 (van den Honert *et al.*, 2013). Furthermore, ISO 55000 is aligned with other major ISO management specifications, such as the ISO 14001 and ISO 9001 standards, improving the benefit of its employment.

The ISO 14001 standard deals with the multiple aspects of environmental management, and the alignment of this standard and ISO 55000 is crucial as an important overlap between these two standards; the decommissioning of physical assets in an environmentally friendly manner. In addition, the ISO 9001 standard addresses quality management through specifying the requirements of a quality management system and, similarly with ISO 14001, there exists overlapping components between ISO 9001 and ISO 55000.

Despite this newly developed PAM standard, van den Honert *et al.* (2013) state it is not without flaws. The ISO 55000 series does indeed better describe how tasks are to be completed when compared to the PAS 55, but fails to provide detailed guidelines on what should be done as PAS 55 does (van den Honert *et al.*, 2013). IAM (2014) also claims the ISO 55000 series does not direct an organisation as to *how well* it needs to perform PAM.

However, organisations can find relief in the continued work being completed to rectify and improve the ISO 55000 series. Within a couple of weeks of its publication, the ISO 55000 series was complimented with a specification called the ISO 55001 Auditor/Assessor Specification. This specification aims to help organisations identify individuals who are able to help the organisation realise the value of PAM, and is an example of the continued improvement work being completed.

2.2.3 The Link Between PAM And PM

In light of the PAM standards listed in Section 2.2.2, the Institute of Asset Management (IAM) saw it fit to produce IAM (2014); a document that provides an overview of PAM, defining the scope of PAM and describing its fundamental concepts and philosophies. IAM (2014) proposes a conceptual model of PAM which, according to IAM, is created to represent the global scope of PAM and its high-level groups of activities. This model is depicted in Figure 2.3, and as can be seen, a diverse collection of elements constitute the working parts of PAM.

Amongst the high-level activities depicted in Figure 2.3 is Asset Management Decision-Making (AMDM). This activity involves the making of decisions regarding issues such as capital investment, operations and maintenance, optimised maintenance and life cycle value realisation (IAM, 2014). It is a process of finding the optimum compromise or balance between competing factors such as capital expenditure versus asset operating costs, asset utilisation versus asset care, and so forth (IAM, 2014).

IAM (2014) notes that, when making the aforementioned decisions, it is necessary to consider the multitude of PAM elements and drivers affected. The full range of an asset's impact throughout its life-cycle should be considered in the formulation of the organisation's asset management strategy; a strategy through which asset performance is translated to stakeholder satisfaction. This process is depicted in Figure 2.4.

Figure 2.3: The IAM conceptual model of PAM

Adapted from IAM (2014)

This suggests then that the activity of AMDM is more than just finding the optimum compromise between factors inherent with an asset's life-cycle. It plays a critical role in the success of an organisation as a result of good PAM (IAM, 2014). AMDM is at the heart of a system used for PAM direction and control; a system which IAM (2014) refers to as an Asset Management System (AMS) and PAS (2008) defines as:

> *"An Asset Management System is an organisation's physical asset management policy, physical asset management strategy, physical asset management objectives, physical asset management plan(s) and the activities, processes and organisational structures necessary for their development, implementation and continual improvement."* - (PAS, 2008)

The improvement of AMDM will thus possibly have a positive affect on the overall success of an AMS, and indeed the success of an organisation. As can be seen in Figure 2.3, AMDM employs deliverables from the *Asset Information* element; an element which IAM (2014) states is key to making good PAM decisions. This then suggests that the improvement of Asset Information will improve the decision-making capability of an organisation with regard to PAM, leading the literature review to investigate the realm of Performance Measurement (PM) and Performance Management (PMa).

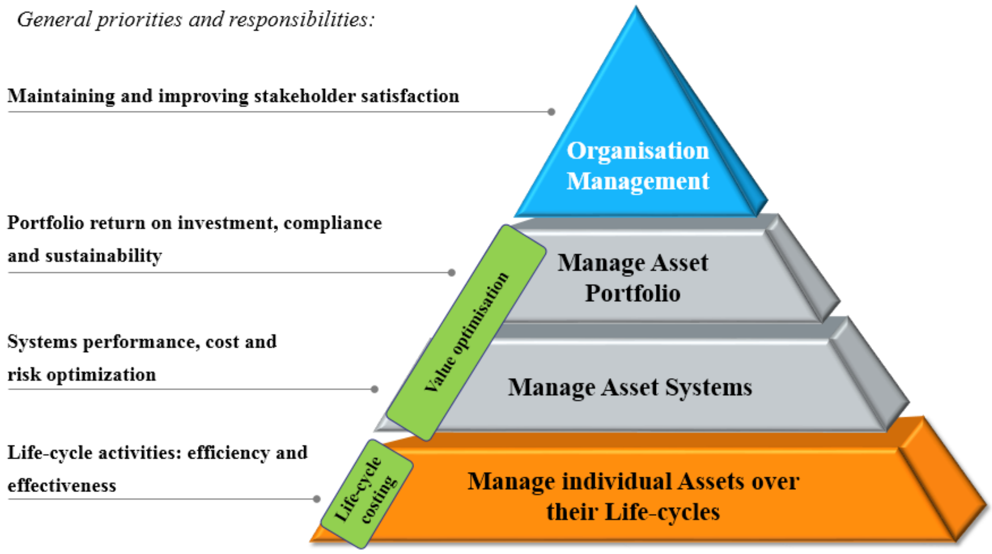


Figure 2.4: The asset hierarchy within an integrated management system

Adapted from IAM (2014)

2.3 Performance Measurement and Management

> *"Measurement is complex, frustrating, difficult, challenging, important, abused and misused."* - (Sink, 1991)

The above quote adequately describes the attitude *measurement* is often approached with. However complex and challenging it is, measurement is still a critical part of many industries today (Cai *et al.*, 2009). The perception of what measurement is, differs from individual to individual, and from organisation to organisation. This increases the difficulty of defining measurement in universal terms.

In addition, people's and organisations' perceptions and understandings of *performance* varies arguably more than that of measurement. According to Otley (1999), *performance* itself is an equivocal term, incapable of being defined simply. Thus, this literature review aims to answer the following question: how do we define measurement and performance in this study to ultimately describe Performance Measurement (PM) and Performance Management (PMa)?

Neely *et al.* (1995) describe PM as the process of quantifying the effectiveness and efficiency of an action, and that a performance measure is the metric used to complete the quantification. However, on a grander scale, Amaratunga and Baldry (2002) write that measurement allows an organisation to assess how well it progresses in achieving its organisational objectives and milestones.

Measurement helps identify areas of strength and weakness, and aids in improving organisational performance. Measurement is not a means to an end in itself, but a critical tool for effective and efficient management, according to Amaratunga and Baldry (2002). For an organisation to effectively use its performance measurement deliverables, it must make the conversion from PM to PMa (Amaratunga and Baldry, 2002).

This section provides a short historic overview of the evolution of PM within organisations. This is followed by a discussion on measurement and performance that will answer the aforementioned question. In conclusion, a brief description of current PM and PMa literature is presented, leading to the introduction of the systems belonging to each.

2.3.1 The Origin Of Performance Measurement

PM originated at the same time performance started to play an important role in industry. Jooste and Page (2004) observed that performance entered the playing field during the 1800's because of the industrial revolution. There were a few different phases of manufacturing ideologies that led to the development of PM and performance measures as they are known today. These phases, Rolstadås (1995) writes, followed the industrial revolution era that occurred between the 1700's and 1800's, and are depicted in Figure 2.5.

The first phase was the English System of Manufacture, and occurred from roughly 1800 to 1850. It was concerned with the perfect manufacture of a single part, one at a time, indicating the quality of craftsmanship (Rolstadås, 1995). The second phase, the American System of Manufacture, saw a complete change in manufacturing philosophy. From 1850 till 1900, perfect manufacture was replaced with the robust manufacture. The focus was placed on manufacturing differing components in a robust manner, without any compromise the end product's capability to operate properly. These two phases comprised the era of craftsmanship (Jooste and Page, 2004).

The Industrial Productivity era followed, and its introduction was as a result of work completed by individuals such as Frederick W. Taylor (Jooste and Page, 2004). Maier (1970) writes that Taylor popularised a new perspective on manufacturing, called Taylorism or the Taylor System. This system was built on apparent scientific studies of employee efficiency and reward systems. Jooste and Page (2004) suggest this was the turning point between the era of craftsmanship and the era of industrial productivity. Machine utilisation and employee efficiency became forever linked to industrial productivity henceforth

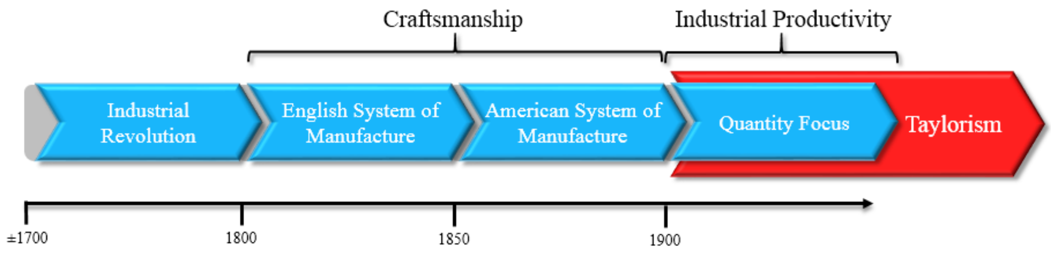


Figure 2.5: The development towards total Performance Measurement (PM): Part 1

Adapted from Jooste and Page (2004)

(Jooste and Page, 2004).

The industrial revolution was an era that saw massive investments being made into factory and machine installations. The performance of these investments had to be evaluated to justify their financial investment, thus the large scale adoption of performance measures took place. Due to the well-implemented accounting systems available at that time, it was a logical place to look for means of measuring performance in financial terms for evaluating purposes. It also provided a rudimentary means of managing performance based on the influence it had on the financial bottom-line. Rolstadås (1995) provides additional information regarding the early methods of productivity. Section 2.4 provides more information on performance measures.

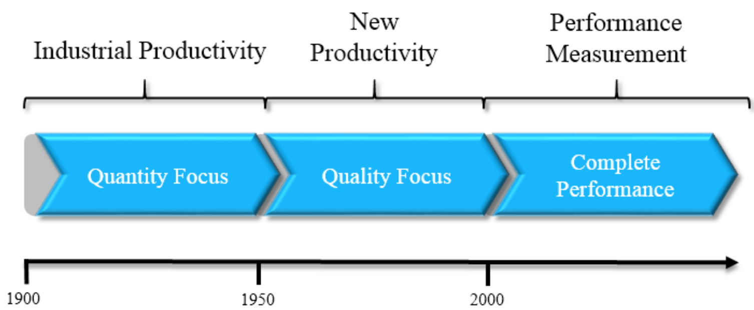


Figure 2.6: The development towards total Performance Measurement (PM): Part 2

Adapted from Jooste and Page (2004)

Figure 2.6 depicts the progression from productivity focused industry to that of complete performance focus; the era of PM. The 20th century saw the world being plunged into two conflicts of unimaginable grandeur. Many countries involved in the two World Wars suffered heavy damages to their industrial capabilities and took many years to rebuild their industrial capacities. Skilled labourers and materials were scarce, which in turn created the atmosphere for innovation (Moore, 2011).

The production philosophies that emerged from this transition between eras, such as Just-in-Time manufacturing and the Japanese developed Kaizen, showed organisations the impact of factors, such as quality and customer satisfaction, on their financial performance. In combination with increasing competition world wide, this led to the issue of what performance characteristics are important for financial success, and how are they to be managed and measured. As Rolstadås (1995) writes, productivity is merely one of multiple characteristics or facets of an organisation that must be measured and improved upon.

2.3.2 Performance Measurement

In recent years, the means and methods of measuring performance has become an important topic of research for both organisations and academics (Folan and Browne, 2005). A large multitude of articles have been published on PM in the late nineties, with Neely (1999) reporting an upward of 3500 articles being published during 1994, 1995 and 1996. With such a vast scholarship available on PM, it would be easy for one to assume that the field of PM has been defined clearly, and that all its characteristics have been clearly linked. However, this is not the case.

Neely *et al.* (1995) and Folan and Browne (2005) write that disparity exists among published information on PM as it was generated by various researchers in different organisational and functional silos. Further complications exist regarding the PM literature, according to Folan and Browne (2005). They state that PM is not owned by academics in any discipline, and this resulted in the traditional functional boundaries being left behind when research on PM was carried out. This, Folan and Browne (2005) say, resulted in PM information being produced in isolation and created the possibility of the information being duplicated, or worse, being contradictory in character.

Even though the aforementioned does plague research being conducted into PM, Bititci *et al.* (2000) identified characteristics that are deemed necessary of PM; they are:

- Sensitivity to an organisation's external and internal environmental changes.
- Initiate the review and re-prioritising of internal objectives when said environmental changes are serious enough.

- Ensuring constant organisational alignment when changes are made to internal objectives and priorities by initiating corrective change to the critical organisational parts.
- Maintaining progress achieved through improvement programmes.

PM is constantly changing and growing to meet the requirements of organisations' new realities according to Folan and Browne (2005). Because of this, the concept of *performance*, and how it is measured and assessed, is continuously in metamorphosis. This, therefore, suggests a suitable starting point for this study in understanding PM and PMa. An adequate understanding of the concept *performance* with respect to this field is deemed necessary. As Lebas (1995) writes, when managers speak of PM and PMa, it raises the question "what is performance?".

2.3.2.1 Understanding and defining performance

The term performance is found often in management and engineering literature. Although there exists similarities between the *performance* perceptions from the management and engineering sectors, there are differences that make it difficult for the majority of people to agree what *performance* actually means. As Lebas (1995) explains, *performance* can mean various things; from efficiency or return on investment, to robustness or resistance.

The following discussion aims to define *performance*, following the guidance of Lebas (1995) and a path similar to the one taken by Otley (1999). In order to achieve the aforementioned, it is necessary to first discuss *measurement*; understanding why we want to measure, and what is to be measured, will better our understanding of *performance*. This sections refers to performance measures in its discussion, a topic which is discussed in Section 2.4.

Why and what to measure

The quote below provides a convenient and detailed description of *measurement* as it is thought of in the context of PM and PMa.

> *"measuring means transforming a complex reality into a sequence of limited symbols that can be communicated and that can be, more or less, reproduced under similar circumstances."* - (Lebas, 1995)

From that definition, a hidden complexity is notable with regards to *measuring*. In general, a measure must capture enough information about what is being measured. However, more importantly, an adequate understanding of the "complex reality" is mandatory for the measure to at least capture the significant core information, increasing the value of the captured data. However, this does not guarantee that the data can be reproduced under similar circumstances (Lebas, 1995; Otley, 1999).

This suggests that a deeper understanding of the measure must exist; what is expected from it and what exactly is being measured. Measuring and its "unseen" characteristics, therefore, needs to be investigated briefly with regard to PM and PMa. According to Lebas (1995), there are two key questions that managers and performance evaluators must ask themselves concerning measuring. These two questions are:

1. Why do we want to measure?

2. What do we want to measure?

Lebas (1995) comments on both of these questions. With the first question, he states that measures are not defined outside of the organisation. They are the result of choices made inside the organisation, with a purpose in mind, which has motivation as a driving factor. Adequately understanding the motivation behind the need and desire to measure allows an organisation to better understand what information a measure needs to capture.

Regarding the second question, Lebas (1995) says the purpose of the measure is insufficient to define what is to be measured to capture the desired data, and that these two questions go hand-in-hand. They follow a logical progression, and they are difficult to answer. In addition, they will always yield unique answers depending on who formulates the answers.

The importance of the causal model in defining performance

Lebas (1995) believes that in order to establish the conditions of PM and PMa, organisations must first understand what causes performance, regardless of how it is defined. Furthermore, the concepts of performance, and indeed the corresponding causal models, must be mutually understood among all stakeholders or involved partners to add to business success.

Considering the accounting view of performance, it may be viewed as constrained to the general view of net profit (the difference between sales and cost). However, Lebas (1995) notes, sales themselves are generated and influenced by performance factors such as customer satisfaction, quality and cost. In continuation, costs are the result of these performance factors being created (Lebas, 1995).

There are different levels of performance factors, or performance affected units. Sales figures, for instance, are the result of performance factors such as

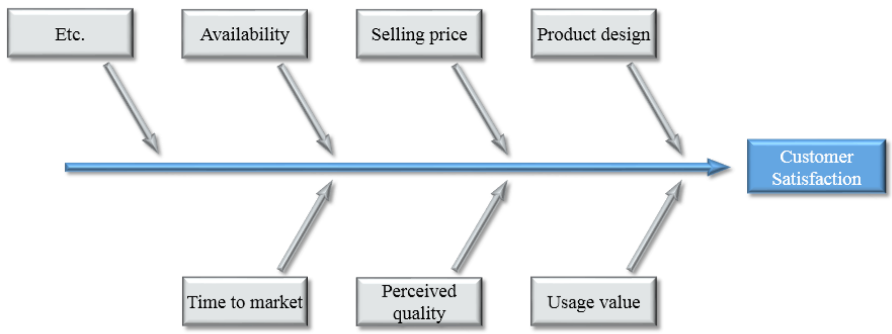


Figure 2.7: Customer satisfaction with influencing performance factors

customer satisfaction. However, customer satisfaction is also influenced by its own performance factors. Consider the simple example of a causal model as shown in Figure 2.7.

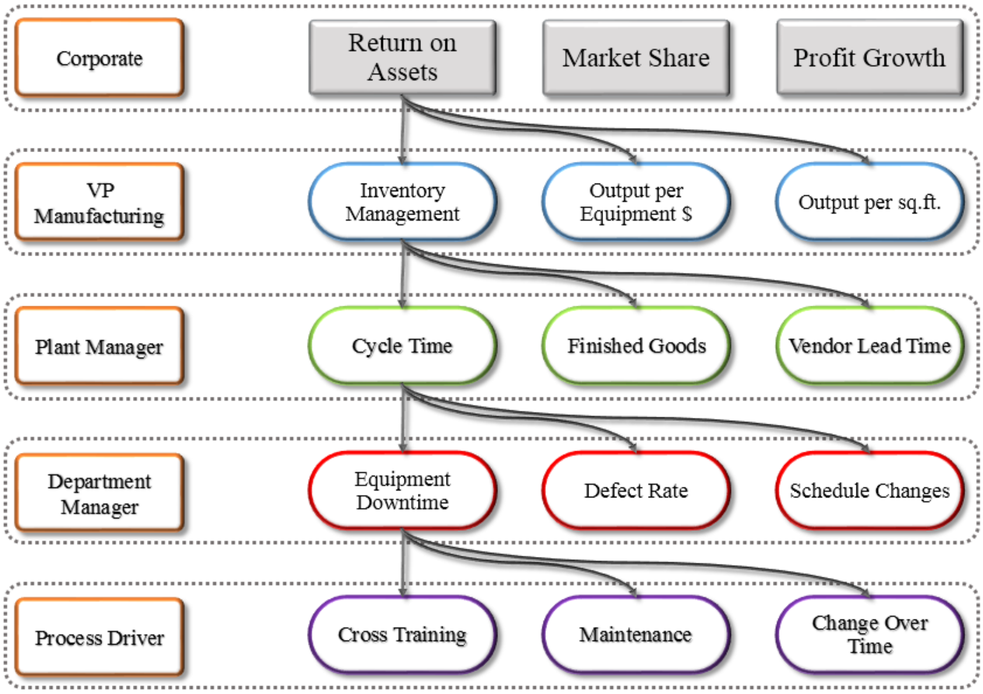


Figure 2.8: Performance causal model over multiple organisational levels of responsibility

Adapted from Beischel and Smith (1991)

Lebas (1995) states that the only way to define the measures that lead to action, is through understanding the underlying performance processes. Understanding the steps that comprise these processes will allow an organisation to identify inadequacies and corrective actions. Lebas (1995) warns that if performance is viewed in the most aggregated way, specifically net profit, the lack of detail allows no corrective actions to be identified.

Comprehending the performance generation process, according to Lebas (1995), promotes the recognition of adequate measures and corrective actions, allowing strategy to be deployed at all the respective levels of responsibility in the organisation. Figure 2.8 depicts a simple causal model example taking multiple responsibility levels of an organisation into consideration.

In the example shown in Figure 2.8, performance is defined by three parameters on the corporate level: return on assets, market share and profit growth. This example shows that each of the corporate level parameters are comprised of more descriptive measures at various levels of responsibility found in an organisation. Beischel and Smith (1991) state that if each of the three measures at each level of responsibility are properly managed, it will guarantee that the measure on the corresponding, higher level will be properly managed as well.

Only at this point, Lebas (1995) believes, the definition of *performance* is adequately understood. The definition of *performance* is completed in the following section.

Defining performance

Lebas (1995) defines performance:

> *"Performance is about deploying and managing well the components of the causal model(s) that lead to the timely attainment of stated objectives within constraints specific to the firm and to the situation."* - (Lebas, 1995)

To reiterate, performance is case and decision-maker specific. After following the research and logic proposed by Lebas (1995), this study considers the proposed definition of *performance* to be an adequate, context-applicable definition. This definition serves the desired purpose of this study, as it includes the causal model which inherently considers performance measures found on various organisational levels and in various organisational departments. However, understanding what performance means does not equate to an effective PM and PMa. To do this, implemented systems are required.

2.3.3 Performance Measurement Frameworks And Systems

In current literature, reference is made to traditional and modern PMS and to how these two types of systems differ, which is of some indirect importance to this study. This difference lies in the types of measures used by each. A traditional PMS employs financial measures, and a modern system employs both financial and non-financial measures. Performance measures are introduced and described in Section 2.4.

Even though the aforementioned difference is a simple one, it has a great impact on the effectiveness and influence of a PMS on the organisation as a whole. Before describing how a PMS operates, an understanding of the progression that lead up to its development is required. Folan and Browne (2005) provides a systematic process of the development of Performance Measurement Framework(s) (PMF) and PMS, a process which will be followed in the following sections.

2.3.3.1 Performance Measurement recommendations

Folan and Browne (2005) use the term performance measurement recommendations to refer to the 'initial building blocks' of both PMF or PMS. These recommendations are defined by Folan and Browne (2005) as pieces of advice regarding performance measurement and characteristics, and with in an accumulated form, may be used as a basis for developing PMF and PMS.

Performance measurement recommendations can be split into two fundamental groups: performance measure recommendations, and both PMF and PMS design recommendations. A brief description of the two groups is provided by Folan and Browne (2005), saying that the first group mainly consists of recommendations for good performance measures, and the second investigates the recommendations regarding PMF and PMS design.

The aim of this study is to introduce the reader to the concept of performance measurement recommendations as it contributes to the description of how PMF and PMS originated. It is not the aim of this study, however, to cover the actual recommendations for PMF and PMS design. Refer to Folan and Browne (2005) for more information regarding PMF and PMS design.

2.3.3.2 Performance Measurement Frameworks

The largest impact on performance measurement literature, according to Folan and Browne (2005), was made by the study of PMF. Since the late eighties, a multitude of different PMF were developed with varying complexities. Folan and Browne (2005) state that the variability among these PMF can be attributed to the sets of performance measurement recommendations used to design each; a set can lead to the design of a structural framework, or procedural framework.

In order to separate the concept of PMF from that of PMS, it is necessary to define a PMF with respect to the components it is made of; performance measurement recommendations. Rouse and Putterill (2003) provide such a definition, and is summarised by Folan and Browne (2005):

> *"A performance measurement framework assists in the process of performance measurement system building, by clarifying performance measurement dimensions or views and may also provide initial intuitions into relationships among performance measurement dimensions."* - (Folan and Browne, 2005)

It is thus clear from this definition that PMF is not the same as PMS. In order to better understand what a PMF is, Folan and Browne (2005) briefly describe the two different PMF's that exist. The first is in the form of a structural framework, and the second in the form of a procedural framework, as previously mentioned.

A structural framework, Folan and Browne (2005) suggest, is a framework specifying a performance measure management categorisation, and describes a procedural framework as a piecemeal process for performance measure development from a strategy. Folan and Browne (2005) state that PMF which follow procedural frameworks are at a disadvantage due to the lack of a structural element to performance measurement which will enable the management of separate performance measures, as well as their selection. And vice versa, as structural PMF lack procedure. In addition, 'procedural' and 'structural' PMF are designed in isolation from one another; only when a PMS is developed are they eventually joined together.

Otley (1999) argues that there exists five main groups of issues that must be addressed when designing a PMF. He states that these five groups are given as questions, such that they remain relatively constant throughout literature. Otley (1999) also states organisations need to continuously develop answers to them due to ever-changing business environments and strategies. The five questions are listed below:

1. Central to the organisation's future success, what are the key objectives? How does the organisation measure the achievement of each objective?

2. What are the organisation's adopted strategies and plans, as well as the determined processes and activities for the successful implementation of said strategies and plans? How does the organisation measure and evaluate the performance of said processes and activities?

3. For the areas in the first two questions, what level of accomplishment does the organisation need to reach in each respective area, how does the organisation set realistic performance targets for each?

4. What are the rewards and penalties for both managers and employees for the successful achievement of performance targets or failure to do so?

5. What are the necessary information flows, such as feedback and feed-forward loops, to empower the organisation to utilise the experience and knowledge gained to improve the organisations present behaviour?

Otley (1999) asserts that the above questions are closely related to some of modern management's core issues. The first question addresses the case of defining goals and how goal achievement is measured, considering both financial and stakeholder satisfaction. The issues of strategy development and implementation is tackled by the second question. The third question, Otley (1999) states, has been researched extensively and remains important, but he does not expand more on this. In the case of the fourth question, reward systems have been neglected in PM due to it being viewed as the human resources' area of responsibility. However, Otley (1999) states that the two fields' interconnection is critical in order to mitigate counter-productive reward systems; a topic touched on in Section 2.4.5.2. And finally, Otley (1999) comments on the last question, saying that its linkage to issues, such as a 'learning organisation', employee empowerment and emerging strategies, need to be improved.

In conclusion, this thesis is not concerned with the PMF available and their differences, nor the validity of the five main groups of issues that PMF need to address. Only an understanding of what the role of a PMF is in the development of a PMS is covered in this study. However, further information is available on the comparisons between multiple major PMF, and the aforementioned questions and their roles in performance measurement, from Folan and Browne (2005) and Otley (1999) respectively. In addition, Bourne *et al.* (2000) provide a detailed discussion on how to implement and update PMS, and will thus not be addressed in this study.

2.3.3.3 Performance Measurement Systems

According to Amaratunga and Baldry (2002), Performance Measurement Systems were created in the past to monitor and maintain organisational control; a process by which an organisation is ensured to implement strategies that will realise the completion of overall objectives and goals. Many organisations in the late 1980's used PMS that were extensions of their financial reporting systems (Atkinson *et al.*, 1997; Kloot and Martin, 2000). Those organisations defended this means of performance measurement because financial reporting systems provided measures that were not only regarded as reliable and consistent, but also integrated with the main objective of generating profits. These companies felt that their operational performance would be clearly shown through the effect it had on their finances.

However, Atkinson *et al.* (1997) state that studies conducted during that time concluded that PMS which are primarily based on financial measures lack the variety of information decision-makers need to manage processes effectively. Atkinson *et al.* (1997) highlights that such PMS lack the robustness and focus which is required for internal management and control. They argue that financial performance measures are obtained from financial accounting systems; they are designed to communicate financial information, not organisational performance information.

Since the 1980's, considerable work has been put into creating PMS which are more effective and efficient at reflecting organisational performance. Modern PMS serves different functions, aiding in communication and strategy formulation (Wouters, 2009). In addition, the structure and characteristics of more modern PMS strengthens an organisation's strategy and guide managers on lower business levels. Wouters (2009) continues the discussion of modern PMS advantages, saying that it can be a type of diagnostic control through the measures employed; employees are evaluated on specific results, which in turn motivates the employees to improve their efforts. Further discussion on employee behaviour is provided in Section 2.4.5.2.

However, most of these PMS are still designed in-house; there are very few academically developed PMS currently available, according to Folan and Browne (2005). The majority of PMS used today are combinations of best practices and various PMF, but even so, Folan and Browne (2005) report that these PMS have varying effectivenesses, ranging from excellent to poor.

Folan and Browne (2005) found three academically developed PMS, and through investigating and comparing these, concluded that the core requirements of a successful PMS consists of two PMF, one procedural and one structural, as well as other performance management tools. When these core requirements are combined, a methodology is produced which becomes the foundation of differing performance management aids, according to Folan and Browne (2005). The three PMS systems investigated were:

1. the Balance Scorecard (BSC),
2. the Business Process Re-engineering (BPR) system, and
3. Medori and Steeple's Performance Measurement System(s) (PMS).

The scope of this study does not include the comparison between the academically developed PMS, nor the procedures for developing and implementing a successful PMS. However, it is beneficial to understand how a PMS works to understand how this study's deliverable is applicable to an organisation's PMS.

For this study, the use of academically developed frameworks and systems are preferred, since they are well recorded, validated and supported by multiple researchers and users. From the above listed PMS, the most popular is the BSC (Lipe and Salterio, 2000). Therefore, it is decided that the BSC is an adequate PMS to be briefly detailed in this study as it will represent most of, if not all, the necessary characteristics of a successful PMS. This is conducted in Appendix A.

2.3.4 Towards Performance Management

The last sections describe a brief progression of PM literature. It describes using performance measurement recommendations to formulate various PMF, which in turn can be combined to yield a multitude of PMS. Folan and Browne (2005) state that this progression has not taken place in reality; this evolution of PM literature was not intentional. Marr and Schiuma (2003) state that PM literature is widely diverse, and that continuous development is required to combine it to deliver a more effective body of knowledge. The implementation of the information generated by the various existing PMF and PMS is nonetheless utilised in organisations, and this is completed through a concept known as PMa.

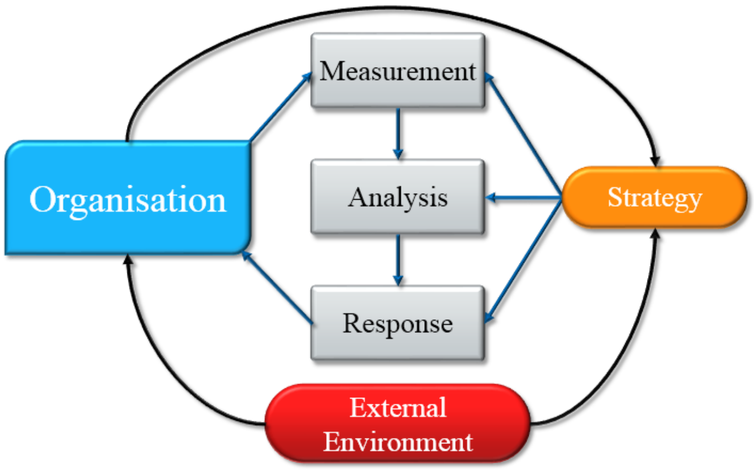


Figure 2.9: Performance management: a simplified process

Adapted from Smith et al. *(2002)*

PMa is defined by Amaratunga and Baldry (2002) as the implementation of PM information to realise positive change within an organisation's systems and processes. This is achieved by employing agreed-upon performance objectives, effective resource allocation and manager direction, and the sharing of performance results for each set objective. The implementation of PMa is done through the use of a Performance Management System(s) (PMaS).

Amaratunga and Baldry (2002) define a PMaS as a structured methodology that implements PM information to aid in the establishment of set agreed-upon organisational performance objectives, to inform managerial personnel of changed policies or variance in organisational direction, to effectively distribute and allocate resources in support of performance objectives and to report on success. Cai *et al.* (2009) add to this definition, stating a complex PMaS employs multiple management operations, which include planning, communication, monitoring, identifying measures, reporting and feedback.

Folan and Browne (2005) write that PM and PMa follow each other iteratively. It is a continuous cycle; management both leads and motivates measurement, and follows it. A capable PMaS, according to Lebas (1995), is one that leans on and supports performance measures that do the following:

- provides freedom to people within their area of influence,
- involves and provides power to people,
- mirror cause and effect relations,
- supports continuous improvement through the creation of discussion topics, and
- supports decision-making processes.

In addition to the factors stated above, Amaratunga and Baldry (2002) state that a PMaS must provide its users with the ability to know if an implemented strategy is working as desired, at any point in the implementation of said strategy. It must also provide reasons of failure if it is not working as desired. Amaratunga and Baldry (2002) continue to say that two key components must be installed for an organisation to effectively proceed from PM to PMa. These are:

1. the correct organisational architecture that accommodates the implementation of PM information, and
2. the ability to affect change in the organisation through the use of PM information.

In support of the aforementioned, Eccles (1990) and Copeland Thomas *et al.* (1994) state that there are multiple PM individuals that believe both PMS and PMaS, regardless of which framework they are founded on, should adequately reflect the cause-effect relationship between a manager's actions or decisions, and the accompanying results. This will facilitate the ability for employees, at all organisational levels, to monitor these cause-effect relationships and learn how their actions support organisational performance overall. A crude representation of PMa is provided in Figure 2.9.

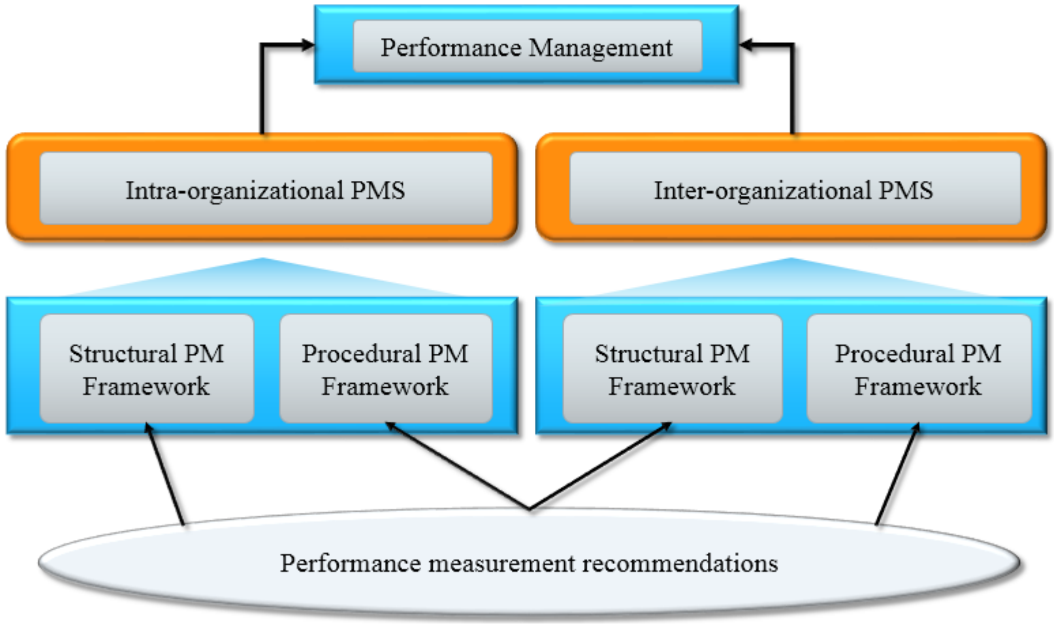


Figure 2.10: The evolution of performance measurement to performance management

Adapted from Folan and Browne (2005)

Folan and Browne (2005) report that in the past, PM literature was satisfied with only detailing the three inner boxes of Figure 2.9, namely *measurement*, *analysis* and *response*. However, further development of more complex PMF and PMS allowed the whole spectrum, shown in Figure 2.9, to be almost completely covered in literature.

Folan and Browne (2005) state PM at present focuses on the organisation as a whole, and how it impacts organisational strategy. The next step for PM is the development of inter-organisational PMS; to measure and improve the working relations and performance between organisations. Figure 2.10 adequately summarises the progression of PM leading to PMa, including the future steps of PM.

