A Framework for the Design of Business Intelligence Dashboard Tools

by

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Abstract

Vast amounts of data are collected on a daily basis, making it difficult for humans to derive at valuable information to make effective decisions. In recent years, the field of Business Intelligence (BI) and Information Visualisation (IV) have become a key driver of an organisation's success. BI tools supporting decision making need to be accessible to a larger audience on different levels of the organisation. The problem is that non-expert users, or novice users, of BI tools do not have the technical knowledge to conduct data analysis and often rely on expert users to assist. For this reason, BI vendors are shifting their focus to self-service BI, a relatively new term where novice users can analyse data without the traditional human mediator. Despite the proliferation of self-service BI tools, limited research is available on their usability and design considerations to assist novice users with decision making and BI analysis.

The contribution of this study is a conceptual framework for designing, evaluating or selecting BI tools that support non-expert users to create dashboards (the BI Framework). A dashboard is a particular IV technique that enables users to view critical information at a glance. The main research problem addressed by this study is that non-expert users often have to utilise a number of software tools to conduct data analysis and to develop visualisations, such as BI dashboards. The research problem was further investigated by following a two-step approach. The first approach was to investigate existing problems by using an in-depth literature review in the fields of BI and IV. The second approach was to conduct a field study (Field Study 1) using a development environment consisting of a number of software components of which SAP Xcelsius was the main BI tool used to create a dashboard. The aim of the field study was to compare the identified problems and requirements with those found in literature.

The results of the problem analysis revealed a number of problems in terms of BI software. One of the major problems is that BI tools do not adequately guide users through a logical process to conduct data analysis. In addition, the process becomes increasingly difficult when several BI tools are involved that need to be integrated. The results showed positive aspects when the data was mapped to a visualisation, which increased the users' understanding of data they were analysing. The results were verified in a focus group discussion and were used to establish an initial set of problems and requirements, which were then synthesised with the problems and requirements identified from literature.

Once the major problems were verified, a framework was established to guide the design of BI dashboard tools for novice users. The framework includes a set of design guidelines and usability evaluation criteria for BI tools. An extant systems analysis was conducted using BI tools to compare the advantages and disadvantages. The results revealed that a number of tools could be used by non-experts, however, their usability hinders users. All the participants used in all field studies and evaluations were Computer Science (CS) and Information Systems (IS) students. Participants were specially sourced from a higher education institution such as the Nelson Mandela Metropolitan University (NMMU).

A second field study (Field Study 2) was conducted with participants using another traditional BI tool identified from the extant systems analysis, PowerPivot. The objective of this field study was to verify the design guidelines and related features that served as a BI Scorecard that can be used to select BI tools. Another BI tool, Tableau, was used for the final evaluation. The final evaluation was conducted with a large participant sample consisting of IS students in their second and third year of study. The results for the two groups revealed a significant difference between participants' education levels and the usability ratings of Tableau. Additionally, the results indicated a significant relationship between the participants' experience level and the usability ratings of Tableau. The usability ratings of Tableau were mostly positive and the results revealed that participants found the tool easy to use, flexible and efficient.

The proposed BI Framework can be used to assist organisations when evaluating BI tools for adoption. Furthermore, designers of BI tools can use the framework to improve the usability of these tools, reduce the workload for users when creating dashboards, and increase the effectiveness and efficiency of decision support.

Keywords: BI tools, BI dashboards; usability of BI tools

Declaration of Own Work

I, *Martin Bradley Smuts (210035447)*, hereby declare that the dissertation for *Magister Commercii in Computer Science & Information Systems* to be awarded in my own work and that it has not previously been submitted for assessment or completion of any postgraduate qualification to another university or for another qualification.

Date:

Signed:

The views and opinions expressed in this dissertation are those of the author and do not necessarily reflect the official views of SYSPRO Pty Ltd. For publication purposes written consent must be obtained from SYSPRO Pty Ltd.