The discussion of the inter-organisational PMS is not a necessary component of this study since this study's deliverable is intended to be used by an intra-organisational PMS. Interestingly, Folan and Browne (2005) state that the research conducted of inter-organisational PMS might well be founded on the existing literature of intra-organisational PMS, but may make some of the existing literature redundant as incompatibilities arise.

In light of this possibility, Folan and Browne (2005) suggest an inter-organisational PM policy that will accommodate existing literature on intra-organisational PM. In support of this suggestion, they provide a list of questions to be addressed for future research, however this falls outside the scope of this study's literature review.

2.4 Performance Measures

In Section 2.3, reference was made to performance measures, such as financial and non-financial measures, with minimal description of what they were. The aim of this section is to provide a general discussion of performance measures and introduce some of the issues that generally accompany them.

Elements of particular importance to this study are the performance measures an organisation deems most important, Key Performance Indicators (KPIs). KPIs will be introduced in this section, and linked to the contents of this study. It is important to note that this section contains material that compliments Section 2.3, and vice versa. Therefore neither sections should be regarded as independent from one another.

2.4.1 Financial Versus Non-financial Measures

As mentioned in Section 2.3.1, two general classes of performance measures exist; financial and non-financial performance measures. These performance measures are part of the foundational elements of Performance Measurement and Performance Management, topics which were discussed in Section 2.3. They do not simply provide the information necessary to manage an organisation's performance but according to van Veen-Dirks (2010), they fulfil decision-facilitating as well as decision-influencing roles.

According to Kaplan (1992) and Kaplan *et al.* (1998), financial performance measures can be generally defined as measures that were developed from management accounting systems to measure an organisation's operations and strategies in monetary terms. Examples include return-on-assets, return-on-investment, value-added and earnings-per-share. Chenhall and Langfield-Smith (2007) state performance measurement was initially focused on evaluating managerial or divisional performance, or to control production activities based on cost.

However, measures based on the management accounting perspective have significant drawbacks. Chenhall and Langfield-Smith (2007) and Kaplan *et al.* (1998) state they tend to be highly aggregated, backward looking and focused on the organisation's internal operations. This, according to Kaplan (1992), Hoque *et al.* (2001), Ittner and Larcker (1998) and Lau and Sholihin (2005), is because financial performance measures are too narrow in focus and incomplete.

Financial measures encourage short-term managerial focus and localised optimisation, fail to provide information on customer requirements and competitor performance, and lack strategic focus (Neely, 1999). In addition, financial performance measures do not yield information on responsiveness, quality and flexibility (van Veen-Dirks, 2010). Financial performance measures do not fully satisfy the need of PMS managers; measures that possess a greater relevance to their respective managerial areas are required (Chenhall and Langfield-Smith, 2007).

Non-financial performance measures are designed to evaluate the non- financial performance characteristics of an organisation. They reflect information on processes, machinery and components an organisation deems important to consider in their decision-making processes; information that could not be shown through financial records (Kaplan and Norton, 1992). It is the aim of an organisation to implement this non-financial performance information to contribute towards their operational, and ultimately, financial success. The modern characteristics of non-financial performance measures are discussed by Ghalayini and Noble (1996), Sioutis and Anagnostopoulos (2014), Caniato *et al.* (2014), Maines *et al.* (2002) and Ramaseshan *et al.* (2013), and will thus not be covered in this study.

Although financial measures were the first to be widely accepted by organisations, as stated in Section 2.3.1, Eccles (1990) notes that some organisations, although few, kept track of non-financial measures during the time when only financial measures were used to measure performance. This allowed organisations to measure other performance characteristics in order to understand what their financial measures were telling them.

The question then arises; why weren't non-financial measures implemented earlier en mass if there were organisations already keeping track of them? Eccles (1990) proposed that the problem laid with accepting non-financial measures to have equal, or greater, influence than financial measures in organisational decision-making. This perspective quickly changed however. During the 1980's, academics and professionals started to began to dismiss the use of financial measures, stating that the sole implementation of these measures can have harmful effects (Eccles, 1990). Organisations realised financial measures effective at reflecting the consequences of past decisions, but cannot indicate future performance (Eccles, 1990; Stalk Jr and Hout, 1990).

Even though the limitations of financial performance measures were posed in the literature (e.g. Ghalayini and Noble (1996)), management accountants and consultants still encourage the continued use of financial measures (Chenhall and Langfield-Smith, 2007). Financial measures still provide valuable information, and when coupled with non-financial information, provides a PMS with all the necessary, and desired, information. This combination of financial and non-financial performance measures have been widely accepted since Kaplan and Norton (1992) incorporated it into the Balanced Scorecard; a PMS which has been proven to work by many implementing organisations. The Balanced Scorecard is discussed in Appendix A.

A mixture of multiple performance measures helps an organisation overcome the limitations of employing a single, previously financial, performance measure (Stivers *et al.*, 1998; van Veen-Dirks, 2010). It is not possible for a single measure to reflect the wide spectrum of information available on a single critical activity which contributes to the organisation's strategic objectives. In addition, the diversity of information retrieved from multiple performance measures have been claimed to assist managers more effectively in operations and decision-making processes (van Veen-Dirks, 2010). However, van Veen-Dirks (2010) warns that many users of performance measures believe employing multiple measures can be harmful or disadvantageous.

Many issues, both identified and unidentified, plague non-financial performance measures, such as those discussed by Rangone (1996). However, the research into those issues are comprehensively covered in the literature. The scope of this study does not include an in-depth discussion of the problems faced when designing, implementing and renewing performance measures of any kind. It is, however, deemed beneficial to mention some of the most common, or critical, issues or problems encountered. This discussion takes place in the following sections.

2.4.2 Key Performance Indicators

According to Atkinson *et al.* (1997), the number of performance measures available to any organisation is vast. An organisation can not effectively employ and monitor all the available performance measures, nor employ all the data collected from them in decision-making processes. As a result, organisations have to choose specific measures to deliver data on their most important, or critical, performance areas or production units. These specifically selected performance measures are referred to as KPIs; quantifiable measures which represents an organisation's performance in achieving its goals and objectives. Some basic characteristics of good KPIs include the following (Liu *et al.*, 2015).

- Actionable: reveal information on processes which are in control of the organisation
- Cost-effective: relative to the size and wealth of the organisation, the cost of collecting data on a KPI and the cost of acting upon that data does not exceed the benefits.
- Easily comprehensible: complexity should be avoided to mitigate confusion.
- Meaningful: a KPI must not exist without context.

Bauer (2004*b*) states KPIs measure strategic value drivers and critical business processes. They align an organisation's employees and stakeholders (on all organisational levels) to the same strategies and performance goals, incorporating accountability and performance tracking. The focus of organisational standardisation, collaboration and coordination is placed on the KPIs, allowing smooth, organisation-wide planning. In addition, KPIs also enable an organisation to carry out performance comparisons between internal departments, even if the organisation has operations in different countries (Ghalayini and Noble, 1996).

However, according to Bauer (2004*b*), organisations face a dilemma when choosing KPIs from the various measures contained in the intelligent systems generally employed. Examples of these systems are enterprise resource planning, supply chain management, and customer relationship management. Bauer (2004*b*) provides some common questions which arise when an organisation faces this challenge:

- How do KPIs differ from general performance measures with respect to this organisation?
- How does an organisation know the chosen KPIs are critical business drivers?
- How does an organisation demonstrate enterprise, and not localised, optimisation through the selected KPIs?
- How does an organisation find an acceptable equilibrium between short term and long term goals when selecting KPIs?
- Does the organisation have the measuring capacity, capability and existing infrastructure to support the chosen KPIs?

The success and efficiency of a PMS and PMaS is dependent on the KPIs being chosen correctly, but also being understood well in the different perspectives they find themselves in (Neely, 1999; Bauer, 2004*b*; Liu *et al.*, 2015). Chenhall and Langfield-Smith (2007) investigate the multiple perspectives of performance measures and KPIs with regard to operations management, traditional financial accounting, human resource management and marketing, and will thus not be repeated in this study.

However, more information regarding the procedures of choosing KPIs is provided in Section 2.4.5.1. Informing the reader of some of the important issues commonly faced, regarding KPIs and performance measures in general, is deemed important; in particular, the main challenge of KPIs. This is discussed in Section 2.4.3 and Section 2.4.4.

2.4.3 The Primary Challenge Of KPIs

Neely (1999) and Bauer (2004*a*) state that it is critical for the key organisational processes and operational units to be measured by the chosen KPIs in order to track the organisation's health. Furthermore, it is vital to avoid confining KPIs to a single organisational silo, but rather define KPIs to be employed enterprise-wide. In addition to these, Bauer (2004*a*) provides the following issues that are commonly encountered in creating and defining KPIs:

- What should an organisation measure?
- What is an adequate number of KPIs to employ?
- What must the measuring frequency be for each KPI?
- Who are the responsible individuals for each KPI?
- What is the adequate level of complexity a KPI should have?
- What are the normalisation processes for each KPI?
- What are the benchmarks an organisation should employ?
- How does an organisation guarantee their strategic drivers will be reflected by the measure?

The above listed questions are similar to those in Section 2.3.2.1, indicating that the organisation must have a sound understanding of what performance is and how to measure it correctly. Although these issues are important, the first challenge that must be resolved regarding KPIs, according to Neely (1999) and Bauer (2004*a*), is twofold. An organisation must guarantee that its strategic drivers are represented by the chosen KPIs, while keeping the KPIs aligned with the organisation's vision on all levels. There are a few intermediary steps in the process of transforming the organisation's vision into KPIs and actions; steps that are depicted in Figure 2.11.

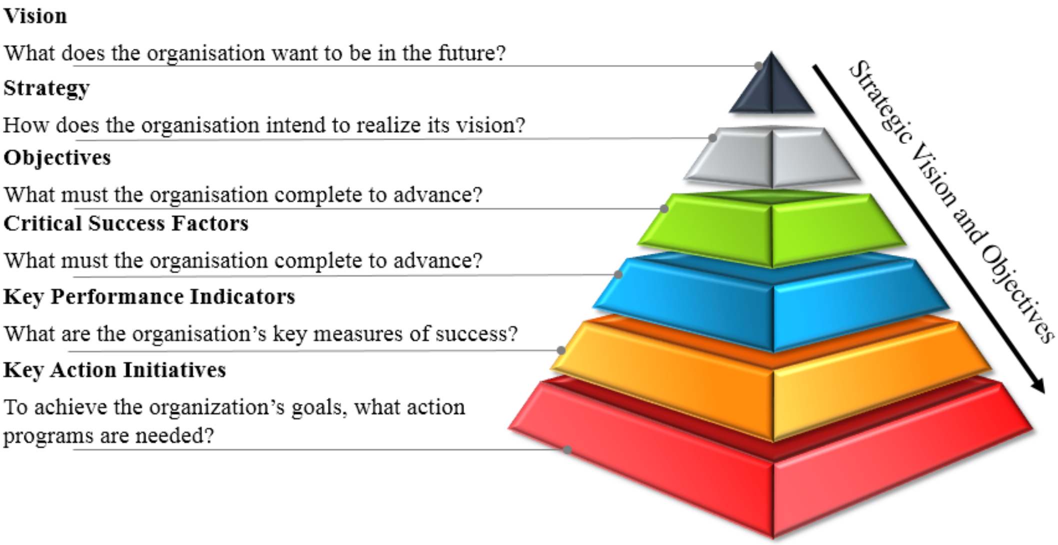


Figure 2.11: The *strategic alignment pyramid*: steps for transforming organisational *vision* into KPIs

*Adapted from Bauer (2004*a*)*

Bauer (2004*a*) states a complete alignment of the *strategic alignment pyramid*, in both directions, is required. Knowing the organisational direction alone is insufficient to select the correct KPI. To improve the process of selecting KPIs, it is beneficial to view a KPI as a balanced measure integrating alternative dimensions, such as business perspectives, measurement categories and measurement families (Bauer, 2004*a*).

Bauer (2004*a*) describes four *dimensions* of KPIs which, when laminated together, may lead to the creation of KPIs which adequately capture information on the aforementioned critical strategic and value drivers. These dimensions are the KPIs's *perspective*, *family*, *category* and *focus*, and are briefly described below.

2.4.3.1 The KPI perspective

Bauer (2004*a*) comments on the Balanced Scorecard, described in Appendix A, saying the perspectives incorporated into this PMS (financial, customer, internal and learning, and growth) share a commonality, despite having distinctly separate focus areas. Bauer (2004*a*) describes the commonality as a link of causality between the Balance Scorecard (BSC) perspectives. Improvement in one perspective will have a chain-effect throughout the other perspectives. Considering the BSC perspectives when selecting and developing KPIs will improve the scope of measurement and will possibly identify previously unknown critical areas of organisational performance.

2.4.3.2 The KPI family

Bauer (2004*a*) suggests it is necessary to select an appropriate *measurement family* when developing KPIs. Some of the more common measurement families from Bauer (2004*a*) are listed in Table 2.1.

Table 2.1: Description of the KPI families

KPI family	KPI family description
Productivity:	Common measures include employee-output and employee-time-usage.
Quality:	Measuring the organisations ability to meet and maintain customer requirements and expectations.
Profitability:	Measuring the organisation's global effectiveness in profit generation.
Timeliness / Cycle time:	Measuring the time taken to complete tasks, and recording when it is completed.
Process efficiency:	Measuring management's effectiveness at employing management tools to improve operational processes.
Resource utilisation:	Measuring management's effectiveness of utilising existing resources.
Growth:	Measure of the organisation's ability to remain competitive through managerial leadership.
Innovation:	Measure of the organisation's development of new products or services to generate new income.

Although the *measurement families* in Table 2.1 are common examples, they help create an improved understanding of the variety of performance characteristics an organisation has. In addition, the significant focus placed on efficient management is evident; another element to keep in consideration when selecting and developing KPIs.

2.4.3.3 The KPI category

According to Bauer (2004*a*), after identifying the aforementioned KPI perspective and family, establishing the category of the KPI and the form it should take is required. Bauer (2004*a*) suggest a KPI should not be a raw piece of information, but rather a combination of information, forming ratios, indexes or weighted averages that have additional meaning to decision-makers. The true challenge lies in translating recorded data into meaningful and comprehensible formats. Bauer (2004*a*) provides more detail on the process of creating a derived measure, and will thus not be repeated here.

2.4.3.4 The KPI focus

The *focus dimension* takes place after the first three *dimensions* have been determined and incorporated into the KPI development process. The *focus* is the final "lamination layer" of the dimensions described by Bauer (2004*a*). It incorporates additional mixtures of perspectives which strengthen and balance the selection and development of KPIs. Factors such as time horizon (short term versus long term), planning (tactical versus strategic), and indicator (lag versus lead) are incorporated (Bauer, 2004*a*).

Bauer (2004*a*) states the screening of the final KPIs are important in order to mitigate employing KPIs which all lean towards short-term goals, and are quantitative and lagging indicators. This can easily occur as these KPIs are the most simple to develop and employ. An adequate mixture of KPIs, focusing on short-term and long-term goals and other aforementioned factors, is desired to gain a more complete picture of present and future organisational performance.

To support organisations in tackling the primary challenge of KPIs, as discussed above, it is deemed beneficial to discuss some critical errors made when measuring non-financial performance measures or KPIs. Being aware of these errors will aid organisations in avoiding them, as well as provide additional information on factors that need considering when selecting and developing KPIs of their own. These errors have been identified by Ittner and Larcker (2003), and are discussed in Section 2.4.4.

2.4.4 Errors In Measuring Non-Financial Performance

In the 1990's, a large majority of companies started measuring non-financial performance attributes, such as employee satisfaction and customer loyalty, believing that this type of information would yield beneficial data to organisational managers. Ittner and Larcker (2003) state that, even though there are various benefits to measuring these types of organisational performance characteristics, very few organisations actually realise these benefits.

According to Ittner and Larcker (2003), failing to identify, analyse and act on the correct non-financial KPIs is the reason why organisations don't realise the benefits these measures can offer. A large collection of organisations and their methods of selecting, developing and employing KPIs were investigated by Ittner and Larcker (2003). They found that many of these organisations adopted so-called "boiler plate" KPIs; measures suggested by existing PMF and PMS, such as the BSC. The organisations did not choose KPIs that supported their strategic plans and direction, nor could they establish cause-and-effect relationships between financial returns and improvements in these measured areas.

Ittner and Larcker (2003) state that these organisations, ones who adopted KPIs in the manner discussed above, have seen performance managers choose KPIs and manipulate them for their own personal gain. This was due to reward structures put into place that rewarded employees based on the performance of their area of responsibility. This is covered briefly in Section 2.4.5.2.

There are secondary, unforeseen problems that may arise when an organisation, and its high-level managerial staff, do not ensure the KPIs employed by the organisation are correctly selected or developed. The focus of this study is more on the primary problems that are encountered. Ittner and Larcker (2003) found the following general mistakes made by the organisations investigated with regard to their KPIs; mistakes that tie in with what was discussed in Section 2.4.3.

1. Failing to link measures to strategy.
2. Failure to validate the links between measures and strategy.
3. Setting incorrect performance targets.
4. Failure to measure correctly.

These general mistakes are briefly expanded on below. Section 2.4.4.5, contains recommendations suggested by Ittner and Larcker (2003) to help organisations employ the benefits offered by non-financial performance measures, and to mitigate the errors found.

2.4.4.1 Failure to link measures to strategy

According to Ittner and Larcker (2003), every organisation faces the obstacle of how to choose their KPIs from the massive collection of performance measures available; an obstacle first introduced in Section 2.4.2. As stated, many organisations adopted existing PMS and their performance measures, believing them to be universally applicable and comprehensive (Ittner and Larcker, 2003). These frameworks, however, explicitly urge organisations to identify their own areas of performance which contribute greatly to their financial success, and select and develop KPIs for these areas (Stivers *et al.*, 1998). Yet, this was ignored by most of the organisations included in the investigation completed by Ittner and Larcker (2003).

The top management of the organisations, who simply adopted a PMS and its KPIs, did not adequately understand the role of a PMS and its importance. Managers on lower organisational levels were ordered to implement elements that were not understood correctly, which resulted in costly errors. This observation highlights the importance of top management understanding what organisational performance is, how it is linked to organisational strategy, and how it must be measured correctly.

According to Ittner and Larcker (2003), the more successful organisations chose performance measures based on causal models; a topic introduced and discussed in Section 2.3.2.1. Through the implementation of causal models, these organisations were able to better identify cause-effect relationships between the chosen drivers of strategic success, and the performance elements the drivers consisted of (Ittner and Larcker, 2003). Unfortunately, less than 30% of the organisations investigated by Ittner and Larcker (2003) proved to have employed causal models to better understand their performance creation processes.

2.4.4.2 Failure to validate links between measures and strategy

From their investigation, Ittner and Larcker (2003) found that very few organisations, less than a 20% of those investigated, provided evidence of improved financial returns caused by improved non-financial areas of performance. These organisations, some of which employed causal models, relied solely on the presuppositions of their managers to determine what was important to the stakeholders, rather than verifying these assumptions. According to Ittner and Larcker (2003), doing this may condemn organisations to measure performance characteristics with KPIs that have little to no true contribution to financial or strategic performance.

Even though managers argue that the links between improved performance areas and greater financial returns are self-evident, the research conducted by Ittner and Larcker (2003) found the aforementioned assumptions to be undeveloped, ill-conceived, or just plain incorrect. Ittner and Larcker (2003) warn that organisations stand to face many potential problems if they fail to conscientiously identify the core performance drivers of their organisational units. Organisations try to avoid doing this by employing KPIs for every performance area to ensure that they measure the correct performance characteristics. However, this leaves the organisation with an abundance of irrelevant, trivial or peripheral information; merely one of the many possible problems that can be caused (Stivers *et al.*, 1998; Ittner and Larcker, 2003).

The presence of irrelevant or peripheral information complicates decision-making. As Ittner and Larcker (2003) writes, amongst this flood of information, decision-makers are not able to isolate or identify which KPIs yield information about how well the organisation is achieving its strategic objectives. Furthermore, if organisations do not provide simple verified cause-effect relationships, decision-makers are unable to determine the relative importance of each employed KPI, making effective resource allocation unlikely (Stivers *et al.*, 1998; Ittner and Larcker, 2003). Again, decision-makers in situations such as this are forced to rely on the aforementioned presuppositions.

2.4.4.3 Setting incorrect performance targets

Ittner and Larcker (2003) acknowledge that setting performance targets is a difficult task. One of the factors complicating this is the delayed effect a performance driver has on the performance entity it is meant to affect. Ittner and Larcker (2003) note that improving non-financial performance may even reduce short-term returns, and that this should be considered when setting financial goals. Ittner and Larcker (2003) suggest that if the returns, in terms of quantity and time, of non-financial performance improvements can be adequately estimated, financial goals can be adjusted more accurately.

However, organisations do not incorporate these considerations in the setting of their financial goals. Organisations choose to improve on performance initiatives that yield short-term financial returns at the expense of neglecting performance initiatives which deliver greater financial returns, but over the long-run (Ittner and Larcker, 2003). In addition, Ittner and Larcker (2003) claim outstanding levels of non-financial performance may yield diminishing returns. An organisation is thus motivated to determine the level of non-financial performance which will yield the best return on investment. Another method to improve the feasibility of performance measurement. Bird *et al.* (2005) provides some guidance in performance target setting, as well as guidance in many other important areas such as the analysis and presentation of performance data.

2.4.4.4 Failure to measure correctly

Ittner and Larcker (2003) define two distinct terms with respect to performance measures and measurement; *validity* and *reliability*. *Validity* refers to "the extent to which a metric succeeds in capturing what it is supposed to capture", and *reliability* refers to "the degree to which measurement techniques reveal actual performance changes and do not introduce errors of their own" (Ittner and Larcker, 2003).

According to Ittner and Larcker (2003), performance measures including KPIs, that lack statistical *validity* and *reliability*, were employed by upwards of 70% of the organisations investigated. Such performance measures and KPIs impairs the ability of organisations to accurately predict financial results, and to recognise superior performance. Furthermore, Ittner and Larcker (2003) state that non-financial assessment methods, if not kept constant across the organisation, may reduce the *validity* and *reliability* of these measures. It is therefore strongly suggested that an organisation keep *validity* and *reliability* in mind when selecting and designing KPIs and performance measures in general.

In addition to the above, Ittner and Larcker (2003) write that many organisations complete data treatment processes prior to determining the objectives and deliverables of the analysis. This sequence of events generally renders the data unsuitable for organisational managers to conduct operations. Knowing what is required from the data is critical before any data treatment is carried out (Ittner and Larcker, 2003). For those organisations that do not, or can not, know what is required from the data prior to data treatment, Ittner and Larcker (2003) suggests identifying tags be attached to each of the recorded data entries until the organisation is able to know what they require from the data.

2.4.4.5 Claiming the promises of non-financial measures

The previous sections briefly discussed the common mistakes that were made by the organisations in an investigation completed by Ittner and Larcker (2003). The four mistakes share a common factor; the general disregard for the recommendations offered by the developers of PMS, such as the Balanced Scorecard, and other publications on measuring organisational performance. The organisations investigated by Ittner and Larcker (2003) seem to have an unwillingness to identify and learn what their respective performance-driving characteristics are, how to measure these characteristics accurately, and how to select and design the correct KPIs for this task.

Ittner and Larcker (2003) state the negligence of organisations to identify the greatest non-financial, influencing factors on long-term financial performance constitutes the foundation of the four aforementioned mistakes. The solution to which, according to Ittner and Larcker (2003), may be found when the steps listed in Table 2.2 are followed.

These steps are described by Ittner and Larcker (2003) as the foundation of a solution; a process that may enable organisations to utilise the benefits of non-financial performance measures, and most importantly, KPIs. For more

Table 2.2: Solution to claiming the promises of non-financial performance measures

Solution step	Step description
Causal model development:	Develop a causal model as a source agreement, widely-accepted, on strategy.
Collate data:	Take inventory of all available data from all information systems that may contain information on performance measures.
Transform data into information:	Validate the developed causal model through the employment of statistical tools.
Continuous refinement of causal model:	There still exist unidentified performance drivers of the already-proven drivers in the causal model.
Actions as a result of findings:	Employ conclusions from non-financial performance data in decision-making processes.
Critically assess results:	Organisations must determine whether the performance measures and supporting elements delivered the desired results.

detail regarding the topics discussed in this section, consult the investigation completed by Ittner and Larcker (2003).

2.4.5 Common Performance Measure Challenges

Section 2.4.3 and Section 2.4.4 discuss some of the most important and critical challenges and errors in the realm of performance measures and KPIs. However, these do not include some of the other notable challenges that are commonly faced. In order to gain a better understanding of the problem this study aims to address, it is necessary to briefly investigate two other common challenges.

Measure selection, discussed in Section 2.4.5.1, constitutes an important, foundational part of PMS and PMaS. In addition, it is necessary to investigate the impact on employee behaviour when reward systems are employed; reward systems that assess the performance of employees based on a PMS' KPIs. It contributes to the necessity of the objective identification of inter-KPI relationships for maintained fairness; relationships that possibly will impact the reward structures, and indirectly, the behaviour of employees. This necessity is discussed in Section 1.2.

2.4.5.1 Measure selection

Selecting the appropriate performance measures from a vast collection of those available to an organisation is one of the most common challenges faced in the design and implementation of PMS. The recommendations and procedures that need to be considered when selecting adequate and applicable performance measures constitutes a large portion of the available literature on Performance Measurement, and is therefore not repeated in this study (Folan and Browne, 2005). However, it is deemed important to explore literature sources which address the challenge and procedure of measure selection in more detail. This will enable an organisation to identify the necessary tools, procedures and other beneficial aids for the process of performance measure selection, as well as KPI selection.

Stalk Jr and Hout (1990), Maskell (1992) and Neely (1999) provide all-inclusive literature reviews and overviews of recommendations, procedures and other considerations with respect to performance measure selection. The research conducted by Adams *et al.* (1995) provides an in-depth review on how to select performance measures while maintaining alignment with an organisation's strategic and operational objectives; an issue of critical importance as mentioned in Section 2.4.3 and Section 2.4.4. Additional literature on this topic include Muckler and Seven (1992), Neely *et al.* (1997), Frigo (2002), Chan and Chan (2004) and Alwaer and Clements-Croome (2010).

2.4.5.2 Abusing performance measures

With the introduction of PM, it was not long until organisational management investigated alternative methods to increase the performance of their business units and assets. One of these additional methods was to implement reward structures and systems that rewarded employees, specifically managers, based on the performance of their respective areas of responsibility. However, coupled with the free-reign managers had in selecting and developing the KPIs employed, as discussed in Section 2.4.4, another costly problem was created in organisations.

Organisations intuitively expect the improvement of KPIs, according to Banker *et al.* (2000), when a reward system is positively linked to those specific KPIs. The efforts of an organisation's human assets are thus directed more to the improvement of these areas of performance; an example of human assets and physical assets interacting, as discussed in Section 2.2. The rewards and compensation received by employees and managers are directly affected by the process of performance evaluation; a process employees and managers are concerned with, changing their behaviour towards the respective KPIs (Kaplan *et al.*, 1998; Lau and Sholihin, 2005).

According to Lau and Sholihin (2005), a vast amount of research has been conducted on the behavioural consequences brought by the performance evaluation of financial performance measures, and how to minimise the abuse of these performance measures. Dechow (1994) argues that the employment of accruals will mitigate financial KPI abuse due to the limitation brought by accounting conventions such as verifiability and objectivity. However, the behavioural consequences of evaluating non-financial performance measures are researched less than their financial counterparts.

Lau and Sholihin (2005) investigated the behavioural changes of employees with regard to assessing financial and non-financial performance measures. The objectives were to identify if there was a difference between the behavioural changes brought by the two types of performance measures, and if the weighting placed on non-financial measures, relative to financial measures, affected the behavioural changes. Using a path analytical model, data collected from a sample of 70 performance managers were analysed. According to Lau and Sholihin (2005), the results indicated that more, positive employee behaviours are possibly generated from long-term non-financial performance measures compared to short-term non-financial measures. In addition, the results revealed information on the relationship between performance evaluation, based on non-financial measures, and employee job satisfaction. The relationship was found to be indirect and fair due to the assessment methods employed (Lau and Sholihin, 2005).

Lau and Sholihin (2005) state that organisations which employ well specified, defined, and weighted financial and non-financial performance measures, maintain higher levels of employee satisfaction and procedural fairness. However, this is not generally the case with organisations employing poorly defined and specified performance measures (Lau and Sholihin, 2005). According to Ittner *et al.* (2003), very few psychology-based studies have investigated the impact relative weightings of performance measures have on employee behaviour towards reward systems. They found result-orientated performance measures will be allocated greater weightings than those allocated to input or driver performance measures. In addition to their own findings, Ittner *et al.* (2003) consulted previously published literature on allocated weightings and their differing circumstances to widen the scope on factors influencing behavioural changes.

A commonality was identified between the causes of negative behavioural changes in employees; employees do not trust poorly structured reward systems, biased or unfair performance evaluation processes, and the managers with incorrect perspectives of the implemented KPIs (Cox *et al.*, 2003). In cases such as these, it is not uncommon to experience the various, sometimes unknown, consequences of the changes in employee behaviour. It is vital to study the mistakes and shortcomings identified by the literature on this topic to benefit from motivated and satisfied employees when reward systems and performance evaluation structures are employed.

However, as Dechow (1994) states, management manipulation is not always detectable, especially over short measurement intervals, and if performance measures were manipulated, the recorded information of those measures are discredited. Other similar research has been conducted by Ittner *et al.* (1997), Lipe and Salterio (2000), Epstein and Roy (2001), and Ittner *et al.* (2003) for additional information.

2.4.6 Relevant Characteristics Of KPIs

The sections prior to this one discussed challenges faced and errors made by organisations in their attempts to employ PMS for improved financial health. These sections contained information allowing a deeper understanding of KPI characteristics, but they do not sufficiently introduce the characteristics needed to further the investigation of this study. This section contains the KPI characteristics specifically required to further this investigation, as well as to provide additional information on KPIs in general in a similar manner to the previous sections.

2.4.6.1 Decision facilitation and influence of KPIs

Information on organisational performance and other performance dimensions is varying in nature since the start of PM; an occurrence that is being incorporated into modern PMS (van Veen-Dirks, 2010). With PMS gaining access to new and innovative types of performance information, such as the knowledge of inter-KPI relationships discussed in Section 2.4.6.2, different roles of KPIs start to emerge, according to van Veen-Dirks (2010). van Veen-Dirks (2010) states that two key roles of performance information are described on PM; decision-facilitating and decision-influencing roles.

Decision-facilitating performance information, according to van Veen-Dirks (2010), will possibly improve performance management decisions. The "belief revision" role of Baiman (1990) and Narayanan and Davila (1998), and the problem "solving role" of Simon (1954), is comparable to the decision-facilitating role of van Veen-Dirks (2010). An example of decision-facilitating KPIs are those that provide information on current processes, possibly improving a performance manager's decisions regarding planning and coordination. It is believed that the information on existing, proven relationships between performance elements would be largely decision-facilitating in nature. More opportunities would be available to decision-makers due to the knowledge of cause-effect relationships. However, this information will also change the behaviour of employees if they are affected; the information would become decision-influencing.

The decision-influencing role is described by van Veen-Dirks (2010) as the capability of this information to solve organisational control problems, ensuring desirable behaviours from employees; an issue discussed in Section 2.4.5.2. This role is similar to the performance evaluation role of Baiman (1990) and Narayanan and Davila (1998), and similar to the score-keeping role of Simon (1954) (van Veen-Dirks, 2010). The information of decision-influencing KPIs may change the behaviour of employees, such as the production manager, due to personal give-and-take circumstances (van Veen-Dirks, 2010). van Veen-Dirks (2010) state that the organisational KPIs strongly linked to the employed reward system will encourage employees to allocate resources and focus more on those KPIs; an additional behaviour-related contribution to the discussion in Section 2.4.5.2.

The requirements of this study suggested that the introduction of the two aforementioned roles of KPIs and their information was beneficial for the improved understanding of the complex impacts KPIs can have on an organisation, and its employees. This knowledge would aid organisations in matters such as PMS development and implementation, KPI selection and Performance Management. The in-depth discussion of these roles, however, does not form part of the scope of this study. For more information on both the decision-facilitating and decision-influencing roles of KPIs and their information, consult Demski and Feltham (1976), Baiman and Demski (1980) and Sprinkle (2003).

2.4.6.2 Relationships between performance measures

The research completed by Cai *et al.* (2009) was focused on KPIs in the realm of Supply Chain Management (SCM), but some notable attributes regarding KPIs were revealed. According to Cai *et al.* (2009), the KPIs involved in SCM are inter-related and correlated, and therefore have cause-effect relationships on the costs and effort involved in "accomplishing" KPIs. Cai *et al.* (2009) describe the "accomplishment" of a KPI as the mechanism of achieving KPI goals.

These correlated relationships are a common occurrence, however, for similar realms, such as Maintenance Management and Information Technology Management. In these managerial areas it is common for the accomplishment of one KPI to have a positive or negative effect on other KPIs, such as increased cost and effort of accomplishment. This suggests that the accomplishment of KPIs may be an iterative and interactive process, one that received the attention of Cai *et al.* (2009).

It is necessary to identify the highly correlated, inter-KPI relationships to gain an improved understanding on how to best manage such effects. According to Cai *et al.* (2009), the classification of the inter-KPI relationships are: *parallel*, *sequential* and *coupled*. These relationship classes are depicted in Figure 2.12 for descriptive purposes.

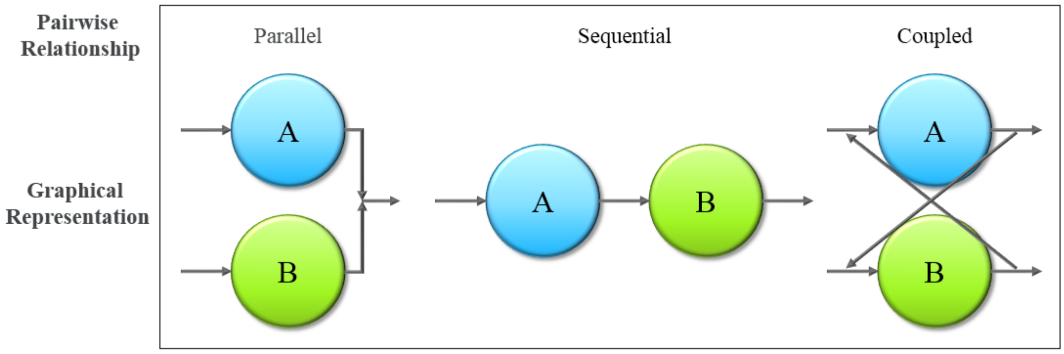


Figure 2.12: Piecewise relationships between pairs of Key Performance Indicators (KPIs)

Adapted from Cai et al. *(2009)*

Cai *et al.* (2009) defines a *parallel* relationships as two KPIs who are independent of one another and have no influence on each other. A *sequential* relationship is described as a simple cause-effect relationship, regardless if the reverse is not applicable. For example, the accomplishment of A increases the cost or effort of accomplishing B, but the accomplishment of B will have no effect on the accomplishment of A (Cai *et al.*, 2009). The last classification, *coupled*, Cai *et al.* (2009) state both KPIs are dependent on one another; they affect the accomplishment efforts and costs of each other.

Cai *et al.* (2009) describes two important elements. The first is the classification of inter-KPI relationships. Whether *parallel*, *sequential* or *coupled*, they only consider the cause-effect relationship between two KPIs. There may be other influences, from the accomplishment of other KPIs, on either of the two considered KPIs; influences that cannot be identified through correlation analysis. Therefore, there exists a deficiency in pair-wise correlation analysis with respect to identifying relationships between performance measures (Rodriguez *et al.*, 2009). A deficiency discussed in Section 2.5.1.2.

Secondly, Cai *et al.* (2009) implement subjective analysis to identify inter-KPI relationships in their research. Although subjective analysis may provide accurate results, and is an adequate analysis method in other research areas, it is vulnerable to human error and biased opinions (Rodriguez *et al.*, 2009). The error in using subjective analysis, with regard to identifying relationships as stated above, is further discussed in Section 2.5.1.1.

Cai *et al.* (2009) propose a framework to help SCM managers better manage their KPIs and the cause-effect relationships existing between them. The framework provides a systematic approach to improving the iterative accomplishment of KPIs through the assessment of the above discussed inter-KPI correlation relationships. It also takes into consideration the importance of a KPI relative to other KPIs. However, very little research has been conducted on the relationships that exist between KPIs (Patel *et al.*, 2008). Cai *et al.* (2009) used no supporting research, despite formulating their framework recently, for the description of the aforementioned correlated relationships. The same can be said about Youngblood and Collins (2003).

Patel *et al.* (2008) state there is a significant lack of academic and governmental publications on inter-KPI relationships which are difficult to access, and this lack of knowledge makes conceptualising operations and performance dynamics more difficult. According to Patel *et al.* (2008), the provision of such publications and the knowledge within would improve the formulation of new performance improvement strategies. But, as Cai *et al.* (2009) state, investigating the complicated relationships that exist in a set of KPIs is a challenging and difficult task - a task with results that differ from organisation to organisation.

There are existing frameworks and systems that incorporate the cause-effect relationships between KPIs, according to Cai *et al.* (2009), but these are inadequate to quantitatively assess these inter-KPI relationships. It is, however, necessary to identify existing frameworks or methodologies that aim to identify, and possibly quantify, relationships that may exist between a set of KPIs. This is completed in Section 2.5.

2.5 Identifying And Quantifying Relationships Between Performance Measures

In Section 2.3, Performance Measurement Systems and Performance Management Systems were discussed, and an academically developed PMS, the Balanced Scorecard, was detailed in Appendix A. The information on PMS and PMaS was accompanied by peripheral topics, such as the historic progression of PM and PMa to the present, and the process of defining the concept of performance.

Section 2.4 introduced performance measures; the measures used by organisations in their respective PMS and PMaS to assess how well they are achieving their performance objectives. A topic briefly touched on in Section 2.4.6.2 was the existence of cause-effect relationships between the performance measures, specifically the KPIs, of an organisation. In addition to the existence of these relationships, it was suggested that assessing these relationships would offer potentially valuable information to organisational decision-makers.

Section 2.3 and Section 2.4 facilitate the necessary discussions to construct an overall understanding of the aforementioned systems, how they originated, evolved and are used presently, and the measures they employ. Section 1.2 identifies a lack of frameworks that aim to assess the aforementioned cause-effect relationships between KPIs or performance elements in general; the gap in the literature this study operates in.

A literature review was completed by Rodriguez *et al.* (2009), investigating the very few frameworks that identifies relationships between performance elements in different ways. Rodriguez *et al.* (2009) found these frameworks to be inadequate for the objective identification and quantification of inter-KPI relationships, and in response to this, developed a methodology called the Quantitative Relationships at the Performance Measurement System (QRPMS).

The following section discusses the reasons Rodriguez *et al.* (2009) had for dismissing the few aforementioned frameworks; reasons that are of particular importance to this study, as stated in Section 1.2. This is followed by a brief description of the investigated frameworks, followed by the introduction of the QRPMS methodology. This section represents a collection of all known frameworks aiming to assess relationships between performance elements in the PM environment, according to Rodriguez *et al.* (2009).

2.5.1 Unsuitable Assessment Methodologies For Objective Identification And Quantification

As stated above, Rodriguez *et al.* (2009) found the frameworks they investigated to be inadequate for the objective identification and quantification of inter-KPI relationships. The reasons for these dismissals are founded on basic flaws and shortcomings in the two analysis techniques used by these frameworks. These two analysis techniques are subjective analysis, and pair-wise correlation analysis.

Although these analytical methods are viable and employable methods in other applications and research, they are inappropriate for the requirements of this study; requirements that are adopted from Rodriguez *et al.* (2009) and stated in Section 1.2. It is noted that there are tools available at the PM and PMa context that may be used in support of multi-criteria decision making, and can possibly be employed to identify the aforementioned relationships. According to da Silveira (2005), these tools are referred to as Multi-Criteria Decision Analysis (MCDA) methods and are classified as follows:

- Objective programming.
- Scoring models.
- Hierarchical techniques.
- Deployment techniques.

MCDA methods generally develop a ranking of varying competitive attributes or priorities, according to predetermined criteria, to maximise performance (da Silveira, 2005). However, Rodriguez *et al.* (2009) state that all MCDA methods commonly involve, or are dependent on, subjective decisions at any point, or are inadequate for the objective identification and quantification of inter-KPI relationships. It is therefore important to explain the problems found with subjective analysis and pair-wise correlation analysis to identify other suitable methods to accomplish the aforementioned.

2.5.1.1 The error in subjective analysis

Subjective analysis, according to Rodriguez *et al.* (2009), is an inadequate technique to employ in a framework which aims to identify inter-KPI relationships between a set of KPIs in an objective manner. Rodriguez *et al.* (2009) state subjective analysis is easily influenced by the biased opinions of analysts, and therefore cannot be considered a mathematically accurate and reliable analysis technique. Any introduction of subjective analysis into the computational elements of a framework compromises the mathematical validity of the results; the framework cannot claim to yield objective results (Rodriguez *et al.*, 2009).

2.5.1.2 The deficiency of pair-wise correlation analysis

Cai *et al.* (2009) attempted to categorise inter-KPI relationships into three groups: *parallel*, *sequential*, and *coupled*. However, the assessment completed by Cai *et al.* (2009) only considers the strong cause-effect relationship between two KPIs. As stated in Section 2.4.6.2, there may be other influences caused by third party KPIs that may have changing affects on the relationship between the first and second KPI. This problem is magnified when such a pair-wise correlation analysis technique is employed to identify relationships between a large set of KPIs. It is for this reason why Rodriguez *et al.* (2009) deems pair-wise correlation analysis as an inadequate technique for employment in frameworks that aim to identify inter-KPI relationships between a set of KPIs.

2.5.2 Inadequate Frameworks For Identifying Inter-KPI Relationships

As mentioned earlier, Rodriguez *et al.* (2009) found very few frameworks that attempt to identify and quantify relationships between performance elements. The following discussion briefly covers each of the frameworks investigated by Rodriguez *et al.* (2009), highlighting their objectives and the reason for their dismissal.

Youngblood and Collins (2003) developed a methodology to quantify trade-off issues between performance measures used on a Balanced Scorecard. This methodology employs Multi-Attribute Utility Theory (MAUT), a quantitative analysis technique which expresses the advantages or disadvantages of multiple-attribute outcomes in terms of the advantages of each attribute considered alone (Torrance *et al.*, 1982). MAUT was employed by Youngblood and Collins (2003) in a BSC framework to evaluate trade-offs between performance measure options and their respective effects on performance objectives. Rodriguez *et al.* (2009) state, however, that the methodology is limited in its analytical capability due to the use of correlation analysis. Due to the reasons stated in Section 2.5.1.2, it is dismissed.

The methodology developed by Cardona Siado and García (2005) also implements the BSC, and aims to identify inter-KPI relationships using two of BSC's perspectives: internal perspective, and innovation and learning perspective. The proposed methodology is composed of four steps: formulation of quality strategy, strategic map design, verification, and strategy execution (Cardona Siado and García, 2005). The MICMAC method is employed in the verification stage, and is described by Elmsalmi and Hachicha (2013) as a structural modelling technique. It describes a system using a matrix linking up its constituent components, identifying the influential, dependant and essential variables critical for system evolution. According to Rodriguez *et al.* (2009), the MICMAC method is a subjective process and is therefore dismissed.

Bauer (2005) suggests a framework for the reduction of a large set of performance metrics to the most important, or useful, measures; measures that are also uncorrelated. The initial description of this framework showed promise, however, the significant use of correlation analysis to "sort" the set of measures makes it an inadequate framework, according to Rodriguez *et al.* (2009). It is acknowledged that using correlation analysis would aid in the understanding of inter-KPI relationships, but as mentioned in Section 2.5.1.2, a large number of possible relationships are overlooked.

Rodriguez *et al.* (2009) expands on another framework, called the Quantitative Model for Performance Measurement System (QMPMS), fearing possible confusion between its deliverables and the those of the aforementioned frameworks. Considering this, the relative ease of sourcing this framework from the literature compared to those previously discussed, deemed it beneficial to discuss this framework in greater detail.

2.5.3 The Quantitative Model For Performance Measurement System

Through their research, Suwignjo *et al.* (2000) identified a gap in PMS capabilities. They found researchers have presented new and alternative PMS, such as the BSC, and suggested design criteria for more inclusive or comprehensive PMS. However, none of the investigated literature, prior to their publication Suwignjo *et al.* (2000) state, sought to represent the effects of different factors on performance elements in quantifiable terms, apart from research completed by Rangone (1996) during that time.

Suwignjo *et al.* (2000) state that the research completed by the Centre for Strategic Manufacturing, University of Strathclyde, revealed that the majority of companies employ both financial and non-financial measures, but they do not seek to logically structure these measures. The logical structuring of these measures would simplify the understanding and management of the relationships between the aforementioned measures (Suwignjo *et al.*, 2000). QMPMS was developed by Suwignjo *et al.* (2000) in reaction to the above, and it aims to:

- Identify factors influencing performance, and the relationships between them.
- Hierarchically structure the identified factors.
- Quantify the influence on performance due to the factors.

Suwignjo *et al.* (2000) state that the QMPMS method employs Analytical Hierarchy Process (AHP) to quantify the performance influences caused by factors affecting performance; factors that are both tangible and intangible (Sarkis, 2003). Rangone (1996) used AHP to compare inter-factory performance to support manufacturing strategies, showing that financial and non-financial quantitative and qualitative measures can be considered, and acceptable trade-offs be found or addressed. This can potentially provide additional information for decision-makers. The work done by Rangone (1996) does not, however, aim to identify relationships between KPIs. With respect to the above, QMPMS has some benefits (Suwignjo *et al.*, 2000):

- Performance-affecting factors are identifiable, and the effects quantifiable.
- The effects of multidimensional, performance-affecting factors can be grossed into one dimensionless unit.
- Individual factor-impact on overall performance is quantifiable, assisting managers in more focussed improvement ventures.
- Inter-factor relationships are identifiable and quantifiable.
- Improved understanding of the complicated behavioural characteristics of performance-affecting factors.
- Support the reduction of performance measurement reports issued.

Rodriguez *et al.* (2009) state that, due to QMPMS employing the hierarchical technique AHP, it is a subjective methodology. Suwignjo *et al.* (2000) acknowledges this, stating that the subjective measurement within QMPMS may yield conclusions that are inaccurate if individual judgement, and not group judgement, is used. Although being a subjective method, it is a supportive and innovative framework enabling performance measures to be mapped in a hierarchical manner; a framework that can be beneficial for manufacturing management and strategy (Sarkis, 2003).

It is important to note that the QMPMS method does not identify relationships between KPIs; it identifies relationships between performance-affecting factors by employing a subjective hierarchical technique (Rodriguez *et al.*, 2009). It is therefore disregarded as a suitable methodology for the purposes of this study.

After an extensive investigation of what is required to objectively identify and quantify inter-KPI relationships, and considering the attempts of previous frameworks, Rodriguez *et al.* (2009) developed the QRPMS framework. The framework strives to accomplish the aforementioned, mitigating the use of subjective analysis and correlation analysis. The QRPMS methodology is expanded on in Section 2.5.4.

2.5.4 The Quantitative Relationships At Performance Management System Methodology

As discussed previously, Rodriguez *et al.* (2009) conducted an extensive search in PMS and PMaS literature to find methodologies or frameworks which identified and quantified relationships between performance measures in an objective manner. However, all of the methodologies found were deemed inadequate due to the reasons mentioned in Section 2.5.1 and Section 2.5.2. Rodriguez *et al.* (2009) sought to rectify this, and as a result, developed the QRPMS methodology; a methodology with the following objectives:

- To become a standard framework applicable to any PMS which has clear traceability between performance objectives and respective performance measures.
- To objectively identify and quantify inter-KPI relationships.
- To use the identified and quantified relationships to draw KPI cause-effect maps.
- To use KPI cause-effect maps to build performance objective cause-effect maps.
- To identify KPIs which, through their variation, could result in the non-achievement of performance objectives which are not linked to the causal KPI.

QRPMS aims to accomplish its aforementioned objectives through a four phase process:

- Phase 1: Design and analysis of the PMS in consideration.
- Phase 2: Initial performance measure data treatment.
- Phase 3: Identification and projection of inter-KPI relationships.
- Phase 4: Presentation and analysis of results.

The detailed discussion of the above listed phases is carried out in Section 3.3, and will thus not be covered here. Rodriguez *et al.* (2009) followed a constructivist approach to collect the necessary knowledge to construct QRPMS, an approach that is detailed in their publication. Figure 2.13 depicts the foundational idea QRPMS is built on; the activity of identifying inter-KPI relationships and sharing that knowledge with higher levels of PMS and PMaS management.

QRPMS was designed to be a generic framework; a framework that can be employed by any PMS, regardless of the industry. However, Figure 2.13 reveals a requirement for the successful implementation of QRPMS. It is critical to have clear traceability between a PMS' performance objectives and their respective performance measures for the identification of relationships (Rodriguez *et al.*, 2009). It is therefore the only condition a PMS must meet

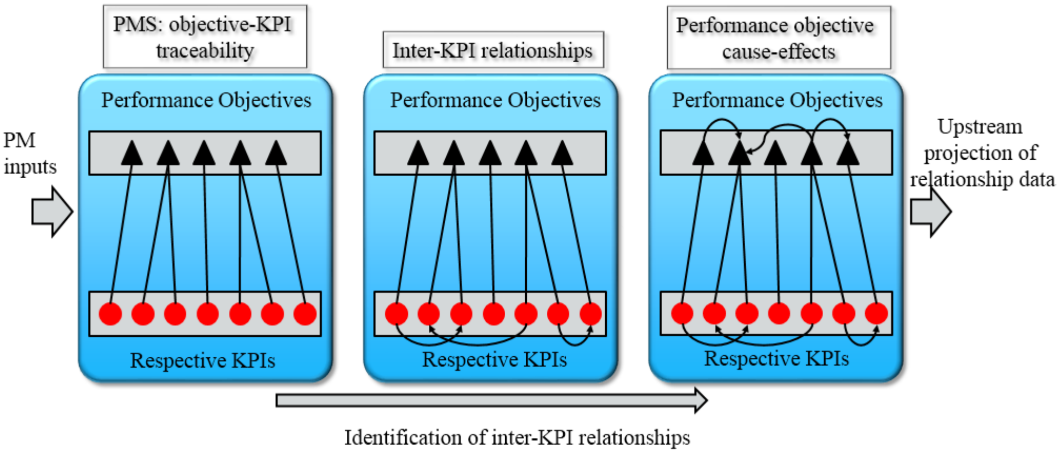


Figure 2.13: Identification and knowledge flow of inter-KPI relationships

Adapted from Rodriguez et al. *(2009)*

before QRPMS is to be implemented. If an organisation does not have a PMS, QRPMS requires that one be designed and implemented, keeping true to this condition.

After reviewing the frameworks discussed in Section 2.5.2 and Section 2.5.3, Rodriguez *et al.* (2009) actively avoided repeating the shortcomings identified. For them, the use of subjective analysis and correlation analysis, at any stage of the QRPMS, was not an option to have a true objective identification and quantification of inter-KPI relationships. In order to accomplish this, Rodriguez *et al.* (2009) used multivariate statistics. A literature review was thus carried out to identify possible candidates, and the techniques investigated by Rodriguez *et al.* (2009) were:

- Factor Analysis (FA)
- Principal Component Analysis (PCA)
- Structural Equation Model (SEM)
- Analysis of Variance (ANOVA)

Factorial Analysis was found to be unsuitable for the requirements of QRPMS. According to Rodriguez *et al.* (2009), it is necessary to define the model in FA. This includes stating what the subjacent variables and observed variables are, what possible relationships there might be and stating the error terms (Hair *et al.*, 2006; Rodriguez *et al.*, 2009). It was therefore not pursued further.

There are also complications regarding Analysis of Variance; independence, approximation to normal distribution, and homoscedasticity are needed for this method, according to Rodriguez *et al.* (2009). Due to the variable types and data dealt with, such as performance measures and their recorded data, the aforementioned are very difficult to attain. It must be noted that another variant of ANOVA is available, which was not commented on by Rodriguez *et al.* (2009). This method, called Multivariate Analysis of Variance (MANOVA), differs from ANOVA by considering several dependent variables. However, these two methods share the same mathematical principals. It is thus assumed that Rodriguez *et al.* (2009) did not assess this method because the problematic implementation of ANOVA is the same for MANOVA. Irrespective of this, Rodriguez *et al.* (2009) continued their search for a more applicable, and easier-to-use, mathematical method.

Fortunately, the other two techniques were found to be more adequate for the needs of QRPMS. Rodriguez *et al.* (2009) state that the decision between the two techniques is based on a ratio. The ratio between the number of variables (the number of KPIs), and the number of observations available for each variable, must at least be 3:1 before the Structural Equation Model (SEM) is employed (Jackson, 1991; Rodriguez *et al.*, 2009).

Principal Components Analysis is, however, a more forgiving method when compared to SEM. According to Wold *et al.* (1987) and Nelson *et al.* (1996), the absence of the aforementioned proportion and the occurrence of missing values in the initial data matrix does not inhibit PCA from delivering good results. This is especially the case when Partial Least Squares (PLS) regression models are employed by a continued model for computing elements of PCA (Geladi and Kowalski, 1986; Martens and Martens, 2001). Based on the previous research completed by Rodríguez *et al.* (2006), Rodriguez *et al.* (2009) concluded that PCA was the most appropriate multivariate statistical method to employ in QRPMS.

Regarding the quantification of the identified inter-KPI relationships, Rodriguez *et al.* (2009) found PLS models to be the most appropriate method for quantifying these relationships. The main benefit of using PLS models is the overcoming of co-linearity, the main problem with classical regression models (Geladi and Kowalski, 1986; Wold *et al.*, 1987; Nelson *et al.*, 1996; Jackson, 1991; Hair *et al.*, 2006).

Rodriguez *et al.* (2009) have shown that the combination of PCA and PLS models succeeds in the objective identification and quantification of inter-KPI relationships. In addition, Patel *et al.* (2008) have previously employed PLS successfully to quantify such inter-KPI relationships. A description of the two mathematical techniques, PCA and PLS, is given in Section 2.6 for a more comprehensive understanding of how they operate.

2.6 Principal Components Analysis And Partial Least Squares

The QRPMS methodology was introduced in Section 2.5.4. As stated, it employs two mathematical techniques to accomplish two critical tasks. A multivariate statistical technique, called Principal Component Analysis (PCA), and a regression analysis model named Partial Least Squares (PLS). This section discusses PCA and PLS models, and expands briefly on the respective fields they are found in; multivariate statistics and regression analysis. This section aims to provide this study with the necessary background information to better understand the purposes and objectives of both PCA and PLS models, and how they are used in the QRPMS methodology.

2.6.1 Multivariate Analysis

Multivariate analysis is becoming an increasingly popular means of analysing complicated datasets, according to Tabachnick *et al.* (2001). It encompasses all the statistical techniques that are generally performed on the analysis of multivariate data; datasets that contain measurements of multiple, different variables. Multivariate datasets are generally more complicated than that however. They may contain many independent variables and/or dependent variables, each having varying degrees of correlation between another (Tabachnick *et al.*, 2001). The multivariate statistical techniques are designed however to address these characteristics of multivariate datasets.

Multivariate statistics simultaneously analyse multiple variables by considering two or more related random variables as a single entity. They aim to yield an overall result taking the relationships between the variables into consideration, as Jackson (1991) and Hair *et al.* (2006) explain. Multivariate statistical techniques are largely progressions and generalisations of the more classical univariate and bivariate analysis methods, but with two general design directions. Hair *et al.* (2006) state that some multivariate techniques merely enable statisticians to perform a single analysis, in stead of many univariate or bivariate analyses, and other multivariate techniques are specifically designed to address multivariate issues.

One of these multivariate issues includes the identification of the underlying structure of a variable set due to the aforementioned degrees of correlation between variables. Of the multivariate techniques able to complete this, one is of interest to this study; PCA. This analysis technique is expanded on in Section 2.6.2.

2.6.2 Principal Component Analysis

PCA is one of the most popular multivariate techniques found in the literature. Abdi and Williams (2010) report that it is possibly the oldest of the multivariate techniques; its origins appearing in literature dating back to the 18th century. Its popularity can be attributed to one of PCA's useful features, dataset dimension reduction. In simple terms, Abdi and Williams (2010) explain, PCA is a technique through which the important information found in a multivariate dataset can be reproduced by fewer variables, called principal components (PCs), with minimal loss of the original information.

PCA derives the eigenvalues and eigenvectors of a covariance data matrix containing observations from multiple, generally inter-correlated, variables (Rodríguez-Díaz *et al.*, 2008; Abdi and Williams, 2010). PCA then computes new, uncorrelated variables (PCs) which exhibit maximum variance along their new axes, accomplished by multiplying the original variables with the obtained eigenvectors (Singh *et al.*, 2004; Jackson, 1991). Tabachnick *et al.* (2001) state the primary objective of PCA is to extract, with each PC, the maximum amount of variance from the dataset.

Tabachnick *et al.* (2001) describes the first PC as the being the linear combination of the original or observed variables that "maximally separates subjects by maximising the variance of their component scores". The second PC extracts the greatest possible variance through the linear combination of original variables that are uncorrelated with the first PC's variables (Tabachnick *et al.*, 2001). All other PCs following are computed from remaining correlations, each extracting the maximum variability possible. In addition, all PCs are orthogonal to their predecessors (Tabachnick *et al.*, 2001; Abdi and Williams, 2010).

The PCs are, according to Tabachnick *et al.* (2001), ranked with the first PC holding the most variance, and the last PC holding the least amount of variance. The number of PCs to retain for further analysis is determined through the employment of a *selection criteria*; criteria which aim to indicate the appropriate minimum of PCs to retain while suffering minimum "information" loss of the original data matrix. PCA determines a number of PCs equal to the amount of original variables in the original dataset, and if all the PCs were retained, it would reproduce the original correlation matrix (Tabachnick *et al.*, 2001). These selection criteria are expanded on in Section 2.7.

In this study, it is assumed that the reader is familiar with general matrix algebra and associated concepts. The terms used in the latter discussion (such as variance, covariance, eigenvectors and eigenvalues) are well-defined by Smith (2002) and will thus not be repeated in this study.

The short description above aims to provide a foundational understanding of what PCA entails. However, it is deemed beneficial to expand briefly on the mathematics used in PCA. This is completed in Appendix B. Although PCA is able to identify the relationships between variables (KPIs), a method is still required to quantify these cause-effect relationships, in both magnitude and sense. According to Rodriguez *et al.* (2009), this can be completed by employing a regression analysis technique called PLS.

2.6.3 Regression Analysis

Regression analysis has arguably become the most popular collection of data analytical techniques since the 1800s when it was first implemented in astronomy (Armstrong, 2011). It, in itself, is an analysis tool; a toolbox for the analyst. The most rudimentary mathematical technique in the aforementioned collection is the *method of least squares*, according to Golberg and Cho (2004). Armstrong (2011) claims regression analysis was, in the past, a very time consuming and expensive procedure to complete. Until the introduction of computers, it took months for skilled analysts to finish a regression analysis.

Regression analysis, according to Golberg and Cho (2004), is an assemblage of statistical methods that model and analyse multiple inter-related variables, where the focus is on the relationship between dependent and independent variables. More specifically, it focuses on the value change of dependent variables while the independent variables' values remain constant, where the 'estimation target' is a function of the independent variables (Golberg and Cho, 2004). This function of independent variables is referred to as a regression equation. Sykes (1993) explains this more simply, saying regression analysis estimates the quantitative effect causal variables have on the influenced variables.

According to Armstrong (2011), regression analysis is generally employed for forecasting and prediction, but is also used to investigate relationships that may exist between the aforementioned dependent and independent variables. Golberg and Cho (2004) state the main purposes of regression analysis (a problem solving approach through data analysis) are the following:

1. Investigation of data; assessing, or possibly refuting, relationships that might exist between variables.

2. Summation and interpretation through a fitted model to obtain a calibration curve.

3. The development of improved theoretical methods and models.

Armstrong (2011) states forecasting and prediction with regression analysis is most effective when small numbers of dependent and independent variables are used, along with a large quantity of data that are dependable and valid. Furthermore, regression analysis is more effective when large, predictable changes are expected (Armstrong, 2011). An essential component of regression analysis, according to Golberg and Cho (2004), is the collection of data on all potentially important factors. The three basic methods for collecting this data are:

1. Observational studies (collecting data through, sometimes random, observations).

2. Retrospective studies (employing historic data).

3. Experimental studies (collection of data from designed experiments).

A warning is issued by Armstrong (2011), stating that regression analysis should not be employed in the search for causal relationships. In addition, data mining, step-wise regression and similar techniques should be avoided in attempts to have the data choose the variables in the regression analysis (Armstrong, 2011).

Golberg and Cho (2004) provide an extensive literature review on the mathematics involved with regression analysis, discussing simple linear regression, multiple regression and additional applications for regression methods. Sykes (1993) and Armstrong (2011) provide a more theoretical based description of regression analysis, with the latter providing information on factors that decrease the accuracy of regression analysis. From the multiple techniques classified under regression analysis, one is of importance to this study; PLS.

2.6.4 Partial Least Squares

According to Geladi and Kowalski (1986), the 1960's and 1970's saw a great amount of research being conducted on PLS and its fields of application. Wold *et al.* (1966) introduced the PLS concept to the academic world, but Tenenhaus *et al.* (2005) state that the final PLS approach, and its main references, were developed by Wold (1980), Wold (1982) and Wold (1985). Despite this research, Geladi and Kowalski (1986) state that many of the publications that resulted from the aforementioned eras described PLS either too complexly or incompletely.

Tobias *et al.* (1995) describe PLS as method for building predictive models, especially when there are multiple, highly collinear variables. It must be noted that PLS does not investigate the underlying relationships between variables, but focuses on predicting the responses of these variables (Tobias *et al.*, 1995). The robustness of PLS proved it to be a good alternative to other, more classical, regression methods, such as Principal Component Regression and Multiple Linear Regression (Geladi and Kowalski, 1986). Even though it was developed as an econometric method, the field of chemometrics employed PLS as an established tool for modelling relationships and is an advocate for its utilisation (Tobias *et al.*, 1995).

PLS, according to De Jong (1993), compresses the predictor data contained in matrix $\mathbf{X}$ into a set of factor scores in a matrix $\mathbf{T}$. $\mathbf{X}$ contains n sample values for m predictors. Then, a set of n observations are fitted to p dependent variables by using factor scores, as De Jong (1993) explains. Similarly to the case of PCA, it is deemed beneficial to expand briefly on the mathematical components of PLS regression.

Appendix B provides a brief overview of the mathematical procedure of PLS, and provides more information on the objective(s) of PLS. However, it must be noted that this is not a complete description of the PLS method; some intermediate steps are left out as the in-depth discussion of PLS does not form part of the scope of this study. Included in this omission is the discussion of the two different PLS models that analysts can select to perform the analysis; models PLS1 and PLS2. In addition, please note that the assumption made in Section 2.6.2 regarding the reader's knowledge of matrix algebra is also made for the discussion in Appendix B. The matrix notation used in Section 2.6.2 is also applicable for the description of PLS in Appendix B.

PLS is employed in the QRPMS methodology to quantify, in both magnitude and sense, the inter-KPI relationships identified by PCA. As Rodriguez *et al.* (2009) state, this is a core objective of the QRPMS methodology; the quantification of the relationships will determine their respective importance. For more information of how this is completed with regard to KPIs, consult Patel *et al.* (2008).

2.7 Selection Criteria For Multivariate Statistics

An overview of the multivariate statistical method PCA was provided in Section 2.6.2, and employs *selection criteria* to determine the number of PCs to be retained for further analysis. This is the same case with Factor Analysis, a statistical technique mentioned in Section 2.6 which also employs selection criteria to select the number of factors to retain. The selection criteria is a small, yet critical part of the aforementioned mathematical techniques, according to Velicer *et al.* (2000), and warrants further investigation.

The studies completed by Fava and Velicer (1992), Wood *et al.* (1996) and Fava and Velicer (1996) empirically demonstrated the damaging effects the extraction of the inappropriate number of PCs in PCA can have on pattern reproduction (Velicer *et al.*, 2000). Fava and Velicer (1992), Fava and Velicer (1996) and Wood *et al.* (1996) urge analysts to employ the most accurate and reliable selection criteria available to mitigate and eliminate the problems identified in their studies; problems related to poor choices in PC retention.

The Guttman-Kaiser criterion (K1) is a very popular selection criteria amongst researchers, according to Yeomans and Golder (1982) and Lance and Vandenberg (2009). However, Lance and Vandenberg (2009) state that it is one of the least reliable, and most inaccurate, selection criteria available. The popularity of an unreliable and inaccurate criterion suggests that employers of such criteria may not be sufficiently aware of K1's deficiencies, nor aware of suitable alternatives for it. It is therefore important to investigate some more dependable and accurate selection criteria. Lance and Vandenberg (2009) provide the following alternative selection criteria to K1:

- Scree plot
- Parallel Analysis (PA)
- Minimum Average Partial (MAP)

The selection criteria listed above do not represent the complete collection of selection criteria available. Other selection criteria include *percent variance*, *sequential tests* and *resampling*, but these selection criteria or selection methods are not recommended by Zhu and Ghodsi (2006) as suitable alternatives for K1 and will thus not be investigated in this study.

The K1 criterion, as well as the three listed alternatives, are discussed in the following sections. The objectives of these sections are to warn analysts of the inadequacy of K1, to introduce alternative selection criteria to K1, and to provide an improved understanding of selection criteria and the important role they play in frameworks such as the QRPMS methodology.

2.7.1 The Guttman-Kaiser Criterion

According to Yeomans and Golder (1982), the K1 criteria remains a very popular selection criteria amongst researchers and consultants in the management and social sciences, despite its well-documented shortcomings. A review of applications conducted by Fabrigar *et al.* (1999) revealed that K1 was the single most implemented method for component retaining decisions. Yeomans and Golder (1982) even acknowledge that some publications implemented it without investigating its shortcomings; without reservation.

The development of the K1 is often mistakenly credited to Guttman (1954), but according to Lance and Vandenberg (2009), Guttman (1954) developed three methods for estimating the lower bound of a population correlation matrix's rank. The criteria that evolved into K1 was one of these three methods, and stated the following:

> *"the minimum dimension of a correlation matrix with unities on the diagonal is greater than or equal to the number of eigenvalues that are at least one"* – (Lance and Vandenberg, 2009)

This criteria was later modified and popularised by Mr. Kaiser, and it was renamed the K1 criteria (Kaiser, 1960, 1961; Yeomans and Golder, 1982). K1 simply states that the PCs with eigenvalues less than 1.0 should be dropped, and not included in further analysis (an eigenvalue of 1.0 equals the average information represented by a single PC, on average). According to Lance and Vandenberg (2009), three things that must be noted:

1. K1 applies to component analysis, and not to common factor analysis.
2. K1 only determines the number of PCs that are extractable, not those that should be extracted (Gorsuch, 1983; Preacher and MacCallum, 2003). It is the analysts responsibility to distinguish the difference.
3. The derivations by Guttman (1954) are based on population data. In a sample correlation matrix, the first eigenvalues are typically larger than the population counterparts, causing too many components to be extracted (Nunnally and Bernstein, 1994).

The work of Yeomans and Golder (1982) aimed to investigate the behaviour of K1 to provide analysts with an improved understanding of the deficiencies inherent in K1. They concluded that the K1 criterion may be inadequate for predicting the number of PCs in a dataset (Yeomans and Golder, 1982). After an assessment conducted by Zwick and Velicer (1986), in which they compared five methods for component retaining determination, they stated K1 cannot be recommended for use in PCA. This assessment was continued by Velicer *et al.* (2000), and they concluded that K1 was highly inaccurate and the most variable of the methods assessed. Cortina (2002) also states that K1 is inferior to the other available criteria.

The aforementioned sources discrediting the K1 criteria provide extensive assessments between the results of K1 and other selection criteria, and are thus not repeated here. The following sections expand on the description of the alternative selection criteria for K1 listed in Section 2.7.1.

2.7.2 The Scree Plot

The scree plot was proposed by Cattell (1966), and is a very simple and quick technique which can be used to determine how many PCs to retain in PCA and other multivariate statistical applications. Zwick and Velicer (1982) included the scree plot in a study in which the effectiveness and accuracy of different selection criteria were compared. This comparison study provided the necessary information for Lance and Vandenberg (2009) to conclude that the scree plot performs adequately, but less optimal than PA and MAP procedures.

As described in Section 2.6.2, PCA computes the sample variance-covariance matrix $\mathbf{S}$ with the eigenvectors of $\mathbf{S}$ being the principal components. For description purposes, a simple example scree plot is shown in Figure 2.14. The eigenvalues of $\mathbf{S}$ as $\boldsymbol{d}_1$, $\boldsymbol{d}_2$, ..., $\boldsymbol{d}_n$ are denoted. The scree plot has the PCs on the horizontal axis (x-axis), and the eigenvalues of $\mathbf{S}$ on the vertical axis (y-axis). The eigenvalues are plotted in sequence with the PCs.

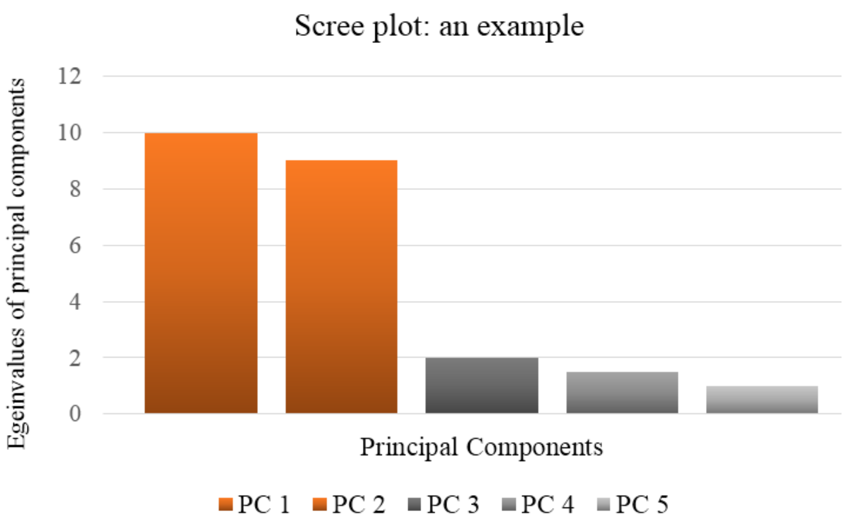


Figure 2.14: The scree plot: an example

In Figure 2.14, the eigenvalues $\boldsymbol{d}_n$ are [10, 9, 2, 1.5, 1] for $n = 1, 2, 3, 4, 5$. They are each plotted against the five respective PCs. According to Zhu and Ghodsi (2006), when following the plot from left to right, the point where the plot reaches a linearly reducing pattern is indicative of the number of PCs that must be chosen. Considering the example scree plot in Figure 2.14, there is a "cliff" in the plotted data and a notable "elbow" that leads to a linear decrease in the plot. The scree plots tells the analyst to drop all the PCs after the "elbow", and retain the PCs in the "cliff" (Velicer *et al.*, 2000). In the given example, only the first two PCs are chosen.

The scree plot is a simple and straightforward selection method. However, the analyst's judgement is required when the scree plot does not provide a plot as convenient as the one in Figure 2.14. If it is difficult to identify a notable "cliff" or "elbow", an analyst has to choose the "elbow" or the start of a linear decline in the plotted data. Therefore, in instances like this, the analyst must employ subjective analysis to determine the number of PCs to retain. In addition, Velicer *et al.* (2000) state that the scree test tends to over-identify PCs when dealing with small sample sizes, therefore making it less accurate.