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List of Abbreviations

Business Analytics	BA
Business Intelligence	BI
Business Performance Management	BPM
Corporate Performance Management	CPM
Computer Science	CS
Computer System Usability Scale	CSUQ
Customer Relationship Management	CRM
Database Management System	DBMS
Design Science Research	DSR
Executive Information Systems	EIS
Enterprise Performance Management	EPM
Enterprise Resource Planning	ERP
Extract, Transform and Load	ETL
Higher Education Institutions	HEIs
Human Computer Interaction	HCI
Information Systems	IS
Information Visualisation	IV
Integrated Development Environment	IDE
Key Performance Indicator(s)	KPI/ KPIs
Online Analytical Processing	OLAP
Relational Database Management System	RDBMS
Research Objective(s)	RO/ROs
Research Question(s)	RQ/RQs
Structured Query Language	SQL
Supply Chain Management	SCM
Transaction Processing Systems	TPS
Visual Analytics	VA

Chapter 1. Introduction

1.1 Background

The generation and processing of data through digital technologies are increasing at an incredible rate (McAfee & Brynjolfsson 2012). The increasing volume and detail of information collected by organisations will fuel exponential growth in future. For this reason, the analysis of large data sets have become an integral focus for modern organisations (Işik et al. 2013). The extraction of hidden patterns and trends in information assists organisations to make improved decisions about future events and behaviours. Organisations are realising the benefits of data-driven decisions, and a wider range of business users are demanding tools to quickly exploit and understand large data sets (Sallam et al. 2015). In order to support the efficient analysis of immense volumes of data, organisations invest in Business Intelligence (BI) systems (Ariyachandra & Watson 2010). BI involves the process of yielding information by transforming raw data into useful insights and knowledge for improved strategic, managerial and operational decision making (Golfarelli, Rizzi, & Castenaso, 2004).

The visual presentation of data is one of the primary components of BI systems and usually takes the form of dashboards (Eckerson 2011; Elias et al. 2013). Dashboards are interfaces that consist of a number of individual visualisations or charts, which are easy to read and show the most important information on a single screen (Few 2007a). The concept of a dashboard is similar to the dashboard metaphor represented in an automobile, indicating the most critical aspects on a single screen that monitor the "health" of an organisation. Yigitbasioglu and Velcu (2012) explain that dashboards are expected to collect, summarise and present critical information from various data sources. The critical information is often referred to as key performance indicators (KPIs) from which the user can initiate further investigation and analysis to uncover insights (Eckerson 2011; Muntean et al. 2010). The collection of data sources is often referred to as a BI architecture consisting of various individual technologies and systems.

Organisations often experience difficulty in identifying methods to utilise their collected data and to manage organisational performance. Consequently, organisations typically struggle to synchronise organisational strategy with operational execution due to the lack of visibility in their information required for the decision making support (Kemper, Rausch, & Baars, 2013; Lempinen, 2012). Many organisations, therefore, implement Enterprise Performance

Management (EPM) systems to aid them in this endeavour (Hawking 2013; Bogdana et al. 2009). EPM forms part of any BI system and offers the benefits of greater rigor, accuracy and transparency to many financial management processes (Chandler et al. 2010). These processes often include budgeting, planning, forecasting and reporting, which can deliver a better understanding of the core drivers of corporate profitability.

EPM systems form an integral part of BI solutions. The focus of BI systems has fundamentally shifted from top and mid-level managers to individuals on varying levels of the organisations in recent years. This creates a situation where organisations are demanding systems that reduce the costs of finding information and assists in answering complex questions with minimal effort. Organisations operate in rapidly changing economic environments, creating a tendency for an expanding end-user population with diverse information needs and preferences that require quick access to interactive and customisable dashboard technology (Elias & Bezerianos 2011; Toker et al. 2013).

The scope of this study falls on the novice users who are defined as users who are competent in using computers, but do not have particular experience with Information Visualisation (IV) and programming (Heer et al. 2008a; Grammel et al. 2010b). The fact that various systems need to be integrated to utilise a BI system often makes it difficult for novice users to learn to create dashboards. Learning and understanding the individual concepts associated with visualisations and dashboards are already difficult for novice users, which creates even greater difficulty in trying to understand the structure of the system itself (Grammel et al. 2010a).

Novice users, such as students, do not have the expertise to integrate the various software components to develop their own dashboards. In addition, the usability of BI systems are not highly rated, which causes an intrinsic delay in the development of dashboards for analysis (Jooste et al. 2014). This creates an unnecessarily long lifecycle delay in the dashboard development process, where end-users first need to consult with experts, such as software engineers and analysts, at different stages to continuously provide feedback on the design, setup and customisation of the final dashboards (Elias & Bezerianos 2011; Satyanarayan & Heer 2014). Moreover, novice users often rely on analysts to conduct data analysis on their behalf and to prepare and present findings before a decision can be made as end-users. Preparing for BI analysis can be a time-consuming task as analysts often do not have the time to learn new

BI tools, the problem is made more serious with the low usability ratings of BI tools (Jooste et al. 2014).

1.2 Relevance to Domain

In recent years, many software tools and development toolkits have been developed with the focus on easy dashboard creation to enhance the exploration and analysis of large business datasets. The BI market often promotes these software tools as *Dashboard*, *Business Intelligence*, *Business Analytics*, *Data Visualisation*, *Data Exploration*, or *Data Discovery tools.* This study will use the terms BI tool or BI dashboard tool to refer to software that support users creating dashboards and the associated data analysis thereof. The aim of these tools is to provide better presentation of data, and guide users to create simple and advanced dashboards (Pantazos & Lauesen 2012). However, developing meaningful dashboards for data analysis is not an easy task for novice users, considering their programming skills and domain knowledge (Heer & Bostock 2010; Huron et al. 2014a). As a result, dashboards are still mostly created by experts; which is a tedious process and makes BI tools inaccessible to a broader audience who often need to make key decisions quickly.

The interactions between users and the features of tools involved in a typical dashboard creation process typically require users to utilise a code editor, which can be challenging even for experienced developers when trying to map the code to visual objects (charts, gauges etc.) and the code to data sources (Pantazos et al. 2013; Elias & Bezerianos 2011). Vendors are continuously providing tools that allow for more features in dashboards without conducting thorough research on whether these features are necessary and work effectively (Heer et al. 2012).

Although various studies have focussed on the design of software tools to support BI and Information Visualisation (IV) research (Elias & Bezerianos 2012; Schröter 2015; Grammel et al. 2010a; Few 2012; Heer et al. 2008a), limited research exists on the design and evaluation of BI tools aimed at novice users (Jooste et al. 2014). Another issue is that organisations have limited guidance in terms of evaluating and adopting an appropriate software tool that fulfils the dashboard and BI requirements of their novice users. Research is required to validate design guidelines for BI tools aimed at novice users, and to propose a framework that can be used for designing, selecting and evaluating BI dashboard tools.

In order to maintain consistency throughout the study, a number of terms need to be clarified. This study will refer to the term "users", which specifically include to the characteristics of novice users explained earlier. The framework will be referred to as the BI Framework, which will include guidance for designing, selecting and evaluating BI tools. A BI tool will be referred to in the context of a development tool which novice users can use to create BI dashboards.

1.3 Problem Statement

The process of creating dashboards is a tedious process due to a number of software components that are often involved (Elias & Bezerianos 2011; Satyanarayan & Heer 2014). These tools often have a steep learning curve and lack intuitive interactive techniques and cognitive aids, which results in difficulties for creating and preparing dashboards for analysis, as well as, sharing findings with others (Pantazos et al. 2013; Elias & Bezerianos 2011). Moreover, a lack of guidance exists for designing, evaluating and comparing the features and the usability of BI tools for users. The main problem statement for this research study is as follows:

"Novice users experience usability problems during dashboard creation as current BI tools are not designed to support dashboard creation in an intuitive manner".

The research problem will be investigated by using the Nelson Mandela Metropolitan University (NMMU) as a case study. A course at the NMMU is offered to Information Systems (IS) students where students are taught introductory BI skills. As part of this course, students need to learn to develop dashboards for a SYSPRO ERP system as the main data source. Moreover, the ERP system is integrated with a modular EPM solution (SYSPRO 2010) that enables students to exercise their dashboard development skills by creating targets, setting objectives and using these as a baseline to measure activities and goals. SYSPRO is a South African enterprise business solution provider that integrates a modular EPM solution within their ERP systems (SYSPRO 2010).