Due to the aforementioned, and the general working procedure of the scree plot, Velicer *et al.* (2000) state that it is a subjective method. Despite this, Zwick and Velicer (1982) found it to be the most accurate method of four selection criteria. According to Velicer *et al.* (2000), many studies found it reasonably effective. The automatic rejection of the scree plot due to its subjectivity should not occur, Velicer *et al.* (2000) warns. It is to be used as a complimentary criteria, not a stand-alone method.

2.7.3 The Parallel Analysis Criterion

The Parallel Analysis selection criteria was developed by Horn (1965) as an alternative to the K1 criteria. According to Velicer *et al.* (2000) and Hayton *et al.* (2004), PA specifically aims to surpass K1 by overcoming K1's main limitation; aggrandising the matrix rank caused by sampling error. Unlike the scree plot, Zwick and Velicer (1986) found PA to be the most accurate selection criteria *across all conditions studied.*

Hayton *et al.* (2004) and Lance and Vandenberg (2009) describe the foundational reasoning of PA. PA suggests that non-trivial PCs, from a real dataset with a valid foundational pattern, should posses larger eigenvalues than the PCs derived from a equal-sized datasets with randomised data. To ascertain this, PA incorporates the creation of many parallel correlation matrices, similar in sample size and number of variables to that of the real dataset, and then computes the eigenvalues of each matrix (Hayton *et al.*, 2004; Lance and Vandenberg, 2009).

After the eigenvalues of the random correlation matrices are determined, each "real" eigenvalue is compared to its respective "random" eigenvalue, which is the average of all the parallel random eigenvalues (Velicer *et al.*, 2000). Only the "real" principal components with corresponding eigenvalues larger than their "random" parallel averaged eigenvalues are retained for further analysis, according to Hayton *et al.* (2004).

Figure 2.15 illustrates the aforementioned, showing the point where the true PC eigenvalues fall below those of the random generated eigenvalues. In

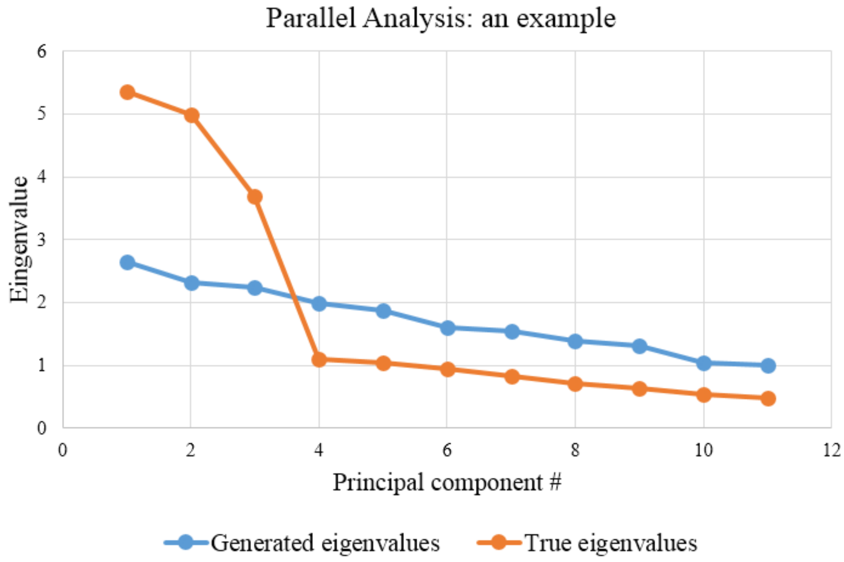


Figure 2.15: Parallel Analysis: an example plot

the case of the example shown in Figure 2.15, the first three PCs of the real dataset will be retained for further analysis. However, the PCs having equal eigenvalues to their parallel counterparts are considered because of sampling errors, according to Zwick and Velicer (1986) and Hayton *et al.* (2004).

Velicer *et al.* (2000) state that there is one issue; the establishment of the number of random correlation matrices to include. Horn (1965) implemented one random correlation matrix, but did propose however that the averaged random eigenvalues must produce an adequate curve when a "reasonably large" amount of matrices are used. Crawford and Koopman (1973) investigated this issue, and through assessing the change in PA's accuracy when using one hundred or one thousand random correlation matrices, found no outstanding and noteworthy difference.

The creation of multiple random correlation matrices is very difficult without the aid of computer technology, and as a result, methods have been investigated to avoid this step in PA. Velicer *et al.* (2000) describe two alternatives that originated from this; the employment of linearly interpolated eigenvalues from tabled format which was constructed by Lautenschlager (1989), and the creation and implementation of regression equations to predict the needed random eigenvalues. Each one of these alternatives are expanded on in detail by Velicer *et al.* (2000) and will thus not be covered here.

As aforementioned, PA was purposely designed to overcome K1's inability to reflect sampling error (Velicer *et al.*, 2000). The ideology of PA, according to Velicer *et al.* (2000), was derived from that of the K1 criteria. PA compares the "real" eigenvalues to those of random correlation matrices, instead of comparing it to a fixed value of 1 like K1 does, accounting for random error. Velicer *et al.* (2000) argues however that the criticisms of the K1 criteria weakens the rationale of PA, therefore judging it to be moderate.

Regardless of the judgement of Velicer *et al.* (2000) on the rationale of PA, Zwick and Velicer (1986) still found it to have a very accurate performance when compared to other selection criteria. Velicer *et al.* (2000) warns though, that this evaluation of PA does not automatically apply to all the available approaches to PA.

2.7.4 The Minimum Average Partial Procedure

Velicer (1976) created the MAP to be used with PCA, and is therefore not appropriate for common Factor Analysis. In the comparative study completed by Zwick and Velicer (1982), the MAP was shown to perform well, being comparable to the scree plot, but more accurate than the K1 criterion. Zwick and Velicer (1986) proved MAP to be more accurate than the scree plot, providing sufficient evidence for Velicer *et al.* (2000) to make MAP a significant a part of their study.

The procedure of MAP is described by Zwick and Velicer (1986) and Velicer *et al.* (2000) as follows. A partial correlation matrix is calculated for each principal component extraction. The average of the squared correlations "of the off-diagonal partial correlation matrix" is calculated (Velicer *et al.*, 2000). The average partial correlation reaches a minimum value, and this point is indicative of the number of PCs to retain.

Zwick and Velicer (1986) and Lance and Vandenberg (2009) state that the successive calculation of partial correlation matrix when a component is extracted aims to remove common variance (shared variance between only two variables). The successive removal of common variance will reduce the average partial correlation to the point where no more common variance exists (Lance and Vandenberg, 2009). It is at this point where only variance, unique to each variable, exists, allowing the correct number of PCs to be extracted and retained. It is also the point where the average partial correlation will start growing. This point is depicted in Figure 2.16 as the minimum, or the lowest point of the plotted data.

MAP identifies a transition point between PCs containing shared variance to components containing unique variance. As aforementioned, MAP was found to be very accurate. In their study, Velicer *et al.* (2000) investigate three MAP variations in depth, and is therefore not repeated in this study. However, Velicer *et al.* (2000) concluded that the three MAP variations deliv-

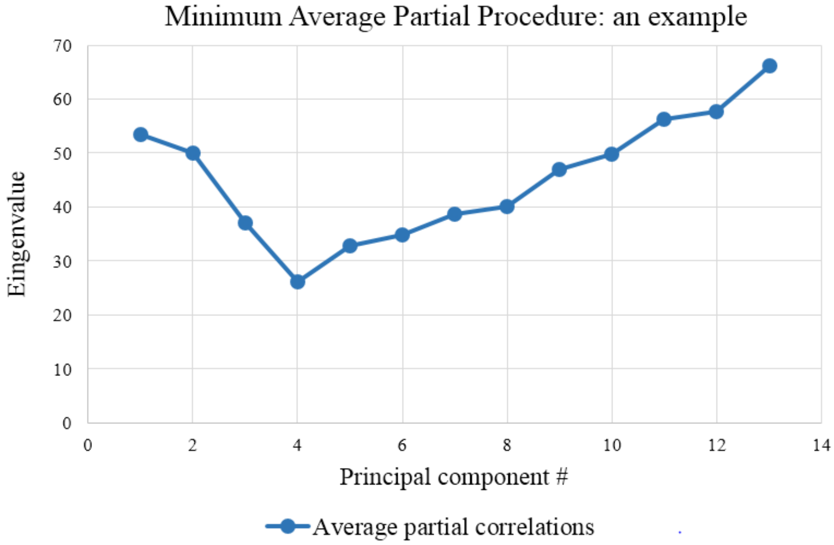


Figure 2.16: An example of the Minimum Average Partial procedure

ered results varying in accuracy, and concluded (albeit marginally) that PA was superior to MAP in accuracy.

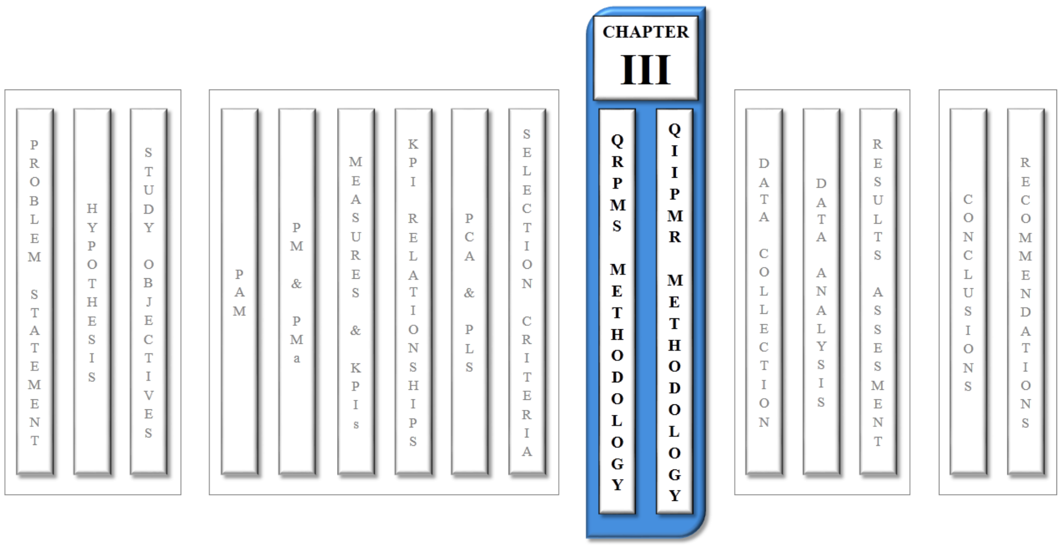
In conclusion, the three selection criteria discussed in Section 2.7.2, Section 2.7.3 and this section are all superior selection criteria to the K1 rule. Parallel Analysis (PA) and Minimum Average Partial (MAP) are highly accurate, yet complicated, selection criteria, with the scree plot offering adequate accuracy and easy implementation. However, Worthington and Whittaker (2006) state PCs should be retained only if the researchers and analysts can explain it, regardless of the validity of the evidence based on empirical data.

2.8 Chapter Conclusion

The aim of this chapter was to introduce and investigate the literature topics needed to conceptualise the problem statement discussed Section 1.2, as well as to provide additional literature to aid in the understanding of the scope and areas-of-influence of this study. Furthermore, specific literature was investigated and included in this chapter to provide the necessary material for the successful development and implementation of a proposed solution of the research question stated in Chapter 1; a solution which is detailed in Chapter 3.

Chapter 3

The Quantitative Identification Of Inter-Performance Measure Relationships Methodology



Chapter Aims:

The aim of this chapter is to develop an improved methodology for the objective identification and quantification of relationships between KPIs; an improved alternative to the QRPMS methodology.

Chapter Outcomes:

⇒ Comprehension of the QIIPMR methodology phases and processes.

⇒ Ability to differentiate between the QRPMS and QIIPMR methodologies.

3.1 Chapter Introduction

In Chapter 2, Section 2.5.4 introduced a methodology that was developed to objectively identify and quantify relationships between a set of Key Performance Indicators (KPIs); a methodology created by Rodriguez *et al.* (2009) and called the Quantitative Relationships at the Performance Measurement System (QRPMS) methodology. However, as stated in Section 1.2, one of QRPMS's critical mathematical components, the Guttman-Kaiser criterion (K1), is unsuitable for employment in the multivariate statistical technique used by QRPMS, Principal Component Analysis (PCA).

According to multiple researchers (as listed in Section 1.2) who conducted comparison studies between K1 and other selection criteria, found K1 to be highly unreliable and grossly inaccurate. The K1 criterion therefore severely reduces the accuracy and reliability of the QRPMS methodology's results. This proves to be a significant problem as the QRPMS, to the knowledge of this study, is the only methodology specifically developed for the aforementioned task, and it is therefore critical to rectify this problem.

The objective of this chapter is to develop an improved methodology for the objective identification and quantification of inter-KPI relationships, and the upstream projection of results in a PMS. This methodology, called the Quantitative Identification of Inter-Performance Measure Relationships (QIIPMR) methodology, is to be built on the literature covered in Chapter 2. This methodology constitutes this study's attempt at addressing the research question stated in Section 1.2.

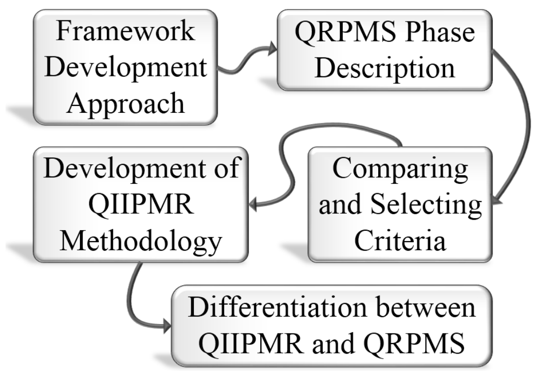


Figure 3.1: The development flow of the QIIPMR methodology

To guide the QIIPMR development process, a "development approach" has to be created; an approach which is specified in Section 3.2. This approach to development coincides with the chapter structure, or flow, which is depicted in Figure 3.1.

3.2 Approach To Framework Development

Section 2.5 presents a literature review on the frameworks that lead to the development of the QRPMS methodology, as well as provided an introductory discussion on the QRPMS methodology. However, an in-depth description of the QRPMS phases does not form part of this section's introduction. It is thus necessary to first discuss, in-depth, the QRPMS phases in Section 3.3. The collated description of the QRPMS methodology in Section 2.5.4 and Section 3.3 therefore describes all the QRPMS constituents, forming the foundation on which the QIIPMR methodology can be developed.

The K1 selection criteria is employed by the QRPMS methodology to select the number of PCs to retain for further analysis, as described in Section 2.6.2. It is, however, desired that the K1 criteria be replaced with a more appropriate selection criteria in the development of the QIIPMR methodology due to the reasons stated in Section 1.2 and Section 3.1. A literature review is conducted in Section 2.7, identifying alternatives to the K1 criterion; alternatives that are superior in accuracy and reliability. To replace the K1 criteria with one or more of these alternative criteria, it is necessary to compare and select the most adequate of them. This selection procedure is covered in Section 3.4, identifying the selection criteria that is to be incorporated into the QIIPMR methodology.

Drawing from the material and conclusions of Section 2.5.4, Section 3.3, and Section 3.4, the development of the QIIPMR methodology can proceed in Section 3.5. Once QIIPMR is developed, its objectives can be stated, and a detailed description of the QIIPMR phases and respective constituents can be provided. Furthermore, the similarities QIIPMR shares with the QRPMS methodology, as well as their differences, can also be clearly identified. In conclusion, the complete QIIPMR methodology, along with its process flow, can finally be depicted in a "process-flow" diagram for visual presentation and interpretation.

3.3 The Quantitative Relationships In Performance Measurement System Methodology

As stated in Section 2.5.4, Rodriguez *et al.* (2009) developed a methodology in response to the shortcomings and inadequacies identified within other proposed frameworks. These inadequate frameworks are described in Section 2.5, detailing their intentions and the factors rendering them inadequate for the objective identification and quantification of inter-KPI relationships. Section 2.5.4 introduces the QRPMS methodology, but as stated in Section 3.2, the detailing of its phases are omitted. The following section completes the phase description of the QRPMS methodology.

3.3.1 The QRPMS Methodology Phases

The QRPMS methodology employs four phases to deliver its intended results. The QRPMS phases vary in difficulty and the time required to complete each may differ depending on the resources and personnel available (Rodriguez *et al.*, 2009). The QRPMS stages are listed below, which are also depicted in Figure 3.2:

- Phase 1: Design and analysis of the PMS in consideration.
- Phase 2: Initial performance measure data treatment.
- Phase 3: Identification and projection of inter-KPI relationships.
- Phase 4: Presentation and analysis of results.

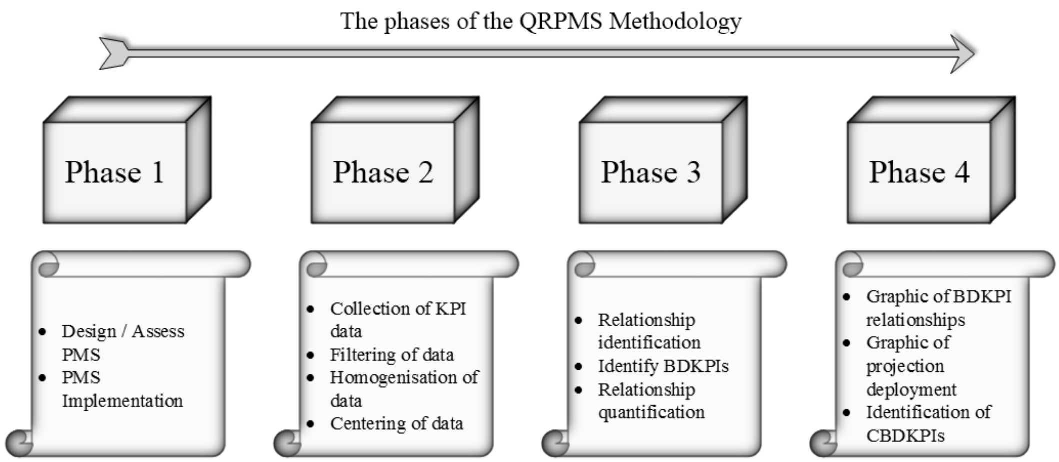


Figure 3.2: Phases of the QRPMS methodology

Adapted from Rodriguez et al. *(2009)*

The description of each of the four phases is carried out in the following sections. Necessary referrals to other sections in Chapter 2 are provided; sections which contain additional background information where required.

3.3.1.1 Phase 1: Design and analysis of the PMS

The QRPMS methodology is designed to be a generic methodology, and therefore it is necessary to assess the environment, or the PMS, it is to be implemented in. The first phase of QRPMS involves a critical assessment of the implementing organisation's PMS. The PMS is required by QRPMS to have clear traceability between its performance objectives and their respective KPIs (Rodriguez *et al.*, 2009). The necessity of this criteria was discussed in Section 2.5.3.

In the absence of an existing or functioning PMS, one must be created and implemented, keeping in mind the aforementioned criteria. An overview of the creation of PMF and PMS is provided in Section 2.3.3. In addition, a popular academically generated example of a PMS, the BSC, is discussed in Appendix A. Section 2.4 provides some helpful information on performance measures and KPIs; information that will mitigate significant errors commonly encountered in their implementation. In addition, recommendations of other literature sources are provided for more in-depth discussions on other significant topics that were not expanded on in this study.

After the completion and implementation of the PMS, it is to be analysed and any identified problems are to be rectified by PMS managers before the implementation of QRPMS. Special focus must be placed on errors affecting the traceability between performance objectives and their performance measures respectively. Once the organisation's PMS fulfils the QRPMS criteria, the QRPMS implementation can proceed to Phase 2.

3.3.1.2 Phase 2: Initial data treatment

The second phase of QRPMS involves the collection and treatment of the KPI-generated data. According to Rodriguez *et al.* (2009), the collection of the necessary data can be easily accomplished if the organisation extensively employs electronic registers to store their data. However, collection will prove more difficult for those organisations who do not store their data electronically. After the collection of the respective KPI data, three actions will be completed:

1. Filtering.
2. Homogenisation.
3. Centering.

Each one of the above listed actions are described below. It is recommended that these actions be performed in order of appearance for improved data treatment efficiency and to mitigate the unnecessary loss of information.

Filtering

The first operation, *filtering*, will reveal any anomalous behaviour within the KPI data; behaviour that can possibly bias the analysis (Rodriguez *et al.*, 2009). Hair *et al.* (2006) state that statistical methods, such as those listed below, may be applied to the data of each KPI to complete the filtering process:

- Mean.
- Standard deviation.
- Mode.
- Histogram.
- Percentiles.
- Normal graphical representation.

When the data filtering operations are contracted out to external analysts, it is recommended that experienced employees from the organisation work with the contractors (Rodriguez *et al.*, 2009). KPI data trends representing normal organisational situations or behaviour, that might seem abnormal to the contractors, can thus be explained by the organisation's employees. Adhering to this recommendation reduces the chance of eliminating potentially valuable information.

Homogenisation

KPIs, and performance measures in general, are recorded at predetermined temporal frequencies; fixed time intervals. These temporal frequencies are commonly yearly, monthly, weekly or daily (Rodriguez *et al.*, 2009). *Homogenisation* is the process in which the recorded KPI-data is manipulated to have the same temporal frequency, without affecting the validity of the data.

Temporal frequency is an important characteristic to consider when comparing data, and is easily explained using an example. The ore tonnage mined by a mining operation is recorded monthly, and for the purpose of this example, constant ore tonnage mined per day, every day of the month, is assumed. A variability exists between the year's monthly recordings due to the varying number of working days in each month. If the temporal frequency was weekly, and constant ore tonnage mined per day was ignored, all the variability present between the year's weekly measurements would thus be caused by varying mining performance.

The above example highlights the importance of using a temporal frequency that does not introduce variation into the KPI data recordings of a single KPI; variation that is not caused by varying performance, but by poor temporal frequency selection. However, this is also applicable when multiple KPI data recordings are to be compared to each other. Rodriguez *et al.* (2009) state that at this point in the QRPMS data analysis, a temporal frequency must be identified to which all the assessed KPIs and their respective data recordings can be accurately conformed to.

Varying homogenisation operations might be required for each KPI, depending on the respective KPI's data distribution presented, to accurately change it to the chosen, overall temporal frequency. Rodriguez *et al.* (2009) state that a mean can be applied for normally distributed data, and the geometric media or median can be applied to very asymmetric data distributions in these efforts.

Centering

The last operation, *centering*, will assign all KPIs equal degrees of importance, according to Rodriguez *et al.* (2009). Although the reason for doing so is not explained by Rodriguez *et al.* (2009), it is assumed to avoid biased allocations of importance; an issue that is briefly discussed in Section 2.4.5.2. However, a complication is encountered in this phase.

KPIs are heterogeneous in nature with respect to their measurement units; financial KPIs generally have units including currency, whereas non-financial KPIs may possess any type of unit (tonnes, hours, ratios, etc.) (Suwignjo *et al.*, 2000). It is therefore, generally speaking, mathematically incorrect to compare KPIs that have varying units. To address this, QRPMS employs a method referred to as *auto-scaling*; a combination of centering and standardisation methods (Hair *et al.*, 2006; Rodriguez *et al.*, 2009). After the completion of this phase, it is possible to construct a matrix containing the treated KPI data, ready to be used by PCA in the next phase.

3.3.1.3 Phase 3: Identification and projection of KPI relationships

As mentioned in Section 2.5.4, the QRPMS methodology implements PCA to objectively identify relationships between a set of KPIs. PLS is then used to objectively quantify the relationships identified through PCA. Both of these mathematical techniques are described in Section 2.6.

The first task in this phase is an initial exploratory analysis, carried out by implementing PCA, in which all the possible inter-KPI relationships are identified. A confirmatory analysis is then carried out by applying the PCA procedure to only those KPIs which have been shown to have cause-effect relationships with other KPIs. According to Rodriguez *et al.* (2009), this is to eliminate any possible "noise" the other, non-related KPIs may contribute to the system.

As described in Section 2.6, PCA requires the analysts to choose the number of PCs to retain for further analysis. In order to complete this, QRPMS employs a selection criteria called the Guttman-Kaiser criterion (K1) criterion; described in Section 2.7.1 (Rodriguez *et al.*, 2009). Using the results obtained from PCA, the KPIs which are shown to have relationships between one another can be identified using a graph such as the example shown in Figure 3.3. Further information on the development of this graph is provided in Section 4.5.3. The KPIs which land between the concentric ellipses displayed in Figure 3.3 are redefined by QRPMS as Business Driver Key Performance Indicators (BDKPIs). Rodriguez *et al.* (2009) state BDKPIs hold a higher importance to organisational management because of the relationships they maintain, and are critical to the evolution of the organisation.

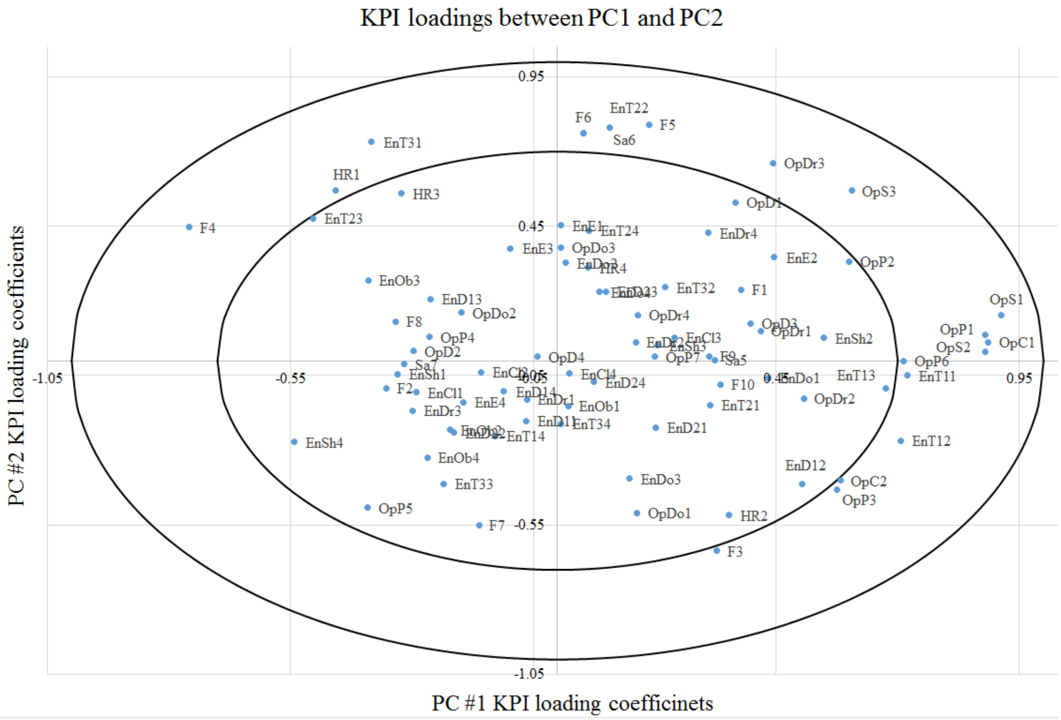


Figure 3.3: KPI loadings between two PCs

The second task is to quantify the inter-KPI relationships through the employment of PLS regression analysis. According to Rodriguez *et al.* (2009), the analysts need to decide which of the two possible models they want to build. These models predict two cases: the prediction of a single *effect* variable from one or more *cause* variables, and multiple *effect* variables from multiple *cause* variables. These are models called PLS1 and PLS2 models, respectively. The analysts are required to specify what the effect variable(s) and cause variables are in order to determine which model can be used (Rodriguez *et al.*, 2009).

Rodriguez *et al.* (2009) and Ilin and Raiko (2010) recommend consulting the information contained in the correlation loadings matrices obtained from PCA to support this decision; the effect and cause variables will boast the highest correlation in these matrices, and willingly maintain it. For more information on PLS and the two aforementioned models, consult Section 2.6.4. In conclusion of this phase, the QRPMS methodology recommends that the organisation's managerial personnel, and external consultants (if any), be included in the design of the chosen PLS model.

3.3.1.4 Phase 4: Presentation and analysis of results

The last phase of QRPMS constitutes the presentation and analysis of the results of the work completed in the previous phases. QRPMS constructs two figures to represent the results; the first figure is called *Graphic of BDKPI relationships*, and the second *Graphic of projections deployment*. Each one is discussed below.

The *Graphic of BDKPI relationships* figure is designed to represent all the strong cause-effect relationships identified between the BDKPIs in the previous phase (Rodriguez *et al.*, 2009). An important characteristic of this graphic is the indication of the intensity, and sense, of each relationship. According to Rodriguez *et al.* (2009), a differentiation is made between two sub-classes of the strong relationships. An average-to-strong relationship is indicated in this graphic by a discontinuing line, and a very-strong relationship by a continuous line. In addition, each cause-effect relationship is indicated to be either negative or positive in the graphic.

The intended deliverable of the *Graphic of BDKPI relationships* figure is primarily to allow analysts to study the multiple cause-effect relationships within their respective performance areas. Secondly, it graphically confirms previously suspected, or subjectively-identified, relationships. An example of this graphic is shown in Figure 3.4.

The examples of performance areas shown in Figure 3.4 are *customer*, *financial*, *internal*, and *learning and growth*. These are based on the BSC perspectives discussed in Appendix A, but can be any performance area defined by the implementing organisation. At this point in the assessment, BDKPI

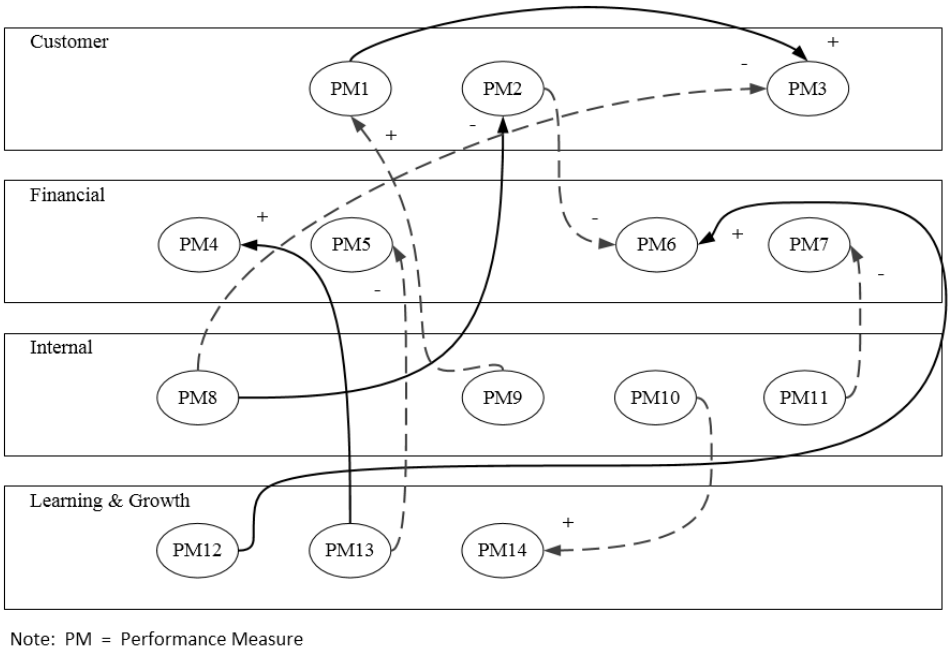


Figure 3.4: Graphic of BDKPI relationships: an example

Adapted from Rodriguez et al. *(2009)*

redundancy may be evident, in addition to the clear identification of main BDKPI causes, according to Rodriguez *et al.* (2009).

The second figure assists in the projection of the identified cause-effect relationships upstream in the respective PMS (Rodriguez *et al.*, 2009). *Graphic of projections deployment* is founded on the *Graphic of BDKPI relationships* figure, and does the following. Each BDKPI is replaced by its associated performance objective, while conserving the relationships. This can be carried out, according to Rodriguez *et al.* (2009), due to the clear and unmistakable traceability between performance objectives and their respective performance measures. An example, based on the relationships shown in Figure 3.4, is shown in Figure 3.5.

Similarly to the *Graphic of BDKPI relationships*, the *Graphic of projections deployment* will allow analysts to study the cause-effect relationships, not between BDKPIs, but between their associated performance objectives. This will again confirm any suspicions, based on research or experience, the analysts or organisational managerial members may have. Rodriguez *et al.* (2009) believe that these two figures will provide decision-makers with additional data (and a better understanding) of the organisation's performance characteristics and behaviour. Improved and more considerate decisions are made available as new alternative decision possibilities are created through the visual inspection of these two figures.

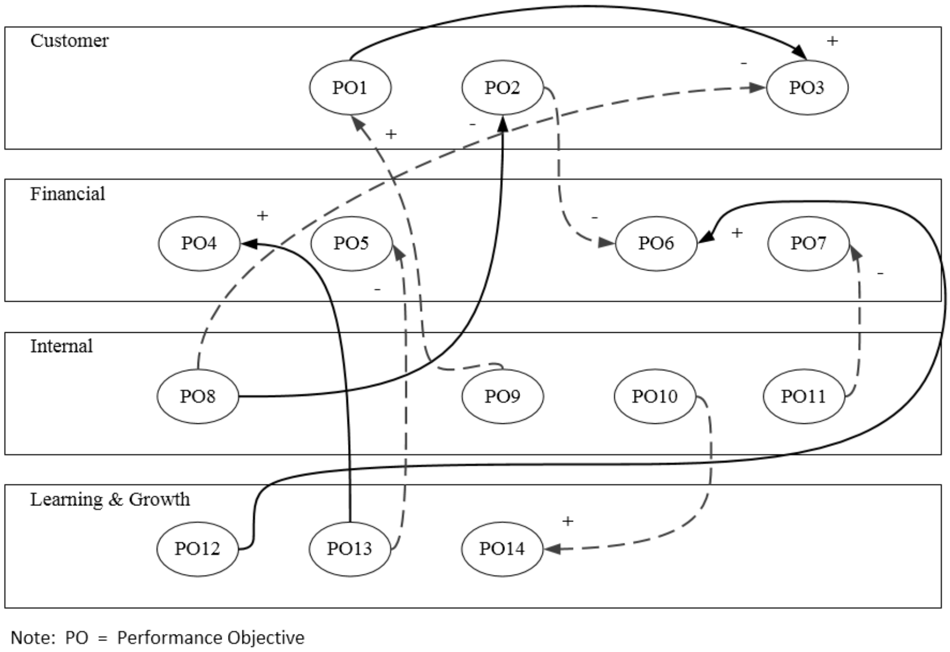


Figure 3.5: Graphic of projections deployment: an example

Adapted from Rodriguez et al. *(2009)*

Furthermore, QRPMS introduces a new factor at this stage of the analysis, named Causal Business Driver Key Performance Indicators (CBDKPIs). CBDKPIs are BDKPIs that prohibited, or influenced, the successful completion of another performance objective. These are identifiable through investigating the *Graphic of projections deployment*, and they are caused by some circumstantial-dependent reason(s). Rodriguez *et al.* (2009) state that organisations need to ceaselessly observe CBDKPIs, as any alteration of them may lead to other BDKPIs experiencing change-related effects, resulting in a causal sequence throughout the set of KPIs.

3.4 Selection Criteria Comparison And Selection

As stated in Section 3.2, it is necessary to select an alternative selection criteria to K1 for incorporation into the QIIPMR methodology. A literature review is conducted in Section 2.7 on three suitable alternatives to the K1 criterion; the scree plot, Parallel Analysis (PA) and the Minimum Average Partial (MAP) procedure. In order to carry out the criteria selection, a comparison between the three alternatives is necessary.

In Section 2.7 it was stated that multiple researchers, such as Zwick and Velicer (1982) and Lance and Vandenberg (2009), carried out comparison studies on selection criteria. Some of their comments were included in Section 2.7 for descriptive purposes. Based on their comparison results and comments on performance, three evaluating factors were selected by this study; evaluating factors against which the alternative selection criteria will be evaluated and compared. These evaluating factors are *ease-of-use, subjective employment*, and *accuracy*. Each of the three selection criteria (the scree plot, PA and MAP) are given a rating for each evaluating factor as indicated below.

- *Ease-of-use*: *Poor*, *Good*, or *Excellent*.
- *Subjective employment*: *Not applicable*, *Mediocre*, or *Fully*.
- *Accuracy*: *Poor*, *Good*, or *Excellent*.

The rating options listed above are based on this study's conclusions derived from the information gathered through the aforementioned comparison studies in Section 2.7. The rating allocated to each selection criteria, respective of the evaluating factor, is completed with respect to the other selection criteria; the selection criteria are only evaluated against each other. For example: the selection criteria which is the most easily implemented will be scored *Excellent*, and the most inaccurate selection criteria will be scored *poor*.

The scree plot, according to Velicer *et al.* (2000) and Lance and Vandenberg (2009), is the most easily implemented selection criteria of the three being assessed. The scree plot also employs subjective analysis to visually determine the number of PCs to retain; an analytical technique not employed by PA and MAP. In addition, the scree plot has adequate performance and accuracy in a study investigated by Lance and Vandenberg (2009), but is less accurate than PA and MAP. Furthermore, Lance and Vandenberg (2009) revealed it has adequate performance and accuracy, but when compared to PA and MAP, is less accurate.

Velicer *et al.* (2000) state that both PA and MAP boast impressive accuracy, but Lance and Vandenberg (2009) found PA to be marginally more accurate than the MAP procedure. Furthermore, the PA and MAP criteria are complicated and calculating-intensive criteria, thus requiring competent personnel to implement them effectively. Although the use of computer programs improved their ease of implementation dramatically, PA is generally more easily implemented than MAP (Hayton *et al.*, 2004). PA and MAP are purely objective, therefore the evaluating factor *subjective employment* does not apply to their mathematical calculations. The allocated ratings are tabulated in Table 3.1.

In order to improve the process of selecting the most appropriate selection criteria to employ in the QIIPMR methodology, the comparison between the

Table 3.1: Comparison ratings of the selection criteria

Selection criterion	*Ease-of-use*	*Subjective employment*	*Accuracy*
Scree plot	*Excellent*	*Fully*	*Poor*
Parallel Analysis (PA)	*Good*	*Not applicable*	*Excellent*
Minimum Average Partial (MAP) procedure	*Poor*	*Not applicable*	*Good*

selection criteria and the allocated ratings are depicted in Figure 3.6. To simplify the graphical comparison, the rating choices *Poor*, *Good*, and *Excellent* were numerically represented by 1, 2 and 3 respectively. The same applies to the rating choices *Not applicable*, *Mediocre*, or *Fully*.

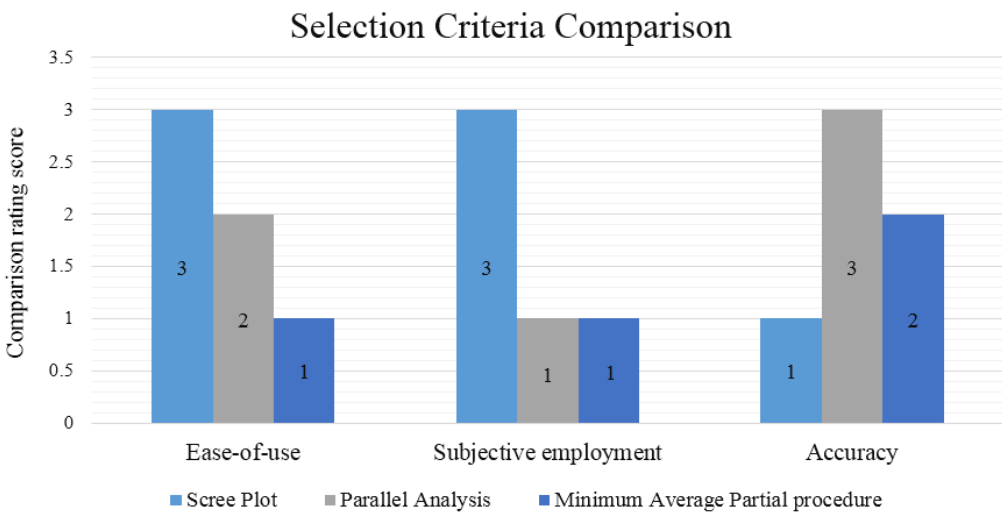


Figure 3.6: A comparison of three selection criteria

After assessing the information contained in Table 3.1 and depicted by Figure 3.6, it was decided to implement two of the three selection criteria in the QIIPMR methodology. Although the PA and MAP criteria share similar characteristics, PA is chosen as the primary selection criteria because it is more accurate and easily executed than the MAP procedure, according to the sources consulted above. In addition, the PA criterion does not compromise the objectivity of the mathematical techniques employed by QIIPMR.

To support QIIPMR analysts in comprehending and validating the results of the PA criterion, it is beneficial to employ the scree plot as a secondary selection criteria. The scree plot will provide an alternative, visual interpretation of the results; results that are independent of the PA criterion's calculations. Therefore, the subjective analysis introduced by the scree plot does not influence the mathematical computations of QIIPMR, but assists in the assessment of results. In addition, the scree plot would also indicate if an error has possibly been made through the execution of either criteria if agreeing results can not be found. Thus the additional resources required to employ the scree plot is justified by the aforementioned benefits it offers.

In conclusion, the PA criterion will be employed by the QIIPMR as the primary criterion to determine the number of PCs to retain, and the scree plot will fulfil the role of a supporting criterion, improving the comprehension of results obtained and facilitating the detection of possible mathematical errors.

3.5 The Quantitative Identification Of Inter-Performance Measure Relationships Methodology

The QIIPMR methodology is this study's suggested answer to the research question described in Section 1.2; a problem which was also briefly described in Section 3.1. The QIIPMR methodology is a modification and improvement of the QRPMS methodology in which the K1 criterion (employed by QRPMS) is replaced with one or more of the alternative selection criteria investigated in Section 2.7. The result is a methodology which is founded on accurate and reliable mathematical techniques which were investigated by means of a literature review carried out in Chapter 2.

The development of the QIIPMR methodology followed a pre-determined approach which was discussed in Section 3.2, and making use of the information contained in Section 3.3 and Section 3.4, the constituents of the QIIPMR methodology could be described. However, prior to describing these constituents, it is necessary to state the primary objectives of the QIIPMR methodology. The QIIPMR objectives are presented in Section 3.5.1, as well as the description of the QIIPMR phases and constituents. Section 3.5.2 concludes the discussion on the QIIPMR methodology with a provision of execution guidelines for the processes inherent in this new methodology.

3.5.1 Objectives And Phases Of QIIPMR

The primary objectives of the QIIPMR methodology are:

- To be a standard methodology employable by all PMS whose links between its performance objectives and their respective KPIs are clearly defined.

- To identify and quantify relationships between a set of KPIs in a purely objective manner.
- To facilitate a deeper understanding in the objective identification of inter-KPI relationships.
- To provide performance managers with objective evidence to support previously suspected cause-effect relationships.
- To identify KPIs critical to driving organisational performance.
- To provide objective evidence of potential non-completion of performance objectives due to non-related KPI variances.
- To provide organisational decision-makers with additional numerical and graphical information for improved decision-making processes.
- To be a mathematically sound and accurate methodology.

As stated in Section 3.5, the QIIPMR methodology is an improved QRPMS methodology whereby a small, yet critical component is improved upon. It is for this reason that many of the QRPMS phases and process are adopted unaltered into the QIIPMR methodology. A brief description of which QRPMS phases are adopted is given below, including any alterations.

- QIIPMR Phase 1: Direct adoption of QRPMS phase 1 and all constituents.
- QIIPMR Phase 2: Direct adoption of QRPMS phase 2 and all constituents.
- QIIPMR Phase 3: Adoption and modification of QRPMS phase 3. The K1 criterion is discarded, and the PA selection criteria and scree plot is incorporated.
- QIIPMR Phase 4: Direct adoption of QRPMS phase 4 and all constituents.

The QIIPMR methodology aims to achieve its aforementioned objectives by completing the four, above-listed phases and respective alterations. These phases are summarised in Table 3.2 and depicted in Figure 3.7.

Table 3.2: Description of the QIIPMR phases and their respective constituents

QIIPMR Phase	Phase description and constituents
Phase 1:	Assessment of the PMS implementing the QIIPMR methodology. • If the PMS passes the QIIPMR criteria, continue the QIIPMR implementation. • If the PMS fails the QIIPMR criteria, redesign the links between performance objectives and respective KPIs. • If no PMS exists, design and implement a PMS that satisfies the QIIPMR criteria.
Phase 2:	KPI data collection and treatment. • Data collection. • Data filtering. • Data homogenisation. • Data centering.
Phase 3:	Identification and quantification of inter-KPI relationships. • Inter-KPI relationship identification. – Exploratory PCA. – Confirmatory PCA. – PC selection through PA and scree plot. • Identification of BDKPIs. • Inter-KPI relationship quantification. – Partial Least Squares (PLS) regression analysis. ∗ Selection of appropriate PLS models.
Phase 4:	Analysis and graphical representation of inter-KPI relationships. • Graphic of BDKPI relationships. • Graphic of projection deployment. • Identification of CBDKPIs.

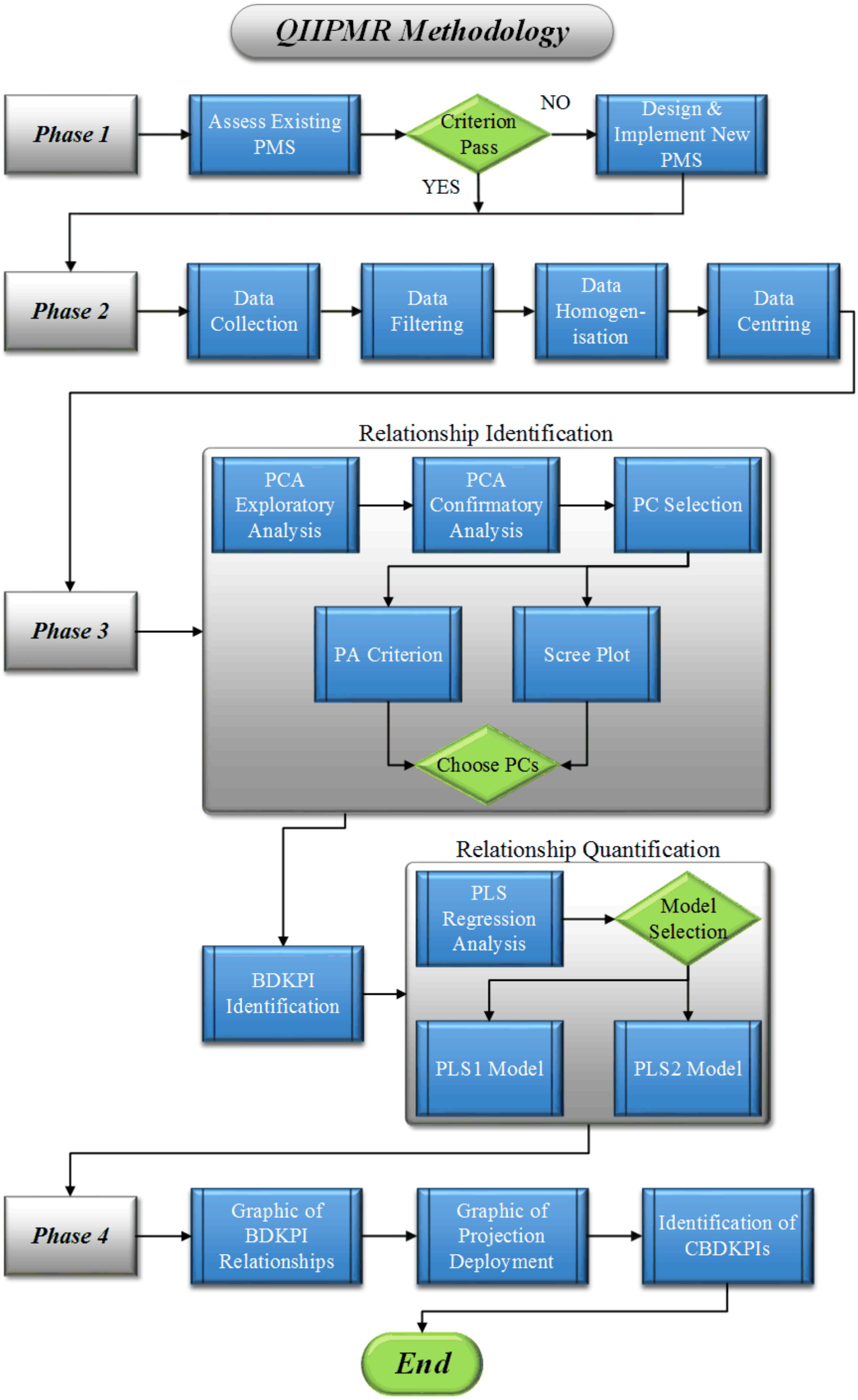


Figure 3.7: The QIIPMR methodology

3.5.2 Execution Of The QIIPMR Phases And Processes

The four QIIPMR phases shown in Table 3.2 and Figure 3.7 specify tasks and processes that are to be completed to deliver the intended results of the QIIPMR methodology. These four phases are detailed in Section 3.3.1.1, Section 3.3.1.2, Section 3.3.1.3 and Section 3.3.1.4, respectively. However, the execution instructions of these tasks and phases were not included in the QIIPMR phase descriptions. It is therefore necessary to briefly summarize where in this study the required literature and instructions can be found for the execution of the tasks and processes in the aforementioned sections.

As can be seen in Figure 3.7, Phase 1 of the QIIPMR methodology involves the assessment of a PMS; a procedure which is described in Section 3.3.1.1. However, if the design of a new PMS is required, the information contained in Section 2.3 and Section 2.4 should be consulted. These sections of the literature study contain valuable guidelines and recommendations, as well as additional literature sources, for the development of a PMS and its KPIs.

The second phase of the QIIPMR methodology involves data handling; a process which is adequately described in Section 3.3.1.2. The third QIIPMR phase, on the other hand, employs a few mathematical techniques as detailed in Table 3.2 and Figure 3.7. The first technique employed, PCA, is discussed in Section 2.6.2 along with a description of its mathematical procedure. The PA criterion and scree plot are discussed in Section 2.7.3 and Section 2.7.2 respectively, and examples of each are also provided. The last mathematical technique employed by the QIIPMR methodology, PLS analysis, is detailed in Section 2.6.4.

The last QIIPMR phase entails the generation of two figures with which the results of the QIIPMR methodology are represented. The development of these figures are explained in Section 3.3.1.4. However, the assessment of results is highly dependent on the KPI data used, and the results obtained. The assessment procedure is best described through the use of an example, such as the case study completed in Chapter 4.

3.6 Chapter Conclusion

As stated in the introduction of Chapter 3, Section 3.1, the objective of this chapter was to develop an improved methodology, founded on the QRPMS methodology, for the objective identification and quantification of inter-KPI relationships. In order for this chapter to develop the QIIPMR methodology, a specified approach was required. This approach was specified in Section 3.2, and is depicted in Figure 3.8.

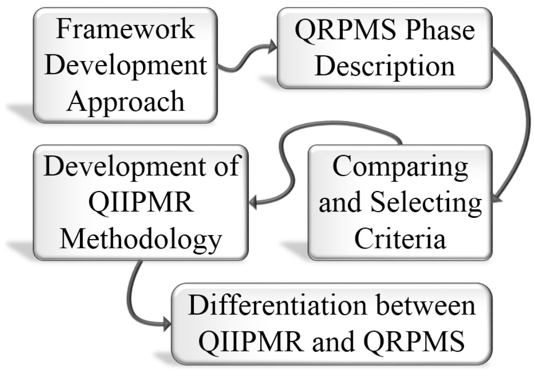


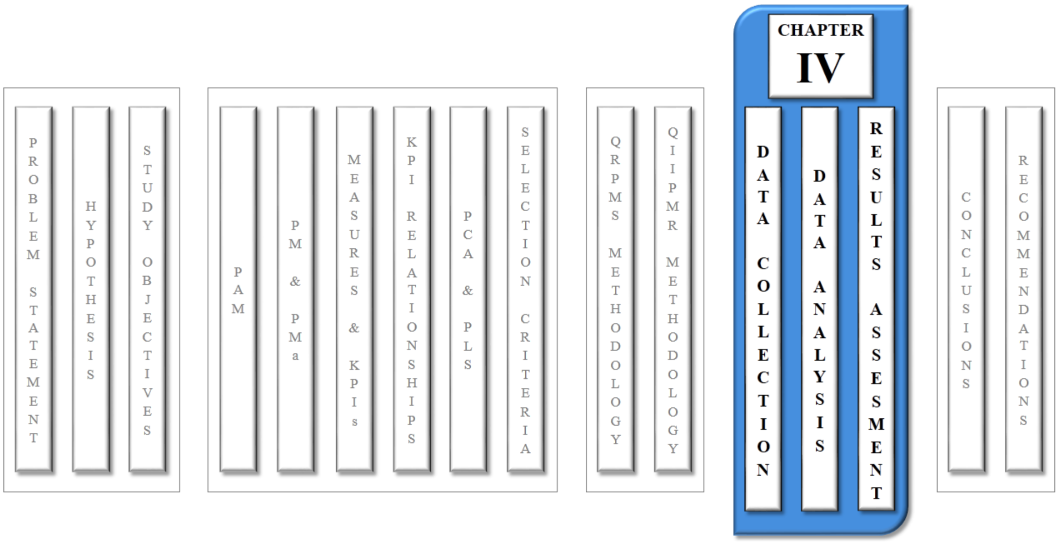
Figure 3.8: The development flow of the QIIPMR methodology.

Through the combined descriptions of the QRPMS methodology in Section 2.5.4 and Section 3.3, the valid components of QRPMS were selected to include in the QIIPMR methodology. The rejected components of the QRPMS methodology had to be replaced; an adequate alternative selection criteria had to be chosen and implemented into QIIPMR. This was successfully completed in Section 3.4.

The result of the aforementioned development approach was the successful development of this study's proposed solution to the problem statement in Section 1.2. The QIIPMR methodology has the potential to provide more accurate and reliable results than its predecessor, the QRPMS methodology. The validation of this claim will be carried out in Chapter 4.

Chapter 4

Case Study



Chapter Aims:

This chapter aims to substantiate the development of the QIIPMR methodology by means of a case study. The case study involves the partial implementation of both the QRPMS and QIIPMR, and a comparison of the results obtained. The result comparison provides the supporting evidences for the aforementioned substantiation.

Chapter Outcomes:

⇒ Comprehension of the case study parameters and environment.

⇒ Understanding the difference between the QRPMS and QIIPMR results.

⇒ Substantiation of the proposed solution of this study.

4.1 Chapter Introduction

In Chapter 3, a methodology is developed for the objective identification and quantification of relationships between a set of Key Performance Indicators (KPIs). This methodology, called the Quantitative Identification of Inter-Performance Measure Relationships (QIIPMR) methodology, is an improved version of the Quantitative Relationships at the Performance Measurement System (QRPMS) methodology developed by Rodriguez *et al.* (2009).

The objective of this chapter is to conduct a case study through which the necessary information can be gathered to evaluate the improvement made to QIIPMR over QRPMS. The evaluation provides the foundation for substantiating the QIIPMR methodology. In order to systematically collate the required information for this substantiation, this chapter follows a predetermined flow of topics. This predetermined flow is presented in Figure 4.1.

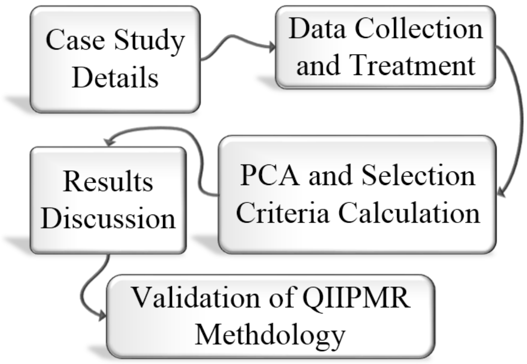


Figure 4.1: The development flow of the case study

The reader is first informed of the case study environment, as well as of any assumptions made and limitations encountered during the case study. Upon completion, the remainder of the chapter details the elements constituting the flow depicted in Figure 4.1.

4.2 Case Study Overview

The opportunity to approach an organisation, which is dependent on Physical Asset Management (PAM) for their financial success, presented itself as a case study. A mining organisation in South Africa was invited to take part in the case study and substantiation of the QIIPMR methodology. Due to a non-disclosure agreement, no further details of the mining organisation can be provided. However, some generic information on the mining operation, whose data is used in this case study, is provided to better conceptualise the origin of the KPI data.

The KPI data is collected from one of the mining organisation's open-pit, thermal coal mines. The particular mine is chosen as it has different organisational silos at site, but most importantly, it manages the entire mining and delivery process (to a single client) of thermal coal. This study can therefore use KPI data from a single business entity solely responsible for the aforementioned process. It allows for a variety of performance data to be assessed, as well as ensuring Performance Measurement (PM) and Performance Management (PMa) standards are maintained throughout all organisational silos. Furthermore, a single PMS is employed to measure and monitor the performance of the mine, eliminating the need to merge different KPI databases and to account for different KPI standards.

The mine is an engineering intensive operation with on-site workshop facilities used to service and maintain their multiple fleets of physical assets. In addition, the productivity and profitability of the mine is greatly dependent on some critical physical assets, such as draglines, shovels and haulers. Therefore, the majority of the mine's overall PM efforts are focused on the productivity and production-availability of their important physical assets. This presents an opportunity to identify the possible relationships that may exist between the KPIs focused on physical asset productivity and production-availability, and the KPIs focused on measuring the mine's financial performance.

The following sections detail the elements and characteristics of the case study. First, the objectives and delimitations of the case study are provided. The specific phases of QIIPMR and QRPMS which are to be completed in this case study are also stated. The assumptions made in the case study are stated where required to improve the understanding and completion of the necessary processes. Finally, the tasks required to deliver the data for QIIPMR's substantiation are executed, and a discussion on the results is provided.

4.2.1 Case Study Objectives And Delimitations

The case study is effectively completed by remaining within its scope, and by executing its sequential objectives. The objectives of this case study are given in Table 4.1.

The delimitations of the case study are defined along with those of the study in Section 1.4. For convenience, the delimitations are repeated below.

- The case study will only employ KPI data from a single thermal coal mine in South Africa.

Table 4.1: Case study objectives

Obj. #	*Research objective*
1.	Identify a suitable source of KPI data. The data source must comply with the PMS criteria (detailed in Section 3.3.1.1) of both QRPMS and QIIPMR.
2.	Collect, filter and approve the KPI data as required by both QRPMS and QIIPMR. The data treatment process is detailed in Section 3.3.1.2.
3.	Complete PCA and compute the PCs of the KPI dataset.
4.	Select the number of PCs for further analysis using the K1, PA and scree plot criterion.
5.	Complete a discussion of the results obtained from PCA and the selection criteria.
6.	Assess and substantiate the QIIPMR methodology.

- The case study will only focus on the substantiation of the alterations made to the QRPMS methodology; a complete iteration of the QIIPMR methodology will not be carried out (expanded on in Section 4.2.2)

This concludes the statement of the objectives and delimitations of the case study completed in this chapter. The following section discusses the appropriate QRPMS and QIIPMR constituents which need to be completed for the QIIPMR methodology to be substantiated.

4.2.2 QIIPMR And QRPMS Constituent Selection For Execution

The assessment and substantiation of the newly developed QIIPMR methodology follows. This requires a comparison of QIIPMR's results and deliverables with that of the QRPMS methodology. QIIPMR employs QRPMS as a foundational framework and therefore many of the QRPMS constituents are adopted unaltered into the QIIPMR methodology. QIIPMR and QRPMS share the same four executable phases; phases which are described in Section 3.3 and Section 3.5.

The phases shared between QIIPMR and QRPMS are similar in all aspects, apart from the third phase. The selection criteria employed by QRPMS and QIIPMR differ when determining which PCs to retain for further analysis. QRPMS employs the Guttman-Kaiser criterion (K1), whereas QIIPMR employs both the Parallel Analysis (PA) criterion and the scree plot. In order to simplify the referencing of these shared phases for the remainder of the case study, they will be referred to as Phases 1 to 4 from henceforth. Furthermore, the focus of differentiating between QRPMS's Phase 3 and QIIPMR's Phase

3 will be placed on the different selection criteria employed.

Phase 3 involves the completion of PCA and PLS for the identification and quantification of inter-KPI relationships, respectively. PCA must be completed to compute the PCs (of the KPI dataset) required to execute the three selection criteria to substantiate QIIPMR. However, the quantification of the selected PCs (through the execution of PLS) is deemed redundant for the requirements of this study for the following reasons:

- The quantification of the PCs retained for further analysis does not contribute justifiable and relevant information for the assessment and substantiation of the QIIPMR methodology.
- The quantification of KPI relationships using the PLS technique has been successfully completed by Rodriguez *et al.* (2009) and Patel *et al.* (2008). Therefore, it is not required to prove or demonstrate this quantification method.

The above shows that only Phase 1 and Phase 2 are required to be completed in full, whereas Phase 3 can be partially completed as it is not required to perform PLS for the assessment and substantiation of the QIIPMR methodology. The identification of the Business Driver Key Performance Indicators (BDKPIs) (using both QIIPMR and QRPMS) concludes the execution of Phase 3 in the case study. The following sections systematically address the case study objectives listed in Table 4.1 in agreement with the above stated.

4.3 Data Collection And Treatment

The KPI data used for the substantiation of the QIIPMR methodology is treated according to the instructions and guidelines of the QRPMS and QIIPMR methodologies. The following sections detail the process of KPI data collection and treatment carried out in this case study, enabling the case study to employ PCA appropriately and collate the information necessary for the aforementioned substantiation.

4.3.1 Data Source Approval

Phase 1, which is described in Section 3.3.1.1, demands that clear traceability exist between the performance objectives and associated KPIs of a PMS. It is therefore necessary to determine whether the PMS of the mine (described in Section 4.2) satisfies this criteria. This “clear traceability” was demonstrated in detail (by an industrial engineer employed at the mine) upon visiting the mine. Therefore, the first case study objective listed in Table 4.1 is accomplished.

4.3.2 Data Requirements And Collection

The KPI data-source (detailed in Section 4.2) primarily contains data on the performance of physical assets and their operational availability. The data of the mine's financial performance and human resources sector constitutes a smaller part of the total data. Due to this skewed characteristic of the dataset, it was considered to establish KPI data requirements to increase the likelihood of identifying inter-KPI relationships between the two "focus groups" of performance in the dataset. In addition, the requirements included additional demands to improve the data treatment process. The KPI data requirements are:

- KPI data on the operational characteristics of physical assets.
- KPI data on the maintenance, and associated processes, of physical assets.
- KPI data on the operational and maintenance cost of physical assets.
- KPI data on the productivity and related performance elements of the mine.
- KPI data on the financial performance of the mine.
- KPI data on the remainder of the functional silos present at the mine.
- Specification of KPI characteristics (temporal frequency, KPI definition, KPI units, KPI calculation and measurement).
- Complete records of KPIs spanning a minimum period of two fiscal years.

The above listed requirements were effectively communicated to the mine representative, serving as a guideline for them to follow. Subsequently, all available KPI data (that adhered to the above requirements) were identified and extracted from the mine's PMS by the mine representative. It is important to note that the mine only issued the KPI data which the mining organisation approved for use in this case study. The author of this study did not participate in the identification and extraction of the KPI data.

4.3.3 Data Treatment

Phase 2 (described in Section 3.3.1.2) provides the guidelines and processes required for the appropriate treatment of KPI data in order to complete PCA in Phase 3. Figure 3.2 and Figure 3.7 depict the processes of the data treatment procedure of Phase 2. The three overarching data treatment actions shown in these figures are:

- Filtering.
- Homogenisation.
- Centering.

Two types of anomalous behaviour were encountered when completing the *filtering* action. Production and finance related KPI data displayed interpretable coherency when assessing the normal distributions of that data. However, asset productivity and maintenance related KPI data displayed erratic characteristics of variation in their data's normal distributions. This erratic nature is identified to be the result of the following factors. Asset productivity is intermittently affected by the necessary movement of assets between mining locations, as well as the inability for assets to operate due to delays in preparation tasks issued to other assets. The unpredictable nature of break-downs results in varying requirements of immediate maintenance (important assets demand more immediate maintenance), contributing to the erratic nature displayed in maintenance performance KPI data. The above stated anomalous behaviour of KPI data was effectively explained with the help of a mine representative.

The format of the KPI data received from the mine reduces the effort required to homogenise the KPI data into a more appropriate format for use in PCA. The KPIs employed by the mine are largely mathematically unrelated; very few KPIs exist as a ratio of other KPIs. In addition to these few ratios, summations of KPIs are also used as a KPI. The introduction of KPIs with complex units is thus avoided, greatly simplifying the homogenisation process. Furthermore, the units of the KPI measurements are simple units (tonnes, Rands, hours, percentages, etc.), further simplifying the aforementioned process. Lastly, the centering of the data was not required as it is automatically done by the computer program used to compute PCA. This program is described in Section 4.4.

Despite some data characteristics simplifying the treatment of the KPI data, the temporal frequency of the KPI data can not be altered to avoid the inclusion of performance variability as per the example given in Section 3.3.1.2. All KPIs are measured on the 14th day of every month, and no weekly KPIs were included in the dataset issued by the mine. Therefore, variability is introduced into the performance data due to varying number of working days in each month. No attempts are made to eliminate this variability due to the following simplifying assumption made during this study.

The added variability is due to varying number of working days, introduced in a bi-monthly pattern (every second month has one extra working day), and not due to varying "daily" performance. Therefore, it is assumed PCA would de-prioritise this bi-monthly introduced variability due to its "predictable", bi-monthly pattern and would put greater emphasis on the "unique" variability introduced (introduced in an unpredictable pattern) by varying performance levels when computing PCs. This assumption is made in order to mitigate possible errors being made in the attempt to eliminate this "bi-monthly" variability. Furthermore, this assumption allows all KPI data issued by the mine to be included in the case study.

To improve the tracking of individual KPIs throughout the case study, each KPI is assigned a unique identifying code. The complete collection of KPIs analysed in this case study is presented (along with their identifying codes and brief descriptions) in Appendix C in a tabular format. In conclusion, the final (sorted and treated) KPI dataset to be used in this case study consists of 84 KPIs, each with 24 observations (monthly recordings over a period of two years).

4.4 PCA and Selection Criteria

The following sections conduct the necessary analyses on the KPI data that are collected and treated as described in Section 4.3. Phase 3 (detailed in Section 3.3.1.3) involves the execution of PCA and PLS. Only PCA will be completed in the case study as explained in Section 4.2.2. There are various statistical computer programs available to carry out PCA; this study employs Statistical Package for the Social Sciences (SPSS). SPSS is a statistical analysis software package developed for social sciences, but has grown popular among marketing and health sciences.

4.4.1 Exploratory And Confirmatory PCA

The method of executing PCA is described in Section 2.6.2 and Appendix B. However, due to the use of SPSS, the task of computing the PCs of the dataset prepared in Section 4.3.2 is greatly simplified. The KPI dataset was imported into SPSS and PCA was completed. As stated in Section 2.6.2, PCA determines a number of PCs equal to the number of original variables in the dataset. Thus, 84 PCs are computed in the first exploratory analysis because the dataset consists of 84 KPIs. The PCs computed are displayed in Table 4.2.

The eigenvalues of each respective PC, as well as the percentage variance the PC explains, are shown in Table 4.2. Following this exploratory PCA, Phase 3 requires that a confirmatory analysis be completed as motivated in Section 3.3.1.3. Included in the results output obtained from SPSS is a correlation matrix (discussed in Section 4.4.2) containing the correlations between the all KPIs in the analysis. This correlation matrix shows that every KPI is

Table 4.2: Data collected from PCA

PC #	PC eigenvalue	Variance explained (%)	Cumulative variance (%)
1	12.833	15.277	15.277
2	9.891	11.775	27.052
3	8.417	10.020	37.072
4	7.600	9.048	46.120
5	5.494	6.541	52.661
6	5.014	5.969	58.630
7	4.434	5.279	63.909
8	4.149	4.940	68.848
9	3.365	4.005	72.854
10	3.174	3.778	76.632
11	3.061	3.644	80.276
12	2.438	2.903	83.178
13	2.040	2.429	85.607
14	1.879	2.237	87.844
15	1.806	2.149	89.993
16	1.565	1.863	91.857
17	1.387	1.651	93.508
18	1.308	1.557	95.065
19	1.291	1.537	96.602
20	0.967	1.151	97.753
21	0.736	0.876	98.629
22	0.628	0.748	99.376
23	0.524	0.624	100.000
24	0.000	0.000	100.000

found to be significantly correlated with one or more other KPIs. Therefore, no KPIs can be excluded for the confirmatory analysis. The PCA results in Table 4.2 thus remain unchanged.

It is important to note that 100% of the total variance in the KPI dataset is explained by the first 23 PCs (as can be seen in Table 4.2). The remainder of the PCs explain an infinitesimal percentage of the total variability, and is thus excluded from the data displayed in Table 4.2. Furthermore, additional results are yielded by SPSS; results not listed in Table 4.2, but discussed in Section 4.4.2.

4.4.2 SPSS PCA Results

The PCA results shown in Section 4.4.1 do not constitute all the results yielded by SPSS. Additional information is also provided; information that is beneficial in the discussion of the case study results in Section 4.5. The complete list of PCA results yielded by SPSS are:

- Descriptive statistics: Table of results showing the mean, standard deviation and number of observations of each KPI in the dataset.
- Correlation matrix: A matrix containing the correlations between every KPI in the dataset.
- Communalities: Based on the number of PCs computed (all possible PCs computed, or limited PCs to be computed), this shows the percentage of variance (of each KPI) extracted by PCA.
- Total variance explained (a table containing the following results):
  - The eigenvalue of every PC.
  - The percentage variance explained by an individual PC.
  - The cumulative percentage variance explained.
  - The rotation sums of squared loadings: A representation of the eigenvalues in the rotated PC solution (using either oblique or orthogonal rotation).
- Component matrix: A matrix containing the un-rotated PC solution (shows the loading coefficient of each KPI in each PC).
- Pattern matrix: A matrix containing the rotated PC solution (using either oblique or orthogonal rotation).
- Structure matrix: A matrix containing the correlations between the KPIs in the dataset and the respective PCs.
- Component correlation matrix: A matrix containing the correlations between every PC computed in PCA.

Some of the above information will not be presented in this case study for two reasons: it is not required for the needs of the case study, or the volume of information is too great to include in this study. For example, *descriptive statistics* will not be included as it does not contribute important information, whereas the *correlation matrix*, *component matrix*, *pattern matrix* and *structure matrix* cannot be included in this study due to their excessive size. However, some extracts of the above listed information is provided in Section 4.5.

4.4.3 Selection Criteria Employment

The next task in Phase 3 is to determine the number of PCs to retain from those computed by PCA in Section 4.4.1. The following section aims to complete this using the selection criteria employed by the QRPMS and QIIPMR methodologies. These selection criteria are: K1, PA and the scree plot. A discussion of the results obtained from these selection criteria will not be completed in this section, but will be carried out in Section 4.5 in combination with the results of the other constituents of this case study.

4.4.3.1 Guttman-Kaiser criterion

The K1 rule is the selection criteria employed by QRPMS, and is discussed in Section 2.7.1. This selection criteria simply states that all PCs with eigenvalues greater than unity can be retained for further analysis. It is important, however, to remember that K1 indicates the number of PCs that are extractable; not the exact number that should be extracted (Gorsuch, 1983; Preacher and MacCallum, 2003).