The current dashboard creation process in SYSPRO requires the use of various disparate software tools. The learning curve for such a disparate environment is inefficient and time-consuming (Kerrigan & Mocan 2008) and needs to be simplified for users, such as students, who wish to learn how to create dashboards and analyse data.

1.4 Research Objectives

The primary aim of this research is to propose a BI Framework for BI tools that support the intuitive interaction and provide sufficient usability for the needs of novice users. A framework can be defined as "parts of a particular system" or "a set of beliefs, ideas or rules that is used as a foundation for making judgements or decisions" (Oxford University Press, 2013). Furthermore, this research study will investigate the specific usability problems which users experience to determine whether the perceived usability of a BI tool is influenced by users' educational backgrounds and experience. The results will then be analysed, presented and discussed to effectively communicate the specific usability problems novice users encounter when creating dashboards and conducting BI analysis. The results could provide valuable insights to organisations seeking to adopt a BI, or to vendors considering the design of a BI for novices. Additionally, improved usability of BI tools can assist in learning BI analysis and improve the overall skill of analysis and decision making.

The main research objective (RO_m) of this study is: **"*To investigate and propose a framework that can guide the design, evaluation and selection of BI tools that support novice users in the creation of dashboards.*"**

RO1: *"To investigate the use and benefits of dashboards and problems that novice users experience when using BI tools to create dashboards."*

RO2: *"To identify the objectives and requirements of a framework that can assist in the design, evaluation and selection of BI tool for novice users."*

RO3: *"To identify the design guidelines and features of BI tools for novice users."*

RO4: *"To evaluate current BI tools according to the identified design guidelines."*

RO5: *"To identify usability criteria that can be used to evaluate BI tools."*

RO6: *"To determine whether any differences exist between novice users' education level and the usability ratings of a BI tool."*

1.5 Research Questions

The proposed main research question (RQ_m) of this study is:

"What framework can be proposed to guide the design and evaluation of BI dashboard tools to support novice users?"

The following subsidiary research questions were formulated in order to answer the main research question:

> ***RQ1:*** *"What are the problems that novice users experience when using BI tools to create dashboards?"*
>
> ***RQ2:*** *"What are the objectives and requirements of a framework that can guide the design, evaluation and selection of BI tools for novice users?"*
>
> ***RQ3:*** *"What are the design guidelines and features of BI tools for novice users?"*
>
> ***RQ4:*** *"What current BI tools can support novice users in creating dashboards?"*
>
> ***RQ5:*** *"What usability criteria can be used to evaluate BI tools?"*
>
> ***RQ6:*** *"Are there differences between novice users' education level and the usability ratings of BI tools?"*

1.6 Scope and Limitations

The scope of this research will be limited to the research field of BI and IV, which primarily focus on the creation of dashboards for novice users. This study considers the front-end user interface of the BI software. However, the concept of a dashboard can be extended to additional activities such as data analysis and data exploration, which enables users to move beyond the static nature of simple graphs and visualisations.

The main deliverable of this study is the BI Framework. The BI Framework essentially provides guidance on the design, selection and evaluation of BI tools and the underlying features that should be provided to users for easy dashboard creation. The BI Framework will be demonstrated in this study and as a result a BI tool will be selected and evaluated with undergraduate students at the Department of Computing Sciences at the NMMU, who were identified as sufficient representative of novice users.

Due to time constraints, the participants used for the field studies and evaluations will consist of students from the NMMU, which is a South African Higher Education Institution (HEI). This might be a possible limitation as students do not have advanced experience in the design of software tools and thus feedback may be limited.