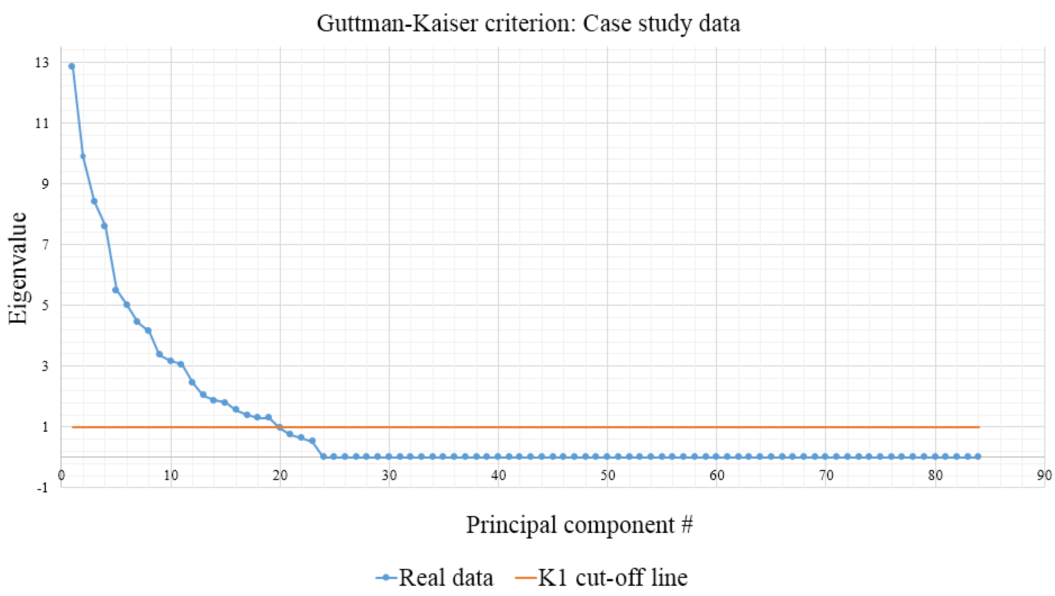


Figure 4.2: Plot of the Guttman-Kaiser criterion (K1) PC cut-off

Refer to Appendix D for a larger image

In order to determine the number of PCs to retain for further analysis using K1, it is beneficial to graphically display the PCs in Table 4.2 against their respective eigenvalues. This is shown in Figure 4.2. When investigating the tabulated and displayed information, it can be seen that the first 19 PCs have eigenvalues larger than one, and are thus extractable according to K1. In addition, Figure 4.2 displays all of the PCs computed by PCA, and as can be seen, the remainder of the PCs have eigenvalues of 0 and thus account for an infinitesimal percentage of the total variability, as previously stated.

4.4.3.2 Scree Plot criterion

The scree plot is discussed in Section 2.7.2, and it solely involves the graphical interpretation of the plotted eigenvalues of all the PCs. Although it is a subjective analytical method, it is used by the QIIPMR methodology as a supporting selection criteria to its primary selection criteria: PA. Figure 4.3 displays the eigenvalues (of all 84 PCs) plotted against their respective PCs.

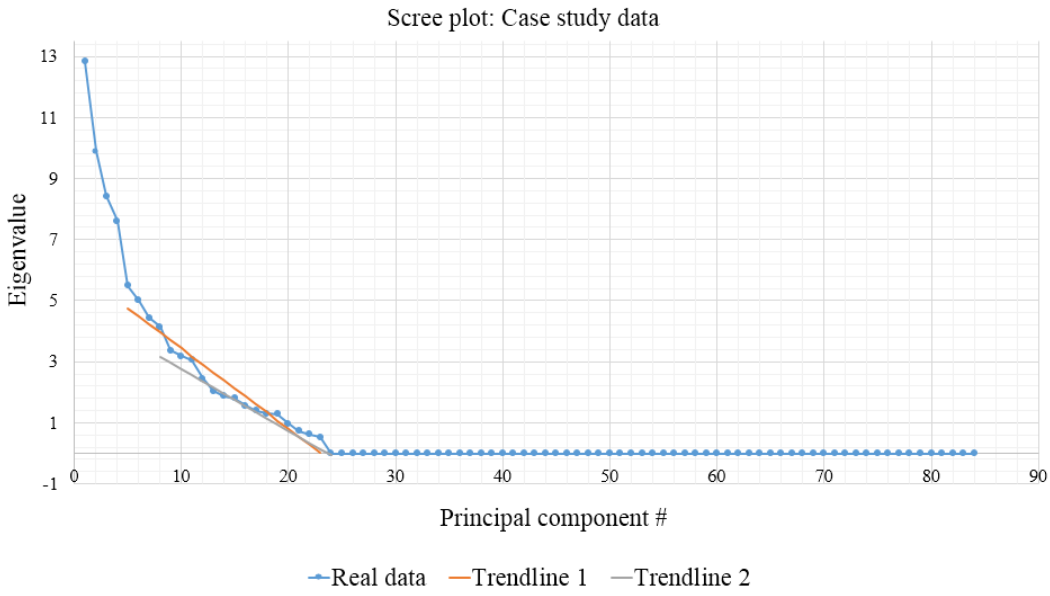


Figure 4.3: Scree plot of the real PCs

Refer to Appendix D for a larger image

In Section 2.7.2, it is stated that the correct number of PCs to retain for further analysis (according to the scree plot) can be identified by assessing the curve of graph in Figure 4.3. All PCs with eigenvalues which are plotted before a linear decrease are candidates for extraction. However, when consulting Figure 4.3, it is difficult to ascertain where the appropriate linear decrease starts. In order to help identify the correct start of an appropriate linear decrease, two linearly decreasing trendlines are included in the plot shown in Figure 4.3.

The first trendline is fitted to all data points between the fifth PC (the first possible start of a linear decrease), and the 23rd PC (the last, non-zero eigenvalue). The second trendline is fitted to all data points between the

8th PC (the second possible start of a linear decrease), and the 23rd PC. From these two trendlines, the scree plot shows that the first four PCs can be extracted with confidence for further analysis. However, due to the difficulty of determining where the linear decrease starts, the identification of additional PCs (for extraction) cannot be confidently, and accurately, determined.

Table 4.3: Data collected from PCA and PA

PC #	Eigenvalues of PCs (PCA)	PA generated eigenvalues (50%)	PA generated eigenvalues (95%)	Cumulative % variability explained
1	12.833	7.63	8.35	15.28
2	9.891	6.89	7.40	27.05
3	8.417	6.34	6.74	37.07
4	7.600	5.88	6.22	46.12
5	5.494	5.48	5.79	52.66
6	5.014	5.11	5.41	58.63
7	4.434	4.77	5.05	63.91
8	4.149	4.45	4.70	68.85
9	3.365	4.16	4.41	72.85
10	3.174	3.88	4.11	76.63
11	3.061	3.61	3.84	80.28
12	2.438	3.36	3.57	83.18
13	2.040	3.11	3.33	85.61
14	1.879	2.88	3.09	87.84
15	1.806	2.66	2.87	89.99
16	1.565	2.44	2.64	91.86
17	1.387	2.23	2.42	93.51
18	1.308	2.02	2.22	95.07
19	1.291	1.83	2.02	96.60
20	0.967	1.62	1.82	97.75
21	0.736	1.43	1.62	98.63
22	0.628	1.23	1.42	99.34
23	0.524	1.00	1.21	100.00

4.4.3.3 Parallel Analysis criterion

The PA selection criteria is detailed in Section 2.7.3. In order to compute the necessary (randomly generated) parallel correlation matrices, SPSS is used. Hayton *et al.* (2004) suggests a minimum of 50 parallel correlation matrices must be computed in the determination of the averaged eigenvalues (of the computed parallel correlation matrices). However, the larger the number of parallel correlation matrices computed, the greater the accuracy of the final results (Hayton *et al.*, 2004). A total of 5000 parallel correlation matrices are thus computed for this case study to improve on this accuracy.

Two levels of statistical confidence are determined when using SPSS to complete PA. The 50th percentile (mean generated eigenvalues) is, by default, computed by SPSS. The inclusion of the 95th percentile is suggested by Hayton *et al.* (2004) for improved accuracy in statistical comparison. The *real* eigenvalues from the KPI dataset (determined by PCA), and the *random* eigenvalues computed by PA, are listed in Table 4.3. SPSS only computes the first 23 eigenvalues for both the 50th and 95th percentiles because 100% of the variability is captured by the first 23 PCs. The data in Table 4.3 is plotted in Figure 4.4.

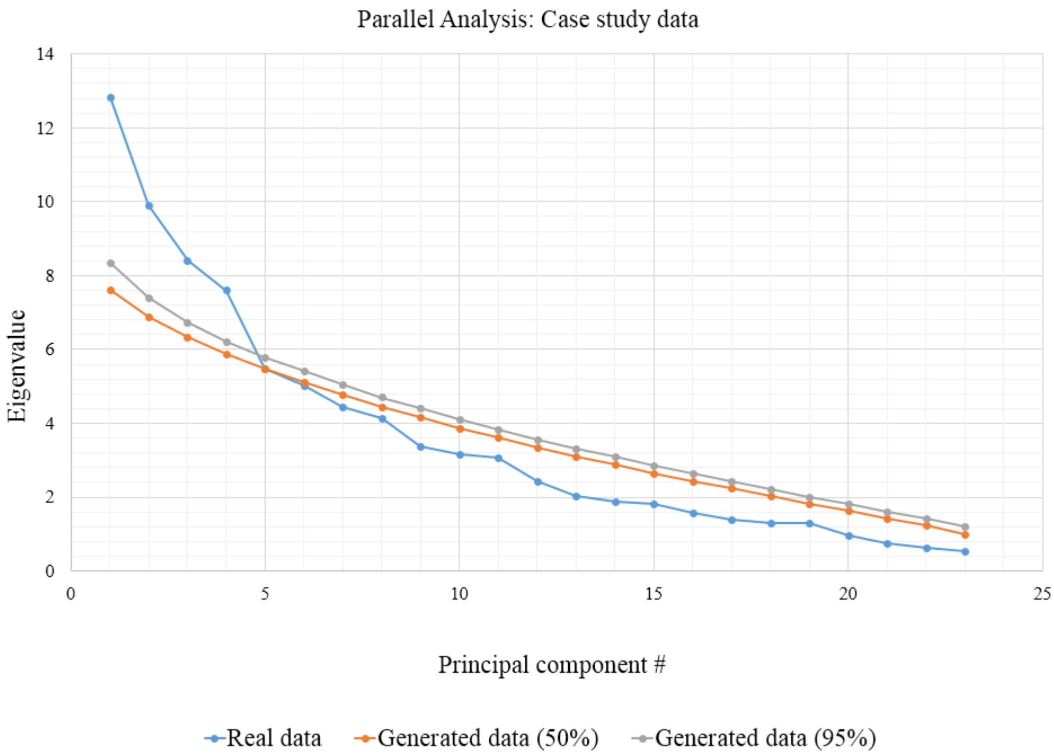


Figure 4.4: Parallel Analysis (PA) plot of the real PCs

Refer to Appendix D for a larger image

According to the PA criteria, the correct number of PCs to retain for further analysis are those PCs that have eigenvalues greater than the averaged eigenvalues computed from the random parallel correlation matrices. Consulting Figure 4.4, it can be seen that the first four PCs are thus extractable, whereas the 5th PC has an eigenvalue barely larger than the mean (50th percentile) eigenvalue and is thus not extractable.

4.5 Results Discussion

The previous section, Section 4.4, involves the computation of the case study results required to evaluate the QIIPMR methodology. The following section aims to discuss the results collated from Section 4.4, which can be crudely grouped into two categories: *selection criteria results*, and *post-confirmatory PCA results*. These two categories are discussed in the following sections.

4.5.1 Selection Criteria Results

The assessment of the results collated from the three selection criteria employed in this case study is completed by the following sections. These sections aim to segment the results assessment for an improved discussion, allowing the reader to adequately understand the approach taken and the arguments made.

4.5.1.1 Approach to selection criteria results discussion

In Section 4.4.3, three selection criteria are used to determine the number of PCs to retain for further analysis; PCs that were calculated in Section 4.4.1. Table 4.4 contains the collective results of the aforementioned selection criteria.

Table 4.4: Case study results: selection criteria

Selection criteria	*# of* PCs to retain
Guttman-Kaiser criterion (K1)	19
Scree plot	4 (definite) + 4 (possible)
Parallel Analysis (PA)	4

As shown in Table 4.4, the K1 rule indicates that 19 of the total (84) computed PCs are retainable for further analysis. However, this poses a problem for analysts as the K1 rule does not specifically state the number of PCs which should retained. Analysts who employ K1 are required to assess the retainable PCs, and make an informed decision on which of those PCs should be retained. This is one of the key deficiencies of K1 when compared to the other two selection criteria. PA and the scree plot identifies the PCs which should be retained for further analysis; specific PCs worth retaining. However, to fully compare these three aforementioned selection criteria, it is necessary to investigate the 19 PCs (identified by K1) to evaluate their retention-value when compared to those few PCs identified by PA and the scree plot.

Table 4.2 and Table 4.3 both show that the first 19 PCs (shown to be retainable by K1) cumulatively explain 96.6% of the variance in the KPI dataset. However, interpreting such a large group of PCs in a meaningful and adequate manner can be complicated and a challenging task for analysts. This complexity is as a result of the great number of variables (84 KPIs) that composes each PC in this case study (PCs are linear combinations of the original variables in a dataset). Regardless of the large number of contributing variables in the PCs, briefly investigating this characteristic of a PC will shed light on each PCs respective retention-value.

Cadima and Jolliffe (1995) state that a PC is frequently interpreted by assessing the loading coefficients of its contributing variables (in this case study, the variables are KPIs). Contributing variables with large loading coefficients (*significant contributing variables*, either positive or negative in nature) attach meaning to a PC, whereas variables with small loading coefficients (*"insignificant" contributing variables*) contribute little meaning (Cadima and Jolliffe, 1995).

With regard to this study, a PC's retention-value can be evaluated by assessing the number of significant contributing variables it has. As previously stated, PCs are linear combinations of the original variables (KPIs) in the case study dataset. Therefore, a PC with many significant contributing variables is indicative of multiple, strong cause-effect relationships between these "significant" KPIs. A PC with multiple significant contributing variables thus has a high retention-value, and is more critical for assessment than a PC with few or no significant contributing variables.

Dunteman (1989) asserts that, when assessing PCs, analysts are required to decide what magnitude a loading coefficient must exceed for that respective contributing variable to be classified as a significant contributing variable. There are complex methods of determining this magnitude for accurate PC evaluation, Dunteman (1989) states. However, for quick evaluations, Chin (1995) suggests contributing variables with loading coefficients larger than 0.6 (in absolute value) can be seen as significant contributors. In order to complete a brief assessment of the PCs shown in Table 4.2, two values to determine significant contributors are selected: 0.6 (as suggested by Chin (1995)), and 0.4 (for a conservative approach). A rudimentary sensitivity analyses can thus be carried out by comparing the use of these two values.

It is important to note that the number of significant contributing variables does not equal the exact number of strong, inter-KPI relationships. Simply identifying the KPIs with significant loading coefficients for each respective PC is not an adequate method for identifying inter-KPI relationships. The method used by the QRPMS and QIIPMR methodologies to identify strong inter-KPI relationships is discussed in Section 4.5.3 using the results from this case study.

Furthermore, the scope of this case study does not include the complete and thorough interpretation of the PCs computed in Section 4.4.1, nor the discussion of the complex methods for determining the magnitude a loading coefficient must exceed to be viewed as significant. This study does acknowledge that a more concrete method of determining an appropriate loading coefficient magnitude is required if an accurate and adequate analysis of the PCs is desired. However, the aforementioned “quick assessment” of the PC loading coefficients provides insightful, supporting information for the discussion of selection criteria results and is therefore necessary to complete this quick assessment.

4.5.1.2 Selection criteria results discussion

As stated in Section 4.4.2, a component matrix is computed by SPSS. It is a matrix containing the loading coefficients of each KPI, for each PC. From this matrix, the number of contributing variables (KPIs) with loading coefficients exceeding the absolute value of 0.4 (conservative) and 0.6 (recommended) was determined for the first 19 PCs. The results are displayed in Figure 4.5 and Figure 4.6 respectively.

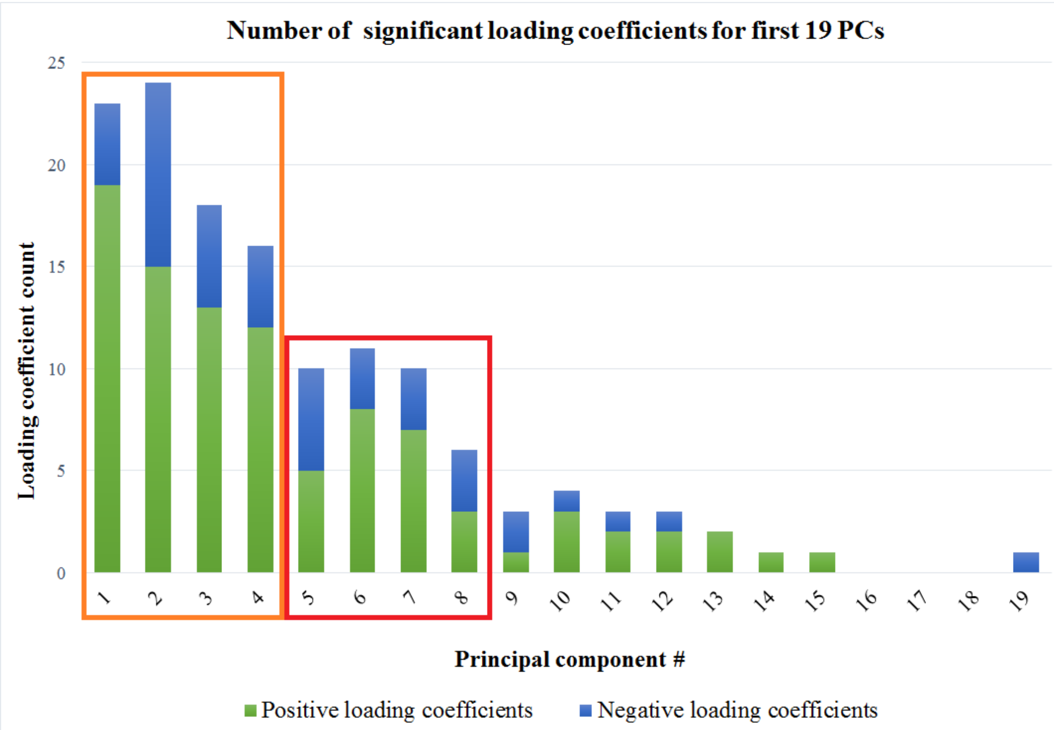


Figure 4.5: Number of KPIs with loading coefficients exceeding the absolute value of 0.4 (for the first 19 PCs)

The conservative set of results (shown in Figure 4.5) are discussed first. When assessing Figure 4.5, it can be seen that the 9th to the 19th PCs have very few significant contributing variables (KPIs). These PCs are thus not indicative of many, strong cause-effect relationships between the KPIs in the dataset, but are however indicative of a few cause-effect relationships between pairs of KPIs. If the retention-value of these PCs are to be evaluated on the number of multiple, strong inter-KPI relationships they indicate, it is apparent that they have very little retention-value or assessment-importance when compared to the remaining PCs.

Visual assessment of the data-trend in Figure 4.5 reveals two groups of four PCs with a similar number of significant contributing variables. The first group of PCs (PC number 1 to 4) have approximately double the number of significant contributing variables, per PC, than the second group (PC number 5 to 8). It is thus apparent that the first 4 PCs in Figure 4.5 contain the largest number of strong inter-KPI relationships of all 19 PCs assessed. This is even more evident when assessing Figure 4.6, where only the first 4 PCs are shown to have more than one significant contributing variable.

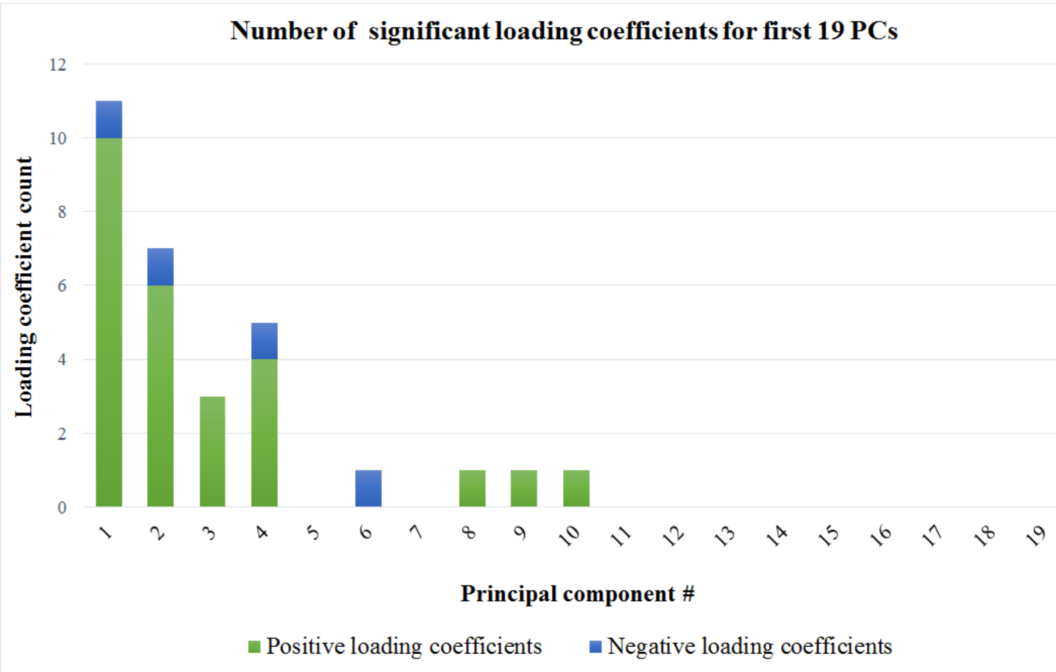


Figure 4.6: Number of KPIs with loading coefficients exceeding the absolute value of 0.6 (for the first 19 PCs)

It must be noted that, in Figure 4.6, the third PC is shown to have less significant contributing variables than the fourth PC. This does not mean the third PC indicates fewer, strong cause-effect relationships between KPIs than the fourth PC, but merely represents the inappropriateness of purely selecting the number of inter-KPI relationships based on the number of significant contributing variables each PC has. Although the third PC has fewer loading coefficients (which are greater than the absolute value of 0.6) than the fourth PC, it still captures or explains a greater percentage of the original data's variance than the fourth PC. This can be seen in Figure 4.7 where the percentage variance captured or explained by each of these 19 PCs is depicted.

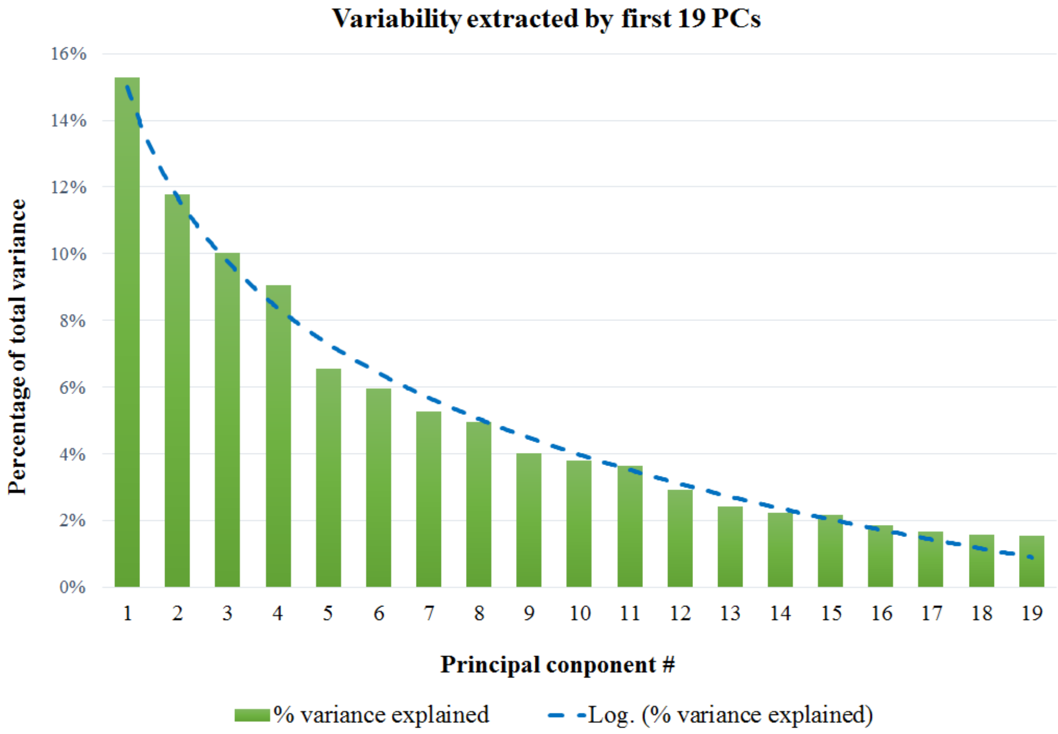


Figure 4.7: Percentage of original data's variance explained by each of the first 19 PCs

Included in Figure 4.7 is a trendline which indicates a logarithmic decrease in the percentage variability explained by each PCs. Figure 4.7 fundamentally shows that the percentage variance captured by each descending PC becomes exponentially less when progressing through the 19 PCs. The first 4 PCs explain the highest percentages of variance (per PC) from those displayed. These results are synonymous to the results depicted in Figure 4.5 and Figure 4.6; these three aforementioned figures indicate the critical importance of the first four PCs when compared to the remaining PCs. This is supported by the results shown in Table 4.2. Of the total variance captured by all 84 computed PCs, 46.12 % is explained by the first 4 PCs. Furthermore, these PCs account for almost half (47.74%) of all the variance captured by the 19 PCs in Figure 4.7.

The aforementioned discussion and comparison of the PCs computed in the case study (in Section 4.4.1) provides the necessary insight and knowledge to adequately assess the results of the three selection criteria: K1, PA and the scree plot, as shown in Table 4.4.

The K1 criterion indicates that 19 of the 84 computed PCs are retainable for further assessment. However, as stated in Section 2.7.1, K1 yields inaccurate and unreliable results. A contributor to the inaccuracy and unreliability is the poor interpretation of what the K1 results are. As described in Section 2.7.1, K1 identifies the number of PCs that are retainable; it does not state the exact number of PCs to retain.

If the K1 rule was employed by an analyst who misunderstood K1 and retained all retainable PCs, then with respect to this case study, the analyst would have retained all 19 PCs identified by K1. This section, however, has shown that only a few of these PCs are worth retaining for further assessment, and an even fewer number are critical to retain for further analysis. Due to the number of contributing variables of the PCs computed in this case study, the adequate analysis of each PC demands a far greater amount of resources when compared to the analysis of simple PCs. The assessment of the unimportant PCs identified by K1 is therefore a costly endeavour, with insignificant returns.

Keeping the aforementioned in mind, it is evident that the employment of K1 (if misunderstood) in the QRPMS methodology can lead to unnecessary costs and added complexity, potentially preventing the completion of the QRPMS methodology. Furthermore, if K1 is properly understood, an analysis of the retainable PCs must still be conducted in QRPMS to determine which PCs are worth retaining, and which are critical to retain. It is thus evident that the K1 rule is inadequate to determine the number of PCs to retain when attempting to identify relationships between a large number of KPIs.

In an ideal situation, the scree plot will give results that are accurately interpretable when the linear decrease of the data trend can be easily and accurately determined. Unfortunately, this was not the case with regard to this case study. As shown in Figure 4.3, it is difficult to ascertain where the linear decrease of the data trend starts. The scree plot, as a result, indicates that the first four PCs should be extracted, but also indicates that the next four PCs may be worth retaining for further analysis.

The PA criterion is the only selection criteria employed in this case study which identified the specific number of PCs that should be retained. The PA criterion did not give unambiguous results, nor demanded the further assessment of its results to determine which PCs should actually be retained for further analysis. As stated in Chapter 3, the scree plot is employed by the QIIPMR methodology to support the results of PA. As shown in Section 4.4.3.2, the scree plot provides similar results to those of PA, successfully accomplishing its intended role in the QIIPMR methodology.

In conclusion, the K1 criterion suggested the retention of multiple, "insignificant" PCs for further analysis. The K1 rule required this study to complete an additional assessment of its results to better determine which of the 19 PCs are worth retaining, but consequently, no specific number of PCs that should be extracted could be determined based solely on the results of K1, and the basic assessment completed previously. The scree plot was more specific than the K1 rule; it showed that the first four PCs should be extracted for further assessment, but it proved difficult to ascertain where the "cut-off" point was for the extraction of additional potential PCs.

The PA criterion indicated that the first four PCs should be retained for further analysis. Therefore, as supported by Yeomans and Golder (1982), Zwick and Velicer (1986) and Lance and Vandenberg (2009), the PA criterion was found to deliver the most accurate and reliable results of the three selection criteria employed in this case study. The scree plot proved to be an adequate supporting selection criteria to PA, and its sole implementation may prove problematic in the assessment of its results.

4.5.2 Post-confirmatory PCA Results Discussion

The first four PCs, which according to the results of PA are to be retained for further analysis, together extract 46.12% of the total variability of the original KPI dataset. Although Figure 4.7 displays the percentage variance explained by each PC, it does not show the percentage variability of each KPI accounted for by these four PCs.

In order to determine the percentage variability of each KPI extracted by the first four PCs, PCA is recalculated while incorporating one limitation. PCA is only allowed to compute the first four PCs. As described in Section 4.4.2, one of the results outputted by SPSS is a communalities matrix; a matrix containing the percentage variance of each KPI accounted for by the number of PCs computed. The results of this matrix are shown in Figure 4.8.

A heat map is incorporated in Figure 4.8, and as can be seen, the majority of the 84 KPIs have approximately 45% of their variability captured by the four selected PCs. Furthermore, only a few KPIs have their variability very poorly captured, as indicated by the dark orange cells. The average variability

KPI	Variability	KPI	Variability	KPI	Variability
OpS1	87.27%	EnSh2	53.62%	EnT22	43.28%
OpS2	87.24%	EnSh3	50.06%	EnT23	48.25%
OpS3	74.19%	EnSh4	62.42%	EnT24	27.08%
OpD1	52.92%	EnD11	21.38%	EnT31	39.34%
OpD2	22.34%	EnD12	46.40%	EnT32	25.55%
OpD3	13.27%	EnD13	22.64%	EnT33	31.48%
OpD4	19.35%	EnD14	28.51%	EnT34	33.15%
OpDo1	73.75%	EnD21	31.81%	EnDo1	54.78%
OpDo2	80.34%	EnD22	49.83%	EnDo2	36.90%
OpDo3	20.80%	EnD23	52.40%	EnDo3	38.20%
OpDr1	21.43%	EnD24	36.47%	EnDo4	50.34%
OpDr2	27.37%	EnE1	39.74%	Sa5	39.57%
OpDr3	44.44%	EnE2	53.39%	Sa6	57.33%
OpDr4	32.92%	EnE3	53.68%	Sa7	85.35%
OpC1	92.08%	EnE4	42.05%	HR1	68.47%
OpC2	59.89%	EnOb1	21.09%	HR2	44.26%
OpP1	92.08%	EnOb2	61.16%	HR3	67.36%
OpP2	74.61%	EnOb3	71.11%	HR4	10.03%
OpP3	60.16%	EnOb4	24.68%	F1	76.22%
OpP4	24.56%	EnCl1	10.76%	F2	72.73%
OpP5	61.13%	EnCl2	11.23%	F3	36.23%
OpP6	59.05%	EnCl3	12.41%	F4	84.97%
OpP7	43.21%	EnCl4	19.91%	F5	65.59%
EnDr1	6.74%	EnT11	67.37%	F6	57.67%
EnDr2	6.61%	EnT12	75.13%	F7	57.07%
EnDr3	11.73%	EnT13	64.90%	F8	31.88%
EnDr4	42.73%	EnT14	22.29%	F9	63.85%
EnSh1	25.82%	EnT21	29.94%	F10	72.73%

Figure 4.8: Individual KPI variance explained by the 4 chosen PCs

of each KPI captured is 46.12%. Coincidentally, this is the exact percentage of total variability captured by the first four PCs. However, to better interpret Figure 4.8, an additional representation of these results are needed. Figure 4.9 reveals the specific number of KPIs of which the captured variances fall in specific percentage ranges.

The in-depth assessment of the results shown in Figure 4.8 and Figure 4.9

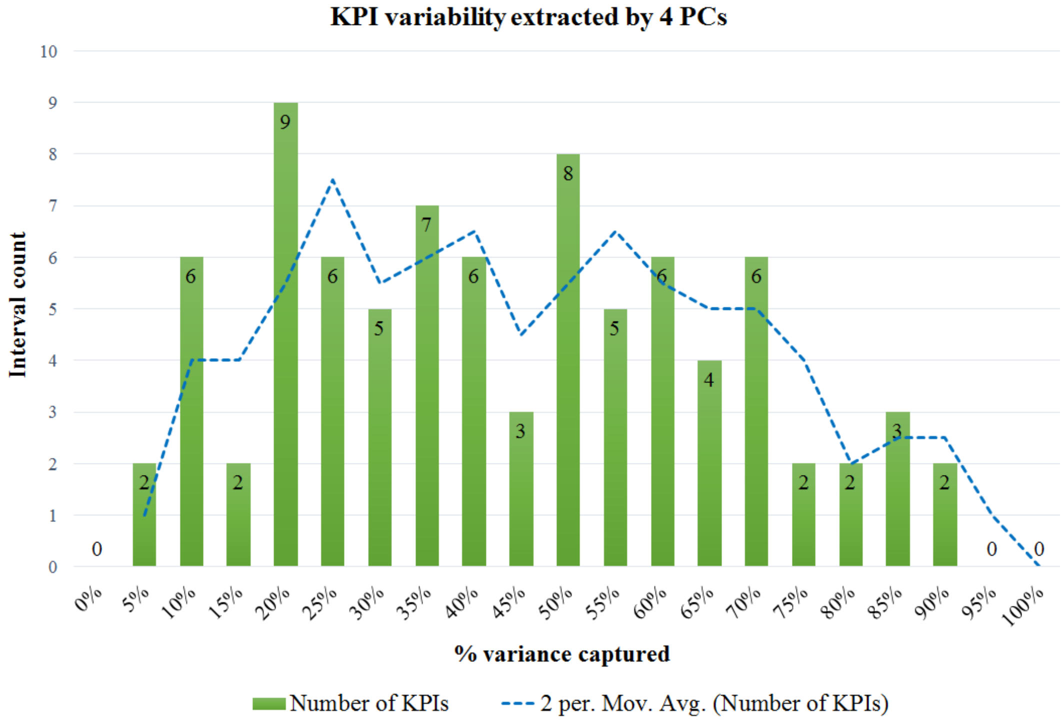


Figure 4.9: KPI variability extracted (in specific percentage ranges) by the 4 chosen PCs

does not form part of the case study scope. The presentation of these results are merely intended to improve the understanding of what the effects are when selection criteria are applied and the chosen PCs are relied on to represent the variance of the original dataset.

In addition, as explained in Section 2.6.2, PCs are computed to be uncorrelated to one another. This claim is supported by the PCA results computed in this case study; results which are shown in Table 4.5. The correlation values between the four selected PCs are of negligible size, and they can effectively be classified as being uncorrelated to one another.

Table 4.5: Post PCA results: correlations between PCs

PC #	# 1	# 2	# 3	# 4
# 1	1.000	-.011	-.065	.003
# 2	-.011	1.000	-.010	-.013
# 3	-.065	-.010	1.000	-.039
# 4	.003	-.013	-.039	1.000

The results in Table 4.5 not only support the aforementioned claim, but provides supporting evidence showing that PCA is adequately and accurately computed in this case study.