1.7 Research Methodology

The Design Science Research (DSR) methodology will be followed throughout this study. The DSR methodology allows a problem to be solved by building an artefact and evaluating that artefact until derived at a suitable solution is derived (Hevner et al. 2004). The underlying methodology of DSR includes an iterative process consisting of six key activities which can serve as a framework for conducting research (Peffers et al. 2007). These activities do not necessarily have to be performed in sequence, but they can be revisited or hurdled during the study in an iterative fashion (Peffers et al., 2007) and are:

- Problem Identification and Motivation;
- Define Objectives of a Solution;
- Design and Development;
- Demonstration;
- Evaluation; and
- Communication.

1.8 Dissertation Structure

An overview of the dissertation structure is provided in this section. The chapters of the dissertation can be mapped onto the activities of the DSR methodology. The applied research strategies in this study are also mapped according to each chapter, along with the research objectives and research questions (Figure 1-1). The structure of this dissertation consists of seven chapters in total. The chapters to follow in this dissertation are as follows:

- **Chapter 2: Research Design.** The chapter provides an overview of the study's research design. Moreover, the data collection and analysis methods are discussed. The DSR adopted in this study is discussed in detail and a motivation for its adoption is provided in terms of its activities, guidelines, methods and strategies that will be followed.

- **Chapter 3: Related Work: Business Intelligence Dashboards.** The chapter is based on the first activity (*Identify the Problem and Motivate*) of the DSR methodology. The chapter presents the importance, benefits and problems associated with dashboard development based on a literature study. A discussion on existing dashboard development tools is also provided. The findings in literature will partially answer RQ_1 and RQ_2.
- **Chapter 4: Objectives of a BI Solution for Novice Users.** The fourth chapter continues the discussion of the first DSR activity (*Identify the Problem and Motivate)* and further investigates the problems that users experience in a real world context. A field study is conducted and the results are analysed to formulate high-level objectives for the BI Framework. The high-level objectives and requirements of a BI tool are also identified. Therefore, the second DSR activity is conducted in the fourth chapter, namely *Define Objectives of a Solution*. The first version of the framework is designed and discussed in this chapter, which answers RQ_1 and RQ_2.
- **Chapter 5: A Framework for the Design and Evaluation of BI tools.** Chapter 5 discusses the *Design and Development* activity. The main contribution of this study is the BI Framework (the artefact) for designing, selecting and evaluating a BI tool. A set of design guidelines that are deemed important for BI tools are proposed as part of the BI Framework. These guidelines can be expanded into a scorecard of criteria and features for when evaluating a number of BI tools. The scorecard will be referred to as the BI Scorecard as it forms as one of the contributions of the BI Framework. The BI Scorecard is demonstrated by informally evaluating a number of BI tools in an extant systems analysis. The results of the extant systems analysis are presented and two tools are selected for further evaluations. A second field study, namely Field Study 2, is conducted to validate the BI Framework. Moreover, one of the two selected BI tools is evaluated for usability in the field study and the results are analysed. Therefore, the DSR activities, *Demonstration* (Activity 4) and *Evaluation* (Activity 5) are performed in this chapter and RQ3, RQ4 and RQ5 are answered.
- **Chapter 6: Final Evaluation.** The sixth chapter involves the final evaluation of this study. The evaluation is conducted with the second selected BI tool. The evaluation is conducted with two user groups on different education levels to determine whether differences exist in usability ratings. Furthermore, the results of the final evaluation are analysed. This chapter addresses RQ_6.

- **Chapter 7: Recommendations and Conclusions.** Chapter 7 is based on Activity 6 (*Communication*), and discusses the findings, contributions, limitations experienced, and future recommendations of this study. The final BI Framework is also presented and the study is concluded.