4.5.3 Identifying Inter-KPI relationships

Identifying Business Driver Key Performance Indicators (BDKPIs) is briefly described in Section 3.3.1.3. The QRPMS and QIIPMR methodologies employ a graphical figure to highlight which KPIs are BDKPIs. Two PCs are plotted against each other, using their respective KPI loading coefficients as the data points. Two concentric ellipses are included in the plot. The largest ellipse indicates the "border maximum"; the maximum (absolute) value (1.0) which loading coefficients can achieve. The second, smaller ellipse indicates the "border minimum"; the minimum (absolute) value a loading coefficient must exceed for that respective variable to be classified as a significant contributor to the PC. Figure 4.10 depicts the aforementioned for the first and second PCs computed in the case study.

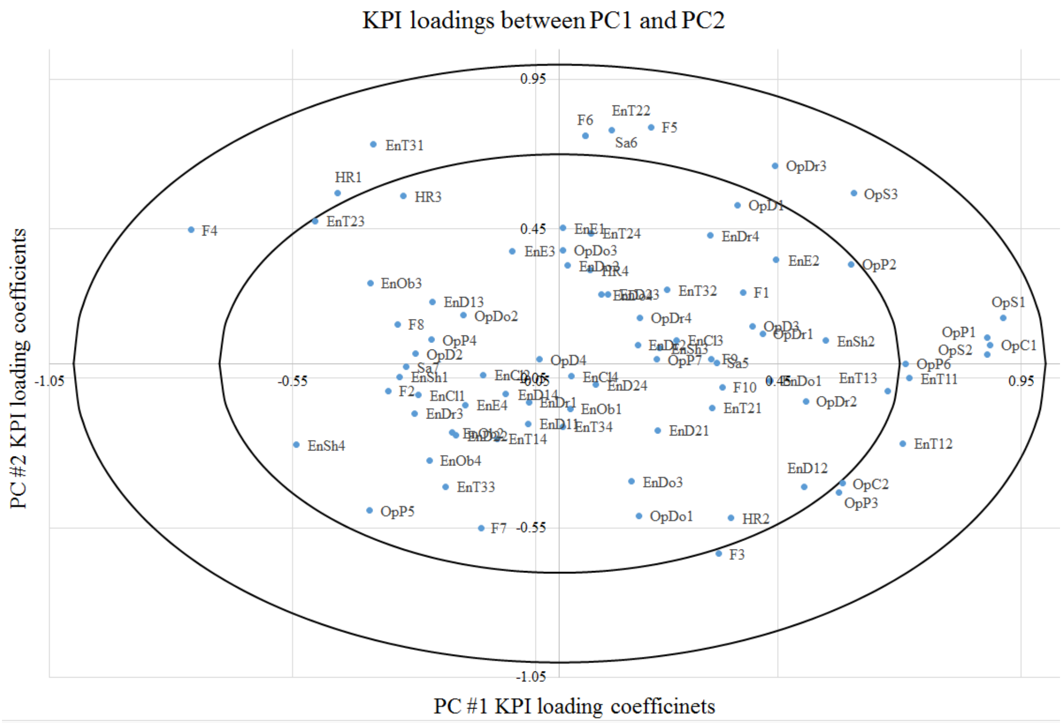


Figure 4.10: KPI loadings between the first and second PCs

Refer to Appendix D for a larger image

Rodriguez *et al.* (2009) use a "border minimum" value of 0.7 in their case study, with no indication of how they decided on this specific value. It is assumed, however, that Rodriguez *et al.* (2009) had a specific reason for choosing this value. Therefore, for the following descriptive purposes, this same value is used in the development of Figure 4.10, Figure D.5 and Figure D.6.

Figure D.5 depicts the graphical comparison between the first and third PCs, and Figure D.6 similarly depicts the first PC against the fourth PC. These two figures are shown in Appendix D. The KPIs which fall in the area between the two concentric ellipses are reclassified as BDKPIs. The BDKPIs identified in Figure 4.10, Figure D.5 and Figure D.6 are listed in Table 4.6.

Table 4.6: QIIPMR results: BDKPIs (computed using PA and the scree plot)

BDKPI	BDKPI	BDKPI	BDKPI
EnD12	EnT13	HR1	OpP6
EnD22	EnT22	OpC1	OpS1
EnD23	EnT31	OpC2	OpS2
EnDo1	F3	OpDr3	OpS3
EnOb2	F4	OpP1	Sa6
EnT11	F5	OpP2	
EnT12	F6	OpP3	

Table 4.6 contains 26 identified BDKPIs (only using the 4 PCs identified by PA and the scree plot). Therefore, 26 of the 84 total KPIs hold a higher importance to organisational management because of their inherent relationships. In addition, these 26 BDKPIs are critical to the evolution of the organisation (Rodriguez *et al.*, 2009). As can be seen, a mixture of KPIs from *Finance*, *Operations*, *Engineering* and *Safety and Human Resources* constitute those BDKPIs listed in Table 4.6, satisfying the desire to identify inter-KPI relationships between the mine's performance "areas of focus".

In order to complete the final comparison of between QIIPMR and QRPMS, it is necessary to compare the BDKPI results (of QIIPMR) listed in Table 4.6 with the BDKPI results of QRPMS. For this comparison, the QRPMS BDKPI results are computed using all 19 PCs shown to be retainable by K1. This is to incorporate the impact of misunderstanding the K1 criterion (as described in Section 2.7.1) into the results comparison. The parameters for determining the BDKPIs remain unaltered, and the results are shown in Table 4.7.

When comparing the BDKPI results of Table 4.6 and Table 4.7, a few observations are evident. The number of BDKPIs listed in the two aforementioned tables are nearly equal; QIIPMR and QRPMS identifies 26 and 29 BDKPIs, respectively. When considering the number of PCs used by each methodology to determine their respective BDKPIs (4 PCs versus 19 PCs), it is apparent

Table 4.7: QRPMS results: BDKPIs (computed using K1)

BDKPI	BDKPI	BDKPI	BDKPI
EnOb3	F7	OpD2	OpP6
EnT11	F9	OpDo1	OpS1
EnT12	F10	OpDo2	OpS2
EnT13	HR1	OpDo3	OpS3
F1	HR3	OpP1	Sa7
F2	OpC1	OpP2	
F4	OpC2	OpP3	
F5	OpD1	OpP5	

that the retention of additional, less important PCs (as is done by QRPMS) yields diminishing returns. Furthermore, it is evident that some of the BDKPIs listed in Table 4.6 and Table 4.7 differ. Only 15 BDKPIs are shared between these two collection of results. Table 4.8 collates the aforementioned BDKPI comparison results.

Table 4.8: BDKPI comparison results

KPI "area of focus"	# of BDKPIs (QIIPMR)	# of BDKPIs (QRPMS)	# of similarities
Engineering	10	4	3
Finance	4	7	2
Operations	10	15	9
Safety & Human Resources	2	3	1
Total:	26	29	15

The results in Table 4.8 show additional, noteworthy differences. QIIPMR identifies more than double the number *Engineering* BDKPIs than QRPMS, and QRPMS identifies 50% more *Operations* BDKPIs than QIIPMR. Similar statements can be made for the *Finance* and *Safety & Human Resources* BDKPIs. These differences between the end results of QIIPMR and QRPMS concludes the following: it cannot be assumed (with respect to determining BDKPIs in this case study) that employing 19 PCs will result in the exact same BDKPIs the first 4 PCs will identify.

One possible reason for the variance between the two sets of BDKPIs shown in Table 4.8 may be due to the recalculation of the PCs while limiting the total number of PCs (which can be calculated) to 4 and 19 (for QIIPMR and QRPMS, respectively). The recalculated PCs may differ with regard to their KPI loading coefficients. However, this is not the case. The loading coefficients

Table 4.9: QIIPMR results: KPI loading coefficients (4 PCs)

KPI	PC 1	PC 2	PC 3	PC 4
OpS2	0.880	0.031	0.194	0.244
F4	-0.759	0.446	-0.038	0.271
EnT11	0.721	-0.050	0.247	0.301
OpP6	0.713	-0.002	0.137	-0.253
EnT12	0.706	-0.267	-0.185	0.383

Table 4.10: QRPMS results: KPI loading coefficients (19 PCs)

KPI	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	Cont.
OpS2	0.880	0.031	0.194	0.244	-0.056	0.065	...
F4	-0.759	0.446	-0.038	0.271	-0.089	0.096	...
EnT11	0.721	-0.050	0.247	0.301	0.166	0.035	...
OpP6	0.713	-0.002	0.137	-0.253	-0.043	0.050	...
EnT12	0.706	-0.267	-0.185	0.383	0.086	0.141	...

of every KPI, for each PC, remain the same, regardless of the aforementioned limitation. In support of this statement, an extract of the PC loading coefficients for both QIIPMR and QRPMS are given in Table 4.9 and Table 4.10, respectively.

Although an exhaustive assessment of why the BDKPIs of QIIPMR and QRPMS differ (in the manners described above) does not form part of the case study scope, the following can be stated. Yeomans and Golder (1982), Zwick and Velicer (1986), Velicer *et al.* (2000), and Cortina (2002) state K1 is highly inaccurate and varying (as discussed in Section 2.7). In Section 1.2, it is suggested that the K1 criterion severely compromises the reliability and mathematical accuracy of the results obtained from QRPMS. The reliability of QRPMS's results is compromised (evident in the above completed results discussion) as it poorly coincides with the results of QIIPMR which uses more accurate and reliable selection criteria. Furthermore, QIIPMR employs the scree plot as a supporting selection criteria to PA, enabling any calculation errors to be identified. Therefore, the results of the QIIPMR methodology are more trustworthy than those of QRPMS.

In conclusion, the results calculated and presented in this chapter are transferred to the following mathematical technique in Phase 3 of QIIPMR, PLS, to quantify, in magnitude and sense, the relationships that exist between these BDKPIs. However, as stated in Section 4.2.2, this computational step will not be completed in this study. This thus marks the end of the case study calculations.

4.6 Substantiation Of The QIIPMR Methodology

As described in Section 4.1, this chapter aims to collate the necessary information and results in order to substantiate the methodology developed in Chapter 3, the QIIPMR methodology. The purpose of the case study is to confirm that the QIIPMR methodology delivers more accurate and reliable results than the QRPMS methodology. As a result, the case study confirms that the research conducted in this study has both theoretical and practical value.

The QRPMS methodology is developed by Rodriguez *et al.* (2009), and it aims to objectively identify and quantify relationships between a set of KPIs through the employment of two mathematical techniques; PCA and PLS. However, the QRPMS methodology employs a problematic selection criteria during the process of identifying these relationships. The K1 selection criteria employed by QRPMS delivers unreliable and inaccurate results, compromising the accuracy and reliability of the overall results delivered by QRPMS. The QIIPMR methodology is developed by this study as an improved version of QRPMS, aiming to yield mathematically accurate and reliable results through the employment of approved and competent selection criteria.

With the help of a mining organisation in South Africa, this study is able to compare the difference between the QRPMS and QIIPMR methodologies using a real world scenario by means of a case study. Using the performance data of an open-pit, thermal coal mine, this study is able to execute both methodologies until, and including, the point where they employ different selection criteria. Following the computational component of the case study is the detailing and comparison of the selection criteria results.

The case study results yield supporting evidence that QIIPMR provides more specific and accurate results than those computed by QRPMS. The primary selection criteria employed by QIIPMR, the PA criterion, requires no additional analysis of its results. The secondary selection criteria employed by QIIPMR, the scree plot, is intended to provide supporting results to those of PA, potentially identifying erroneous results. The scree plot, with respect to its role in QIIPMR, demands little to no additional analysis of its results if it corresponds with PA. When executing the selection criteria employed by QRPMS, the K1 criterion, significant additional analysis is required to render its results more interpretable and appropriate. Regardless of the additional analysis, the results of K1 did not match the accuracy and specificity of those results yielded by PA and the scree plot.

The inaccuracy and unreliability of the K1 results affect the validity, accuracy and trustworthiness of the BDKPIs identified by QRPMS; effects which are encountered when comparing the BDKPI results of QRPMS and QIIPMR. The two sets of BDKPI results differ in notable manners. The in-depth investigation of these differing BDKPIs results does not form part of the study scope, and can thus not be explained. However, it highlighted the inaccuracy and unreliability of QRPMS.

In conclusion, the QIIPMR methodology yields results that are accurate and reliable. Its results are not potentially compromised, in contrast with the QRPMS methodology. Furthermore, QIIPMR requires less resources for analysis to be expended when compared to QRPMS, effectively making QIIPMR a more economically feasible methodology to employ.

4.7 Chapter Conclusion

This chapter presents a case study through which the necessary information and results are collated to adequately compare the differences between QIIPMR methodology and the QRPMS methodology. Implementing the results of this comparison, the chapter aims to substantiate the QIIPMR methodology as an improvement over QRPMS. In order to achieve these objectives, Chapter 4 follows a predetermined topic flow which is depicted in Figure 4.11.

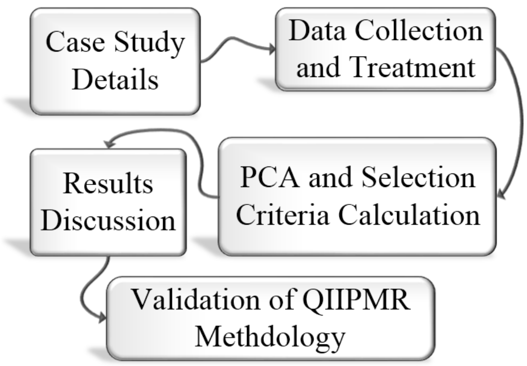


Figure 4.11: The development flow of the case study

Through the sequential completion of the tasks shown in Figure 4.11, this chapter successfully accomplishes its objectives and aims. The QIIPMR methodology is shown to yield more accurate and reliable results than the QRPMS methodology, while reducing the resources (financial or otherwise) required to objectively identify and quantify inter-KPI relationships.

Chapter 5

Conclusion And Recommendations

Chapter Aims:

Chapter 5 aims to collate the results obtained from the previous chapters in this study in order to present a final study conclusion, and states the limitations encountered. Furthermore, recommendations for future research are outlined.

Chapter Outcomes:

⇒ Understand the interaction of the literature topics involved in this study.

⇒ Comprehend the results obtained and final study conclusions.

⇒ Be made aware of further research opportunities and recommendations.

5.1 Summary And Conclusion

Physical Asset Management (PAM) is increasingly being acknowledged by industry as an important contributor to the financial success of organisations, especially those who are dependent on their physical assets for organisational value creation. Amongst the PAM improvement opportunities identified by researchers and organisations is the provision of more meaningful and innovative information to the *asset management decision-making* component of PAM.

According to Ittner and Larcker (2003), Jagdev *et al.* (2004), Merchant (2006) and Harmon and Wolf (2008), Performance Measurement (PM) of physical assets can be improved through extracting additional information from Key Performance Indicators (KPIs). Rodriguez *et al.* (2009) strives the complement the information used in *asset management decision-making* with detailed information about the relationships which exist between a set of KPIs. The Quantitative Relationships at the Performance Measurement System (QRPMS) methodology, proposed by Rodriguez *et al.* (2009), aims to objectively identify and quantify relationships between a set of KPIs.

QRPMS employs two mathematical techniques, Principal Component Analysis (PCA) and Partial Least Squares (PLS), to identify and quantify inter-KPI relationships, respectively. Further investigation of the constituents of the QRPMS methodology revealed a critical step in the final stages of PCA. The QRPMS methodology employs the Guttman-Kaiser criterion (K1) to determine the appropriate number of principal components (PCs) to retain for further analysis. However, Yeomans and Golder (1982) and Lance and Vandenberg (2009) found K1 to be one of the least reliable and most inaccurate selection criteria available.

Employing the information collated as part of this research, an improved version of the QRPMS methodology is developed. This improved methodology, called the Quantitative Identification of Inter-Performance Measure Relationships (QIIPMR) methodology, employs QRPMS as a foundational framework and exchanges the K1 rule with a more accurate and reliable selection criteria - the Parallel Analysis (PA) criterion and the scree plot.

In order to effectively substantiate the QIIPMR methodology, it is compared to the QRPMS methodology using a case study. With the support of a mining organisation in South Africa, real world KPI data from a open-pit, thermal coal mine is used in the case study. The case study effectively identifies the improved capabilities of QIIPMR over QRPMS through a comprehensive comparison of the results delivered by their respective selection criteria.

The two selection criteria employed by QIIPMR (PA and the scree plot) yield specific, reliable and corresponding results. The selection criteria employed by QRPMS (the K1 rule), on the other hand, yields results which require additional analysis to discern the usable from the unusable results. A results comparison shows the results of QRPMS to be less accurate and reliable than the results of QIIPMR. Furthermore, the additional analysis of results required QRPMS increases its implementation cost when compared to QIIPMR. These conclusions are employed in the substantiation of the QIIPMR methodology.

Upon completion of the aforementioned, it can be claimed that the research objectives of this study, as listed in Table 1.2, are successfully accomplished. With respect to each sequential research objective listed in Table 1.2, the following can be concluded:

1. The literature review establishes the fundamentals of PAM, PM, PMS and KPIs, providing clear links between these respective topics, and the topic of inter-KPI relationships.

2. The realm of inter-KPI relationships are investigated, and the severe lack of literature on this topic is identified. Furthermore, the methodologies which employ relationships between performance elements, and their deficiencies, are investigated.

3. Three alternative selection criteria to the K1 rule are investigated, increasing the knowledge required to evaluate the capabilities, or rather deficiencies, of the K1 rule more appropriately.

4. The QRPMS methodology is detailed thoroughly, allowing this study to gain a comprehensive understanding of its constituents.

5. An improved version of QRPMS, the QIIPMR methodology, is developed and successfully employed in a case study using real world data.

6. The differences between QRPMS and QIIPMR (the different selection criteria employed by both) are evaluated, providing the necessary results to adequately validate the QIIPMR methodology.

7. The final conclusions of this study are founded on the results of the case study, and the null hypothesis can be rejected with confidence due to supporting evidence.

In conclusion, the successful completion of all the study research objectives enables this study to reject the null hypothesis, with which the following can be stated:

> *The Quantitative Relationships at the Performance Measurement System (*QRPMS*) methodology can be improved and modified to yield more accurate and reliable results through the employment of an alternative selection criteria used in the execution of Principal Component Analysis (*PCA).

During the process of completing this study, some limitations were encountered. These limitations are discussed in Section 5.2.

5.2 Limitations

Limitations are encountered during the development and validation of the QIIPMR methodology. It is essential to list these limitations in order to provide the reader, and potential employer of QIIPMR, with more comprehensive information on the QIIPMR methodology. The aforementioned limitations are:

- The QIIPMR methodology requires the PMS of the QIIPMR-employing entity to adhere to a defined criterion. The PMS must have clear traceability between its performance objectives and their respective KPIs. If this criterion is not met, the QIIPMR may not be employed as it is dependent on this clear traceability to deliver specific results.
- The KPI data used in the execution of QIIPMR must be adequately treated and sorted, as directed by Phase 2 of QIIPMR. If this is not completed, QIIPMR results may be yielded which are inaccurate, incorrect, inapplicable or non-interpretable.
- The users of QIIPMR must have the necessary knowledge and expertise to adequately execute PCA and PLS, and understand the results yielded by both mathematical techniques. If inexperienced or unqualified users execute QIIPMR, severe errors are likely to occur, compromising the results of QIIPMR.
- If external analysts or consultants are contracted to perform QIIPMR on behalf of an organisation, it is essential to assign applicable and informed organisational representatives to these external individuals to provide insight into the performance data and trends that may exist. The correct knowledge is required for the treatment and assessment of KPI data to mitigate the unnecessary exclusion of data.
- With respect to the literature available about inter-KPI relationships, this study found that very little research has been conducted on this topic. The development of the QIIPMR methodology was therefore limited to research such as that completed by Rodriguez *et al.* (2009).

The above listed limitations are adequately approached and managed during the course of this study, allowing the results and deliverables of this study to remain valid and applicable.

5.3 Recommendations For Future Research

Although the research objectives of this study, which are listed in Table **??**, are successfully accomplished and the null hypothesis rejected, there remains additional opportunities for future research. This section aims to discuss the additional knowledge gaps which are identified during the course of this study. If addressed, these aforementioned gaps may improve the research conducted, and results yielded, by this study.

- The literature review completed in this study reveals a lack of research on the relationships that exist between a set of KPIs. Several frameworks and methodologies, which aim to identify and employ relationships between various performance elements, are identified. However, these frameworks and methodologies are significantly limited on supporting research conducted on the relationships between performance elements, such as KPIs. This study therefore recommends additional research on the inter-KPI relationships, and the intricacies which accompany it. Only through completing additional research on this field can methodologies, such as QIIPMR, be improved and made more accurate.

- This study aims to develop a methodology which can provide additional information for improved decision-making in PAM. Through incorporating the QIIPMR methodology directly into future PMS, either academically or in-house developed, an organisation will be better equipped to realise and employ the benefits of QIIPMR. This would not only provide additional information for decision-making processes, but may prove beneficial in the design and development of new or existing KPIs. Therefore, this study recommends the incorporation of QIIPMR into a PMS structure for the aforementioned reasons.

- The statistical program used to execute Principal Component Analysis (PCA) in the case study identified the potential value of transforming the QIIPMR methodology into a single software product. This will provide a product which will mitigate errors possibly caused by the incorrect execution of the mathematical techniques employed in QIIPMR, as well as improve its ease of employment. This study thus recommends the development of such a product for researchers focused on information technology and software development.

- With regard to PAM, this study recommends research to be conducted about identifying other types of meaningful relationships between performance elements (such as performance influencing factors) which may provide additional and innovative information for the improved execution of the PAM constituents.

The above listed recommendations for future research have the potential to improve, and further, the research completed in this study. These recommendations have varying outcomes, from research publications to product development. Ultimately there is potential for, the decision-making constituent of PAM to benefit from the pursuit of any of these recommendations.

Appendices

Appendix A

The Balanced Scorecard

In 1992 R.S. Kaplan and D.P. Norton designed the Balance Scorecard (BSC) as a framework to supplement traditional financial performance measures by incorporating additional, non-financial performance measures focused on critical aspects of business (Lipe and Salterio, 2000; Banker *et al.*, 2004). The BSC was a very popular step in PMS improvement, being experimented with by an estimated 60 percent of Fortune 1000 firms, Lipe and Salterio (2000) reported. (Refer to Section 2.4.1 for a description of the aforementioned types of performance measures.)

In addition to complementing financial measures with additional non-financial measures, Banker *et al.* (2004) points out that the BSC serves as a tool for organising the strategic objectives of an organisation. These strategic objectives can be divided into four perspectives; *customer*, *internal process*, *learning and growth* and traditional *financial* perspectives.

Kaplan and Norton (1992) assert that through the integration of these four perspectives and their associated performance measures, managers are better equipped to understand cross-functional relationships, leading to improved decision-making and problem solving. This assertion is supported by Lipe and Salterio (2000) who state that the use of the BSC is intended to help decision-making by aligning performance measures with organisational objectives and strategies.

Furthermore, Kloot and Martin (2000) argue that once strategic concerns are locked into performance, management rather than measurement, becomes the target of performance. Bititci *et al.* (1997) further support this claim by defining performance measurement as the process organisations undertake by integrating its corporate and functional strategies with its performance.

In order to improve the understanding of how the integration of the aforementioned perspectives of strategic objectives aids in improved decision-making,

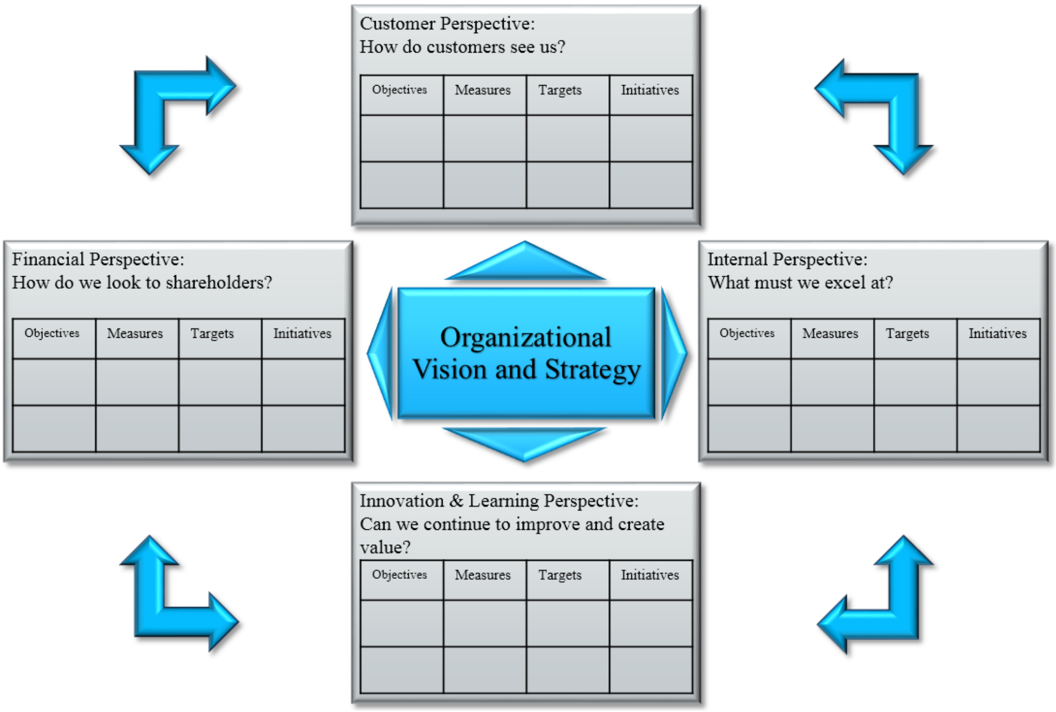


Figure A.1: The Balanced Scorecard: strategy from the four perspectives

Adapted from Kaplan and Norton (1996)

it is necessary to briefly discuss what Kaplan and Norton (1992) suggest BSC contributes. The BSC uses a combination of leading and lagging performance measures to represent the organisation's strategy in the most effective way. Financial measures to indicate past performance, and operational measures to drive future financial performance (Lipe and Salterio, 2000; Banker *et al.*, 2004). As mentioned above, and depicted in Figure A.1, the BSC divides strategic objectives into four perspectives that provide a quick and extensive view for managers. They are described by Kaplan and Norton (1992) as follows:

1. *Customer perspective*: How do customers see us?
2. *Internal perspective*: What must we excel at?
3. *Innovation and learning perspective*: Can we continue to improve and create value?
4. *Financial perspective*: How do we look to shareholders?

Kaplan and Norton (1992) state that the customers' perspective of an organisation's performance has become a priority for top management. This is therefore reflected in the BSC through the *customer perspective*, where the

BSC demands that measures be implemented to reflect the factors that drive customer satisfaction. Kaplan and Norton (1992) mention that customer's concerns generally fall into four categories: quality, service and performance, time and cost. Organisations who wish to implement the BSC should set goals addressing these four customer concern categories, and employ specific measures for each of the goals.

The *internal perspective*, Kaplan and Norton (1992) state, should include the measures which originate from internal business processes that have the most significant impact on customer satisfaction, allowing managers to focus on those critical operations. Kaplan and Norton (1992) suggest that organisations also include measures which represents the organisations' core capabilities; 'build on one's strengths to maintain industry competitiveness'.

The third perspective, *innovation and learning*, plays an important and vital role in managerial decisions. Kaplan and Norton (1992) explain that the customer and internal perspectives outlines the parameters an organisation perceives to be most critical for competitive success in the current market. However, these two perspectives have targets for success which continuously change due to global competition, market trends and various other reasons. It is thus critical for an organisation to be able to change according to these changing targets of success; to continuously improve its processes and products to remain a competitor. Therefore, Kaplan and Norton (1992) included this perspective in the BSC to enable organisations to measure their ability to innovate, improve and learn.

The last perspective, the *financial perspective*, provides the organisation with the measures necessary to see whether the organisation's strategy implementation and execution contributes to the improvement of the traditional bottom-line (Kaplan and Norton, 1992). Although many critics of financial measures voiced their concerns during the time of the BSC development, Kaplan and Norton (1992) argues that financial measures can not be neglected. Well-designed financial control systems will enhance an organisation's total quality management program, rather than inhibit it (Kaplan and Norton, 1992).

In addition, Kaplan and Norton (1992) points out that the supposed linkage between improved operating performance and financial success is an uncertain claim. Improved operational performance will most definitely have an impact on financial performance, but it is necessary to identify which operational strategies contribute positively to the financial bottom-line, and which do not. As Kaplan and Norton (1992) state, not every long-term operations strategy is profitable.

According to Youngblood and Collins (2003), this type of PMS is beneficial to organisations in many ways; the inclusion of information from all four of the aforementioned perspectives will provide decision-makers with concise and comprehensible data for improved decision-making. When the data from the four perspectives are investigated simultaneously by a multi-disciplinary team, the error of sub-optimising areas at the cost of overall performance is mitigated (Youngblood and Collins, 2003).

Many academics and professionals warn against the sole use of financial measures to evaluate performance, but it is worthy to note that the BSC has many critics as well. Even though the BSC incorporates information from different perspectives to enrich the information used by decision-makers, Atkinson *et al.* (1997) state that the BSC fails to:

- define the employees' and suppliers' contributions made in reaching the objectives set out;
- identify community's role within the operating environment of the organisation;
- enable management to assess stakeholder contributions to the organisation's objectives by not viewing performance measures as a two-way process; and
- enable stakeholders to evaluate the capability of the organisation to fulfil the present and future obligations it made to stakeholders.

In addition, Lipe and Salterio (2000) present a study which revealed that many organisational decision-makers base their evaluations solely on BSC measures that are common across the different business silos. Silo specific measures are neglected. Banker *et al.* (2004) mention that this observation may be viewed as an occurrence that undermines the principle benefit of the BSC; to capture the organisation's desired business strategy in all important areas. Kaplan and Norton (2000) comment on this observation, stating that all measures should be used, and not just the common measures found across all business silos.

Youngblood and Collins (2003) put forward that the BSC delivers meaningful information on different performance measures, but does not, however, weigh measures in terms of importance nor does it consider issues such as inter-measure relationships nor trade-offs between measures. Nonetheless, there are tools available for use by the BSC, such as Multi-Attribute Utility Theory (MAUT), that could aid in choosing between measures with interactions and trade-offs.

Folan and Browne (2005) write that Kaplan and Norton continued to publish literature in support of the basic BSC and its performance management components, unlike the authors of the other two academically produced PMS listed in Section 2.3.3.3. This makes the Balanced Scorecard a very popular PMS among organisations and PMS professionals as it provides a tried and tested PMS, and has abundant supporting literature. For a detailed discussion on how to implement the Balanced Scorecard, consult Kaplan and Norton (1996).

Appendix B

Overview Of Mathematical Techniques

B.1 The PCA Method: A Brief Mathematical Description

Smith (2002) provides a convenient and easy-to-follow description of PCA and its procedure. Her work will be used in combination with Jackson (1991) for the following description of PCA. There are five general steps in the execution of PCA:

1. Mean normalisation and (optional) feature scaling.
2. Computation of the original covariance matrix.
3. Computation of the eigenvectors of the original covariance matrix.
4. Obtain a matrix containing the eigenvectors.
5. Represent original data in terms of a reduced dimension.

Each one of the above listed steps is discussed in brief below. Please note that matrices are symbolized by upper case bold, vectors by lower case bold, and elements by lower case italics, as used by Jackson (1991).

B.1.1 Mean Normalisation And (Optional) Feature Scaling

According to Smith (2002), the mean of each variable's observations (each variable in the original data set) must be subtracted from the respective observations. This effectively creates a reduced data set in which each variable's mean observation is zero, allowing PCA to function properly (Smith, 2002).

B.1.2 Calculating Original Covariance Matrix

Jackson (1991) states that the "official" starting point for PCA is the covariance matrix **S**; for a p-variable problem, the covariance matrix is:

$$\mathbf{S} = \begin{bmatrix} s_1^2 & s_{12} & \cdots & s_{1p} \\ s_{12} & s_2^2 & \cdots & s_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ s_{1p} & s_{2p} & \cdots & s_p^2 \end{bmatrix} \tag{B.1.1}$$

where the variance for the ith variable is ${s^2}_i$ and covariance between the ith and jth variable is:

$$\mathbf{s}_{ij} = \frac{n \sum x_{ik} x_{jk} - \sum x_{ik} \sum x_{jk}}{[n(n-1)]} \tag{B.1.2}$$

where $k = [1{:}n]$ and n is the number of samples, or observations, of each variable. Jackson (1991) writes that if the covariances do not equal zero, it is indicative of a linear relationship existing between the respective ith and jth variables.

B.1.3 Calculating Eigenvectors

The method of PCA is founded on a fundamental product from matrix algebra, says Jackson (1991). The covariance matrix **S** has the dimensions p x p and is symmetric and non-singular in nature. It can thus be reduced by pre- and post-multiplying it by a particular orthonormal matrix, **U**, to give a diagonal matrix **L**. This is indicated below.

$$\mathbf{U}'\mathbf{S}\mathbf{U} = \mathbf{L} \tag{B.1.3}$$

The diagonal entries of **L** are the eigenvalues of **S**, and the columns of matrix **U** are the eigenvectors of **S** (Jackson, 1991). For a p variable problem, there will be p number of eigenvalues and p number of eigenvectors, each containing p elements, according to Jackson (1991).

The characteristic equation, Equation B.1.4, provides the first step in determining the eigenvalues of **S**, and contains the identity matrix **I**.

$$\left[\mathbf{S} - l\mathbf{I}\right] = 0 \tag{B.1.4}$$

The above equation yields the pth degree, characteristic equation in l, from which l_1, l_2, ..., l_p can be determined. In order to compute the elements of **U** in Equation B.1.3, the eigenvectors must first be obtained by solving the following equations for $i = 1, 2, ..., p$.

$$\left[\mathbf{S} - l\mathbf{I}\right] \mathbf{t_i} = 0 \tag{B.1.5}$$

$$\mathbf{u}_i = \frac{\mathbf{t}_i}{\sqrt{\mathbf{t}_i'\mathbf{t}_i}} \tag{B.1.6}$$

Smith (2002) states that the eigenvectors provide information regarding the patterns in the data; they are data characterising "lines". In addition, Smith (2002) notes that the eigenvectors are unit eigenvectors; they have lengths of 1.

B.1.4 Obtaining Eigenvector Containing Matrix

After obtaining all the eigenvectors $\mathbf{u}_1$, $\mathbf{u}_2$, ..., $\mathbf{u}_\mathrm{p}$, the orthonormal matrix $\mathbf{U}$ can be constructed as shown below.

$$\mathbf{U} = \left[\mathbf{u}_1 \;\vdots\; \mathbf{u}_2 \;\vdots\; ... \;\vdots\; \mathbf{u}_p\right] \tag{B.1.7}$$

Jackson (1991) describe the aforementioned mathematical process as a *principal axis* rotation; a process of expressing the original data in terms of new axes. According to Jackson (1991), the eigenvectors, which matrix $\mathbf{U}$ is comprised of, characterise these new axes.

B.1.5 Computing Principal Components

The final step of the *principal axis* rotation is to compute the PCs with Equation B.1.8.

$$\mathbf{z} = \mathbf{U}' \left[\mathbf{x} - \bar{\mathbf{x}}\right] \tag{B.1.8}$$

The vectors $\mathbf{x}$ and $\bar{\mathbf{x}}$ have dimensions p x 1 of observations on the original variables, and their averages (Jackson, 1991). The ith PC is computed with Equation B.1.9 below.

$$\mathbf{z}_i = \mathbf{u}_i' \left[\mathbf{x} - \bar{\mathbf{x}}\right] \tag{B.1.9}$$

The above changes p correlated (original) variables x_1, x_2, ..., x_p into p *uncorrelated* variables z_1, z_2, ..., z_p; the principal components (Jackson, 1991). Jackson (1991) and Abdi and Williams (2010) clarifies that the individually "changed" observations are called *z-scores*.

B.1.6 Representing Original Data

Smith (2002) describes a "short cut" that can be taken; the eigenvector that has the largest eigenvalue, results in the first PC. Thus, once the eigenvectors $\mathbf{u}_1$, $\mathbf{u}_2$, ..., $\mathbf{u}_\mathrm{p}$ have been calculated, they can ranked in terms of their eigenvalues (highest to lowest), effectively forming the list of PCs in order of significance Smith (2002).

The appropriate number of PCs can then be identified for retention through the implementation of selection criteria (a critical topic according to Velicer *et al.* (2000)) which discussed in Section 2.7. If the original data set had p number of original variables, then p eigenvalues, p eigenvectors and p PCs will be calculated. If k number of PCs are retained, the final data set will have k dimensions (Smith, 2002). This concludes the process of data set dimension reduction, as stated in Section 2.6.2.

The next step, after selecting the number of PCs to retain, is to construct a *feature vector*, as explained by Smith (2002). A feature vector is a matrix containing the eigenvectors of the respective retained PCs in the matrix columns. This is indicated by Equation B.1.10 for k number of retained eigenvectors.

$$\mathbf{FV} = \left[\mathbf{u}_1 \;\vdots\; \mathbf{u}_2 \;\vdots\; ... \;\vdots\; \mathbf{u}_k\right] \tag{B.1.10}$$

Smith (2002) states the final data can then be calculated using Equation B.1.11, which is similar to Equation B.1.8.

$$\mathbf{F} = \mathbf{FV}'\left[\mathbf{x} - \bar{\mathbf{x}}\right] \tag{B.1.11}$$

Where $\mathbf{F}$ is the matrix containing the final data in terms of the selected PCs. For further information regarding executing PCA, in-depth descriptions of the PCA method are provided by both Jackson (1991) and Tabachnick *et al.* (2001). The above description of PCA proved that it is possible to identify an underlying structure to a set of variables. This characteristic of PCA is used by QRPMS to identify cause-effect relationships between a set of KPIs.

B.2 Brief Mathematical Description Of PLS Regression

According to Geladi and Kowalski (1986), a linear regression model can be found between the matrices containing predicted variables, $\mathbf{X}$, and observable variables, $\mathbf{Y}$. PLS consists of two relation types; outer relations of both $\mathbf{X}$ and $\mathbf{Y}$, and an inner relation (Geladi and Kowalski, 1986). The outer relations of $\mathbf{X}$ and $\mathbf{Y}$ are represented by Equation B.2.1 and Equation B.2.2 respectively.

$$\mathbf{X} = \mathbf{TP}' + \mathbf{E} = \Sigma \mathbf{t_h p_h}' + \mathbf{E} \tag{B.2.1}$$

$$\mathbf{Y} = \mathbf{UQ}' + \mathbf{F}^* = \Sigma \mathbf{t_h u_q}' + \mathbf{F}^* \tag{B.2.2}$$

The matrices **X** and **Y** have dimensions n x m and n x p, respectively. The matrices **T** and **U**, shown in Equation B.2.1 and Equation B.2.2 respectively, have dimensions n x l and are the respective projections of **X** and **Y**. **P** and **Q** are orthogonal *loading* matrices with dimensions m x l and p x l respectively, whereas the error terms are represented by matrices **E** and **F**. These matrices and the aforementioned equations are depicted in Figure B.1.

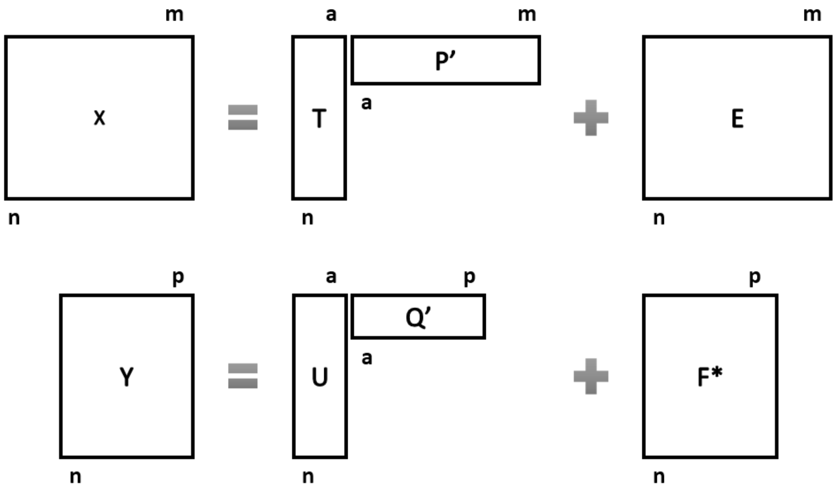


Figure B.1: A depiction of the general model underlying PLS

Adapted from Geladi and Kowalski (1986)

De Jong (1993) states the first step in utilizing Equation B.2.1 and Equation B.2.2 is to determine **T** and **U**. This is accomplished by centring **X** and **Y**, from which orthogonal factors scores and companion factors scores are calculated, one by one, to give **T** and **U** respectively.

Geladi and Kowalski (1986) write that the aim is to describe **Y** as accurately as possible, therefore reducing the absolute value of $\mathbf{F}'$ as much as possible, and to obtain a relationship between **X** and **Y**. According to Geladi and Kowalski (1986), comparing the **Y** score, **u**, against that of the **X** score, **t**, the aforementioned inner relation can be constructed. The inner relation is shown by Equation B.2.3.

$$\hat{\mathbf{u}} = b_h \mathbf{t}_h = \frac{\mathbf{u}_h{}' \mathbf{t}_h}{\mathbf{t}_h{}' \mathbf{t}_h} \mathbf{t}_h \tag{B.2.3}$$

Geladi and Kowalski (1986) states there is also a mixed relation, which is shown by Equation B.2.4, in which the absolute of $\mathbf{F}$ is to be reduced.

$$\mathbf{Y} = \mathbf{TBQ}' + \mathbf{F} \tag{B.2.4}$$

This section aimed to briefly summarize the regression analysis method of PLS; the explicit description of this method does not form part of this study as it has already been completed by Wold *et al.* (1983), Geladi and Kowalski (1986), Naes *et al.* (1986) and Haaland and Thomas (1988). Of particular interest is the publication of Martens and Martens (2000) in which the combination of PCA and PLS is discussed; making a more effective methodology to address some type of issues encountered. However, this does not form part of this study's scope.

Appendix C

Designation Of Case Study KPIs

The unfamiliar abbreviations and acronyms used in this Appendix are listed below for convenience, along with descriptions and definitions where required.

- Basic Cubic Meter (BCM): Volume of unspecific material.
- Calorific Value (CV): Quality of the mined coal.
- Direct Operating Hours (DOH): The total time the equipment unit, plant or module is in operation.
- Equipment Availability (EA): Operating availability described as a ratio of controllable time less engineering downtime.
- Total Monthly Employees (FME): Total working personnel on the mine (only possible to measure monthly).
- High Potential Incidents (HPI): Incidents that could lead to injuries causing lost operating time.
- Lost Time Injury (LTI): An injury that halted production or mining processes.
- Run of Mine (ROM): Unprocessed coal that has been mined (includes impurities).
- Total Cubic Meters (TCM): Summation of prime material and rehandled material.

Table C.1: KPIs for *Operations*

KPI designation	KPI Unit	KPI description
OpS1	BCM	Volume moved by the Sand fleet
OpS2	%	Sand fleet DOH as a % of total time
OpS3	BCM/DOH	Sand fleet transport/removal rate
OpD1	m	Drilled distance of the GD70 unit
OpD2	m	Drilled distance of the Drilltech unit
OpD3	m/DOH	Drill rate of the GD70 unit
OpD4	m/DOH	Drill rate of the Drilltech unit
OpDo1	TCM	Volume pushed by the D475 Dozer fleet
OpDo2	%	DOH of the D475 Dozer fleet
OpDo3	TCM/DOH	Push rate of the D475 Dozer fleet
OpDr1	TCM	Volume moved by the Dragline fleet
OpDr2	%	DOH of the Dragline fleet
OpDr3	TCM/DOH	Removal rate of the Dragline fleet
OpDr4	%	Material rehandle of/by the Dragline fleet
OpC1	tons	Run of Mine (ROM)
OpC2	tons/DOH	Coal truck handling rate
OpP1	tons	Sales tons
OpP2	DOH	Operating duration of the primary Tip
OpP3	tons/DOH	Material feed-rate to the Tip
OpP4	%	Coal yield as a % of total mined material
OpP5	CV	Mined coal qualities
OpP6	tons	Coal received by the stockyard
OpP7	tons	Dispatched / sold coal

Table C.2: KPIs for *Engineering* - Table 1

KPI designation	KPI Unit	KPI description
EnDr1	%	EA of the Dragline fleet
EnDr2	hours	Mean time to failure of the Dragline fleet
EnDr3	%	Planned Maintenance vs Unplanned Maintenance of the Dragline fleet
EnDr4	ZAR/TCM	Mean Unit Cost of the Dragline fleet
EnSh1	%	EA of Shovel Unit 1
EnSh2	hours	Mean time to failure of Shovel Unit 1
EnSh3	%	Planned Maintenance vs Unplanned Maintenance of Shovel Unit 1
EnSh4	ZAR/ton	Unit Cost of Shovel Unit 1
EnD11	%	EA of Demag Unit 1
EnD12	hours	Mean time to failure of Demag Unit 1
EnD13	%	Planned Maintenance vs Unplanned Maintenance of Demag Unit 1
EnD14	ZAR/ton	Unit Cost of Demag Unit 1
EnD21	%	EA of Demag Unit 2
EnD22	hours	Mean time to failure of Demag Unit 2
EnD23	%	Planned Maintenance vs Unplanned Maintenance of Demag Unit 2
EnD24	ZAR/ton	Unit Cost of Demag Unit 2
EnE1	%	EA of the EX3600 excavator units
EnE2	hours	Mean time to failure of the EX3600 excavator units
EnE3	%	Planned Maintenance vs Unplanned Maintenance of the EX3600 excavator units
EnE4	ZAR/ton	Mean Unit Cost of the EX3600 excavator units
EnOb1	%	EA of the overburden drill units
EnOb2	hours	Mean time to failure of the overburden drill units
EnOb3	%	Planned Maintenance vs Unplanned Maintenance of the overburden drill units
EnOb4	ZAR/ton	Mean Unit Cost of the overburden drill units
EnCl1	%	EA the CAT994 loader units
EnCl2	hours	Mean time to failure the CAT994 loader units
EnCl3	%	Planned Maintenance vs Unplanned Maintenance the CAT994 loader units
EnCl4	ZAR/ton	Mean Unit Cost the CAT994 loader units

Table C.3: KPIs for *Engineering* - Table 2

KPI designation	KPI Unit	KPI description
EnT11	%	EA of the R170 truck units
EnT12	hours	Mean Time to Failure of the R170 truck units
EnT13	%	Planned Maintenance vs Unplanned Maintenance of the R170 truck units
EnT14	ZAR/Ton	Mean Unit Cost of the R170 truck units
EnT21	%	EA of the CAT789 truck units
EnT22	hours	Mean Time to Failure of the CAT789 truck units
EnT23	%	Planned Maintenance vs Unplanned Maintenance of the CAT789 truck units
EnT24	ZAR/Ton	Mean Unit Cost of the CAT789 truck units
EnT31	%	EA of the EH3500 truck units
EnT32	hours	Mean Time to Failure of the EH3500 truck units
EnT33	%	Planned Maintenance vs Unplanned Maintenance of the EH3500 truck units
EnT34	ZAR/Ton	Mean Unit Cost of the EH3500 truck units
EnT41	%	EA of the CAT773 truck units
EnT42	hours	Mean Time to Failure of the CAT773 truck units
EnT43	%	Planned Maintenance vs Unplanned Maintenance of the CAT773 truck units
EnT44	ZAR/Ton	Mean Unit Cost of the CAT773 truck units
EnDo1	%	EA of the D475 dozer units
EnDo2	hours	Mean Time to Failure of the D475 dozer units
EnDo3	%	Planned Maintenance vs Unplanned Maintenance of the D475 dozer units
EnDo4	ZAR/Ton	Mean Unit Cost of the D475 dozer units

Table C.4: KPIs for *Safety* and *Human Resources*

KPI designation	KPI Unit	KPI description
Sa1	Count	HPI (level 4 & 5)
Sa2	Count	Total injuries (includes first aid and medical treatment cases)
Sa3	Count	LTI
Sa4	Count	Fatality
Sa5	Days	Days without injuries
Sa6	Days	Days without LTI's
Sa7	Shifts	Fatality free shifts
HR1	Count	Total FME
HR2	Count	Number of employees
HR3	Count	Number of contractors
HR4	ROM/FME	Ratio of ROM and FME

Table C.5: KPIs for *Finance*

KPI designation	KPI Unit	KPI description
F1	ZAR	Revenue
F2	ZAR	Total cost of production
F3	ZAR	Operating Profit
F4	ZAR	Cost of production per sales ton
F5	ZAR	Total Labour
F6	ZAR	Total Stores
F7	ZAR	Total Expenditure
F8	ZAR	Total Sundry Debits
F9	ZAR	Total Non-Cash Cost
F10	ZAR	Total cost of production

Appendix D

Plotted Data Of Selection Criteria

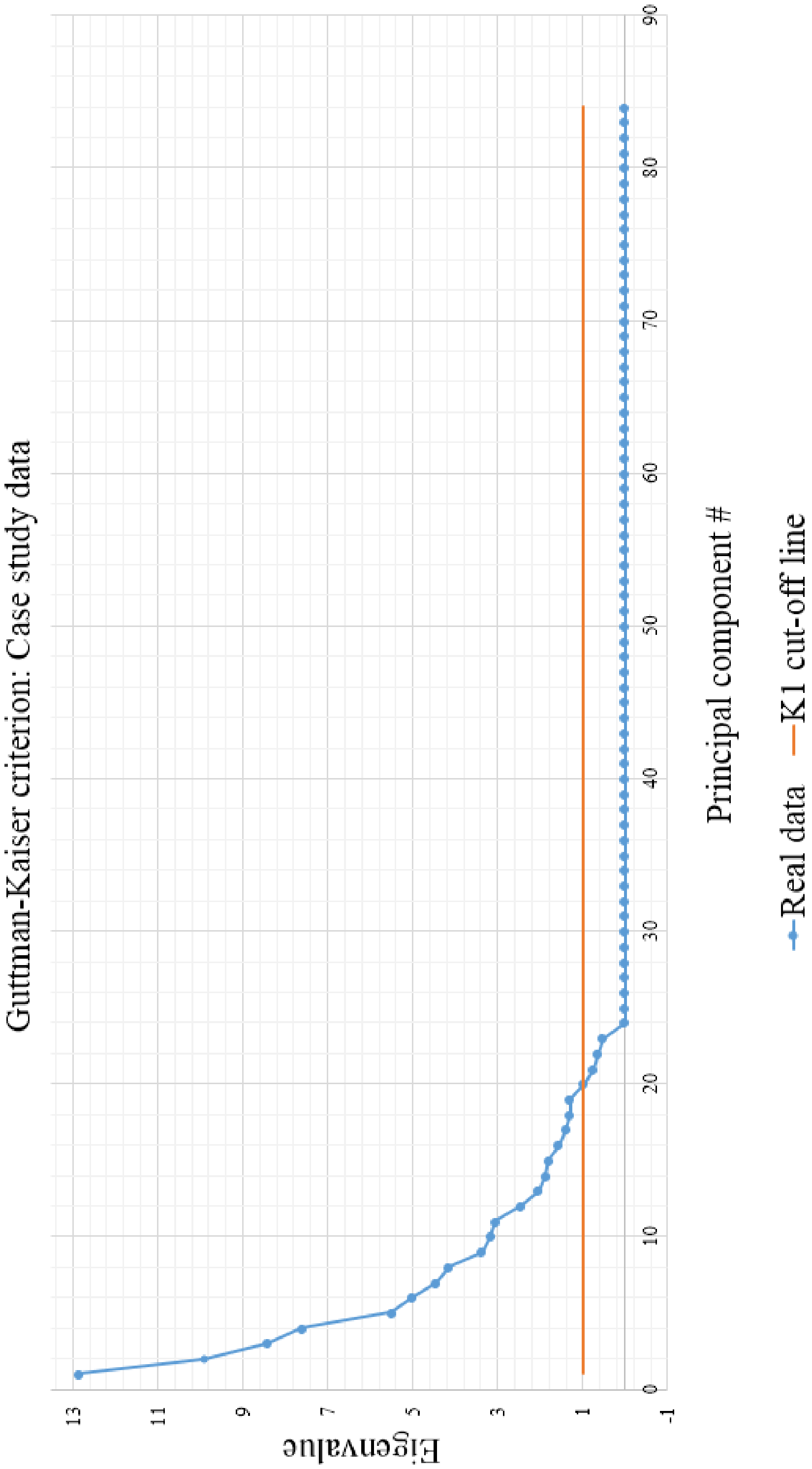


Figure D.1: Plot of Guttman-Kaiser criterion (K1) PC cut-off

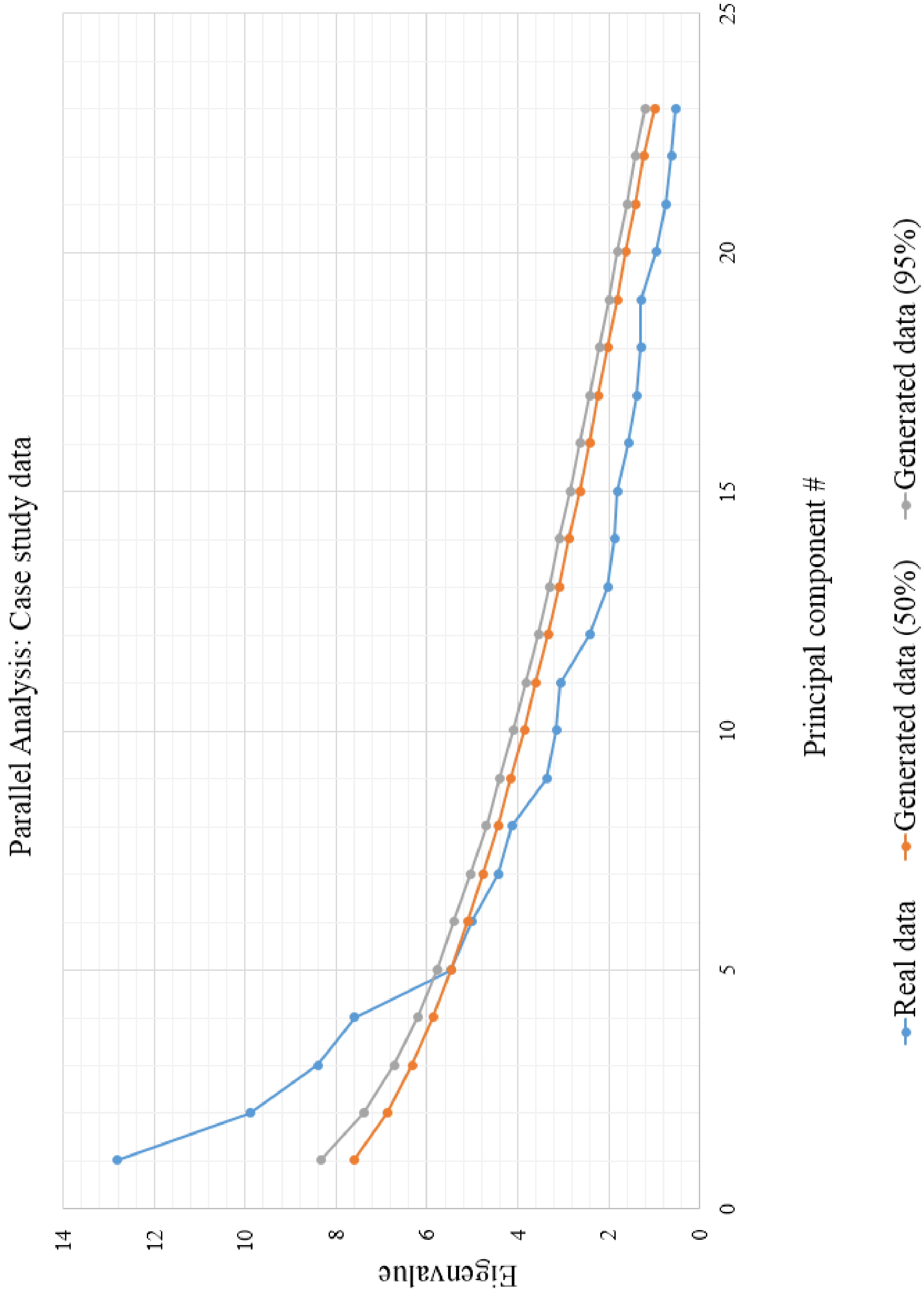


Figure D.2: Parallel Analysis (PA) plot of the real PCs

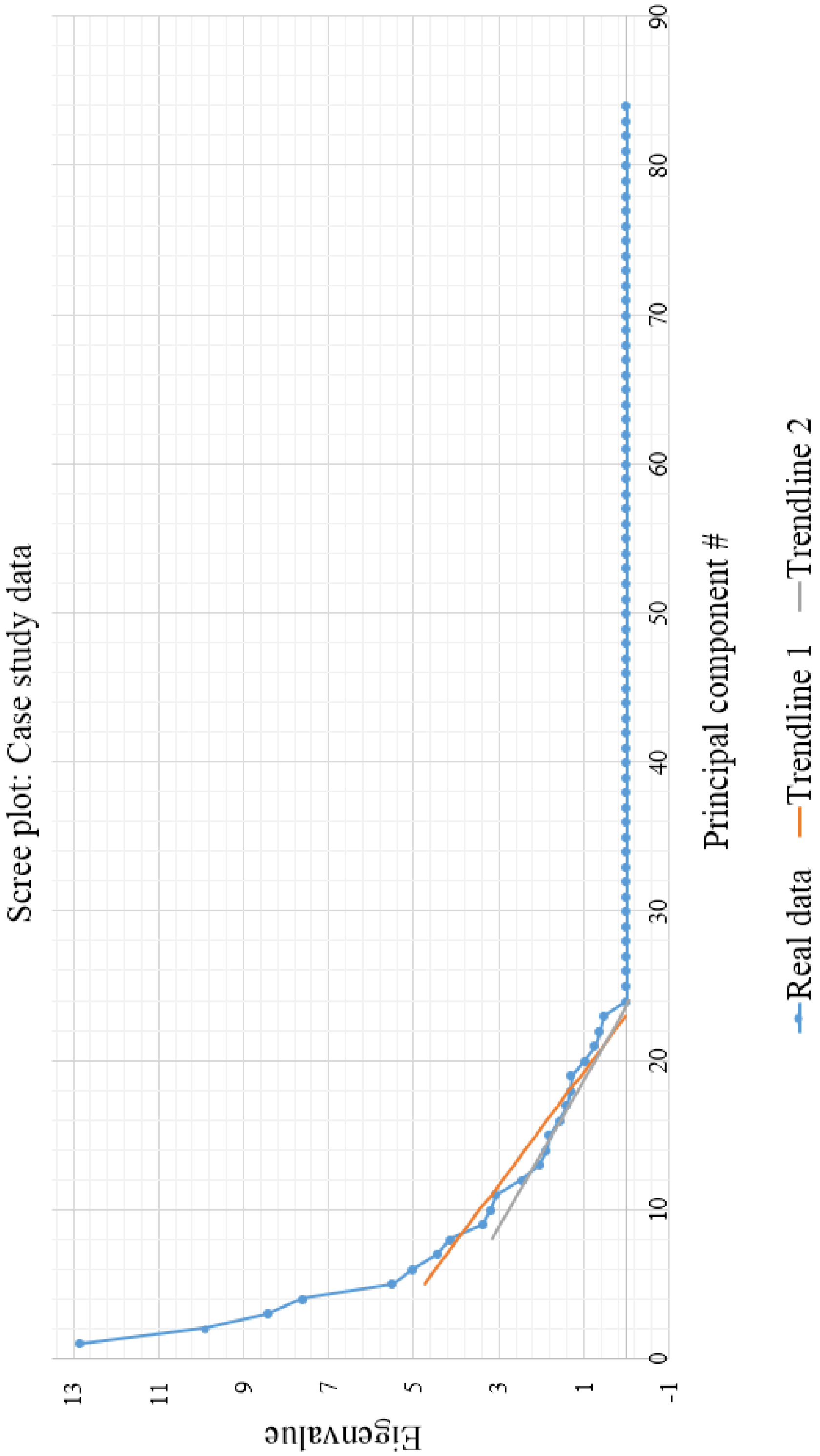


Figure D.3: Scree plot of the real PCs

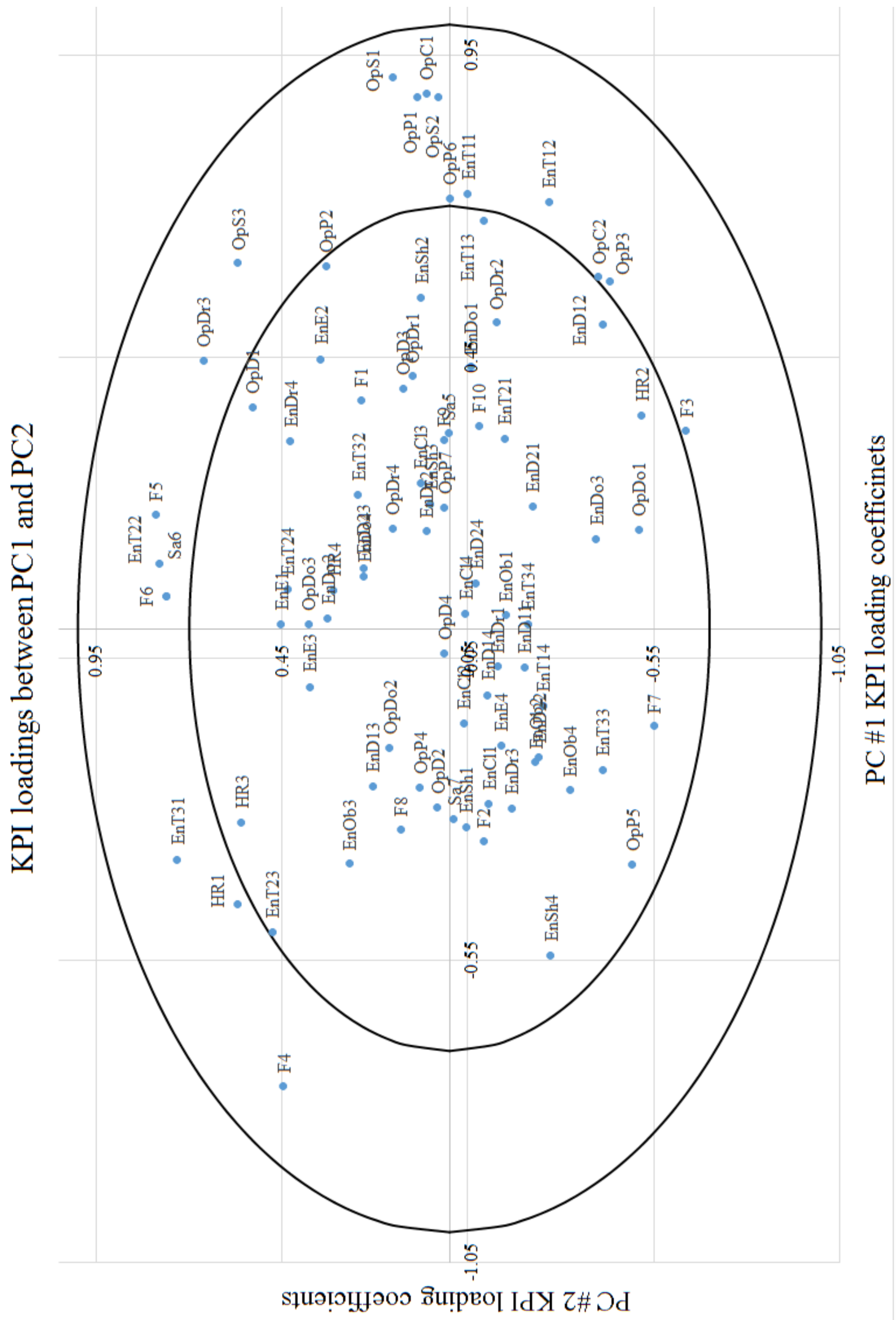


Figure D.4: KPI loadings between the first and second PCs

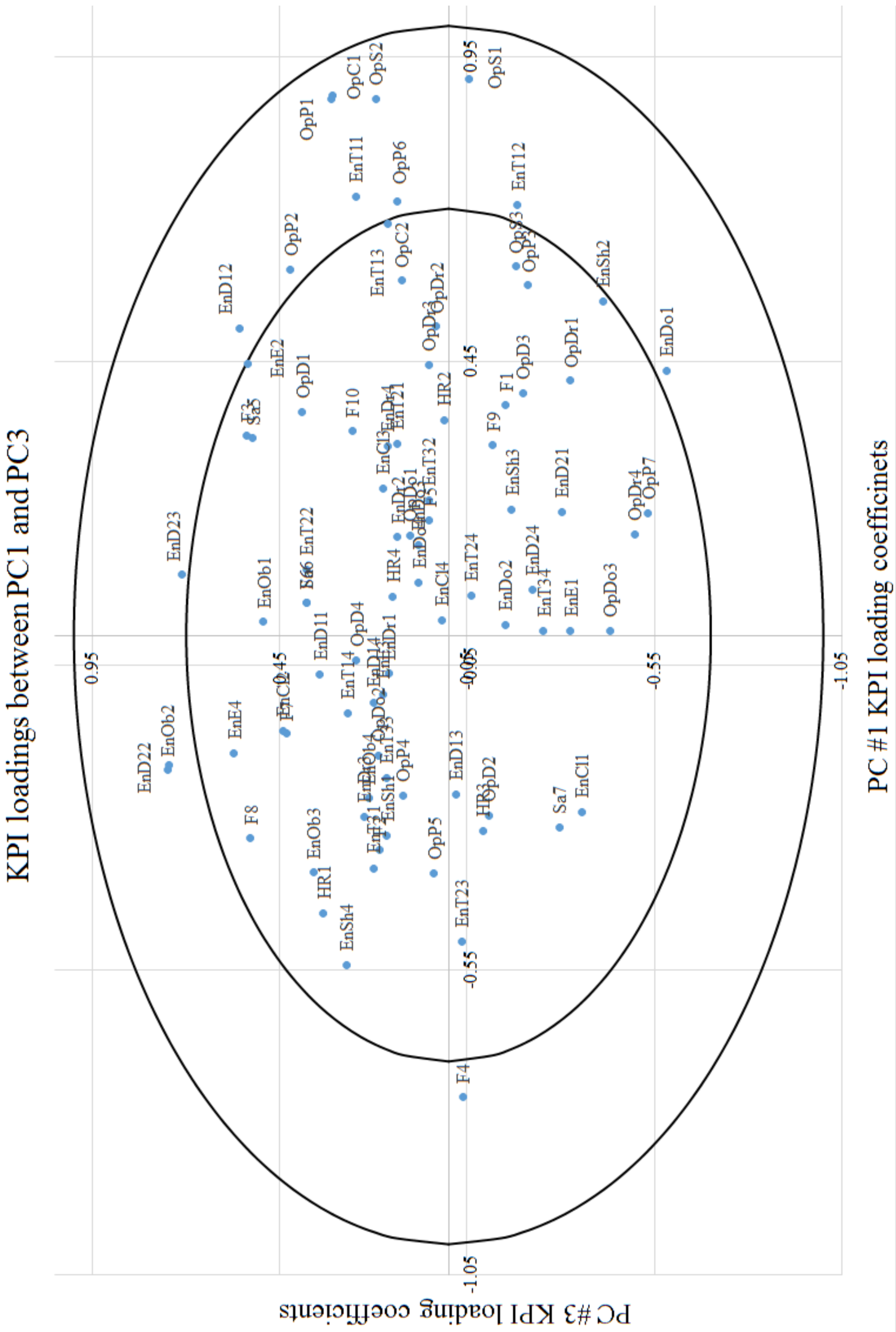


Figure D.5: KPI loadings between the first and third PCs

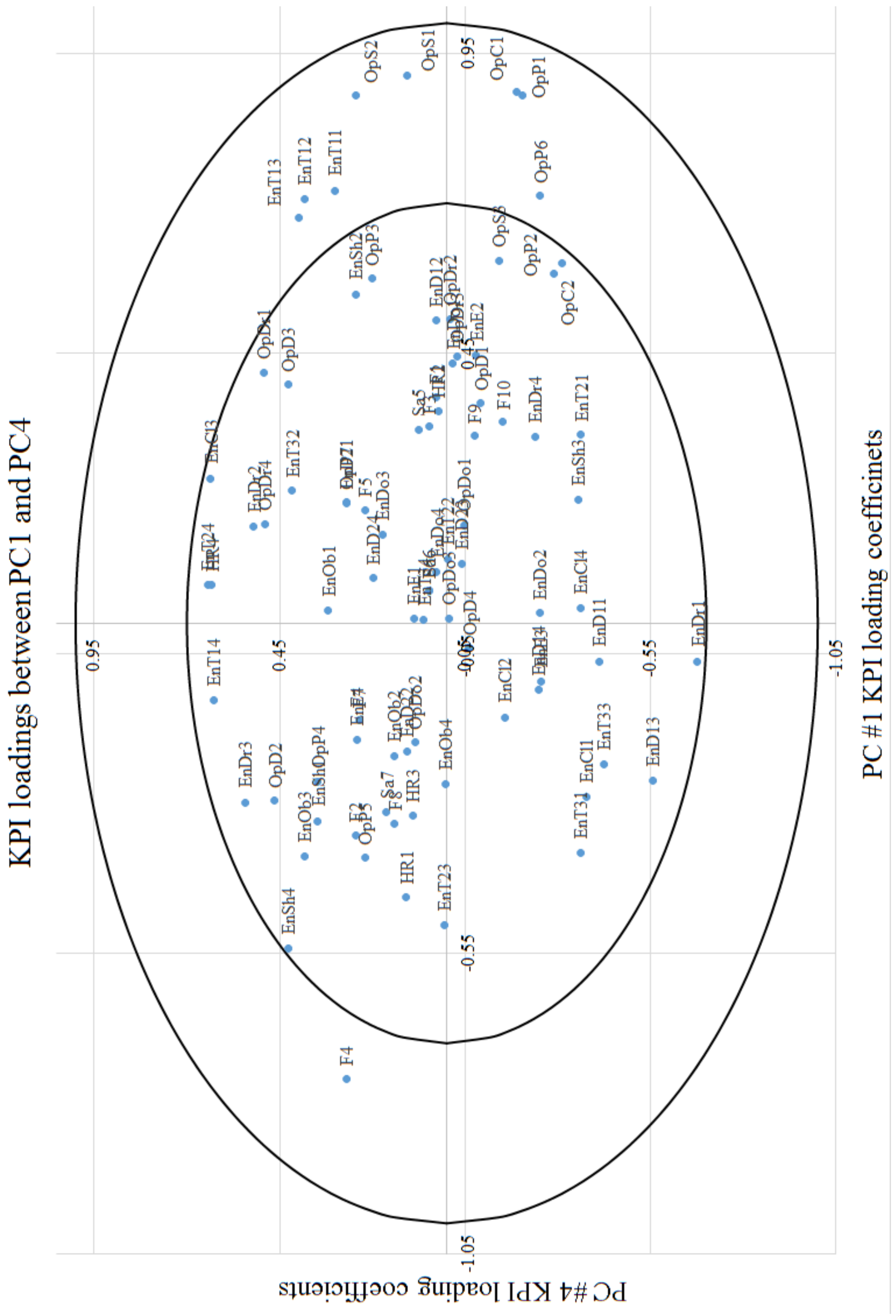


Figure D.6: KPI loadings between the first and fourth PCs

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