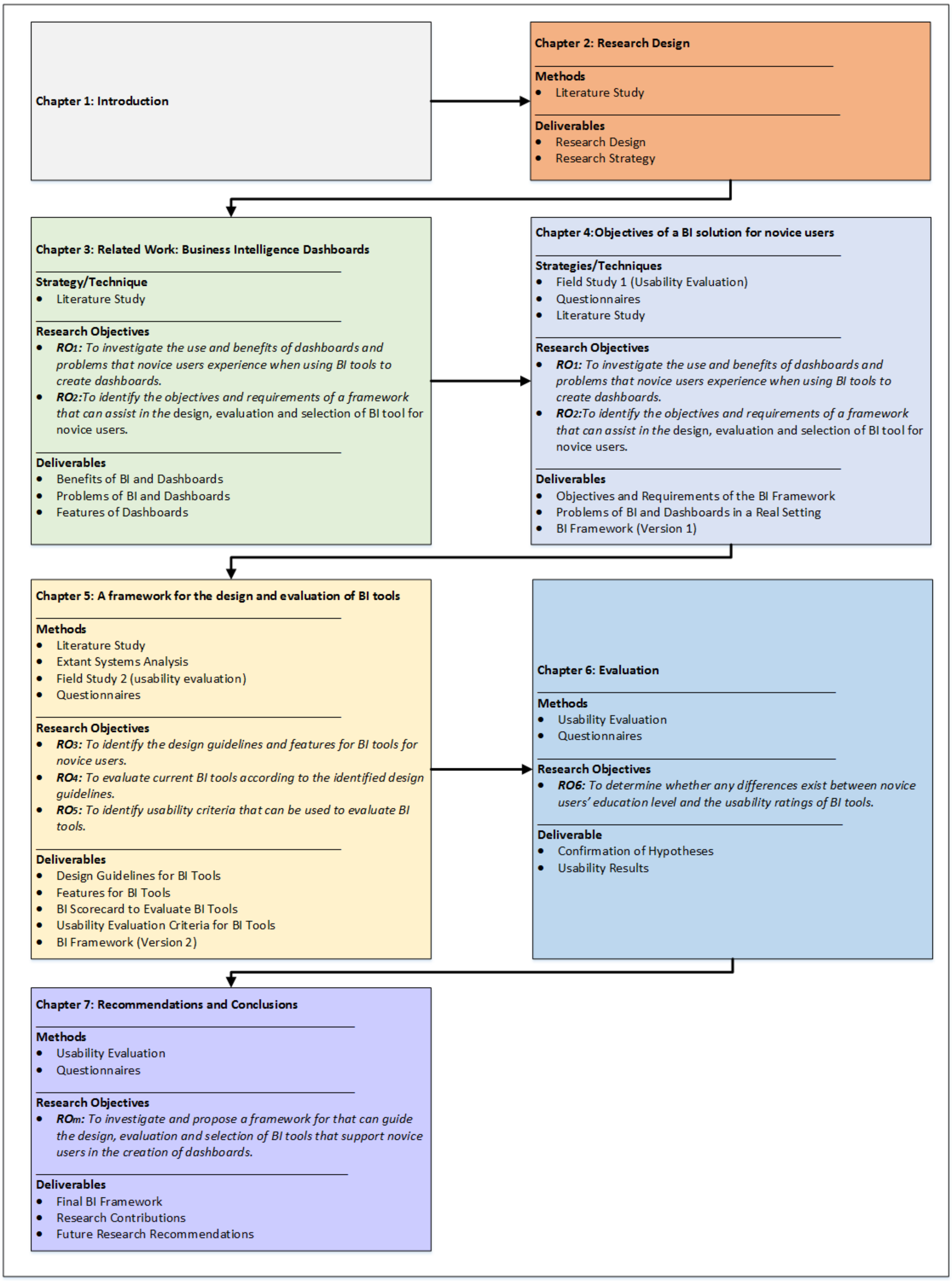


Figure 1-1: Dissertation structure

Chapter 2. Research Design

2.1 Introduction

The previous chapter provided an overview of the study's relevance, the problem that it aims to solve, as well as its primary objectives, scope and limitations. This chapter outlines and discusses the research design of this study. A research design is used as a strategic framework that guides the researcher's intended actions to answer the research questions of the study (Durrheim 2006). The research design also describes the research methodology and methods to be used in a research study (Saunders et al. 2009). A research design is a logical sequence that connects the empirically collected data to the study's research questions and, ultimately, to its research conclusions (Yin 2013). The process of designing a study is demonstrated by Saunders et al. (2009), who state that the design process is similar to peeling off layers of a "research onion". The layers of the onion represent the means that were used to decide on the data collection techniques and analysis procedures (Figure 2-1).

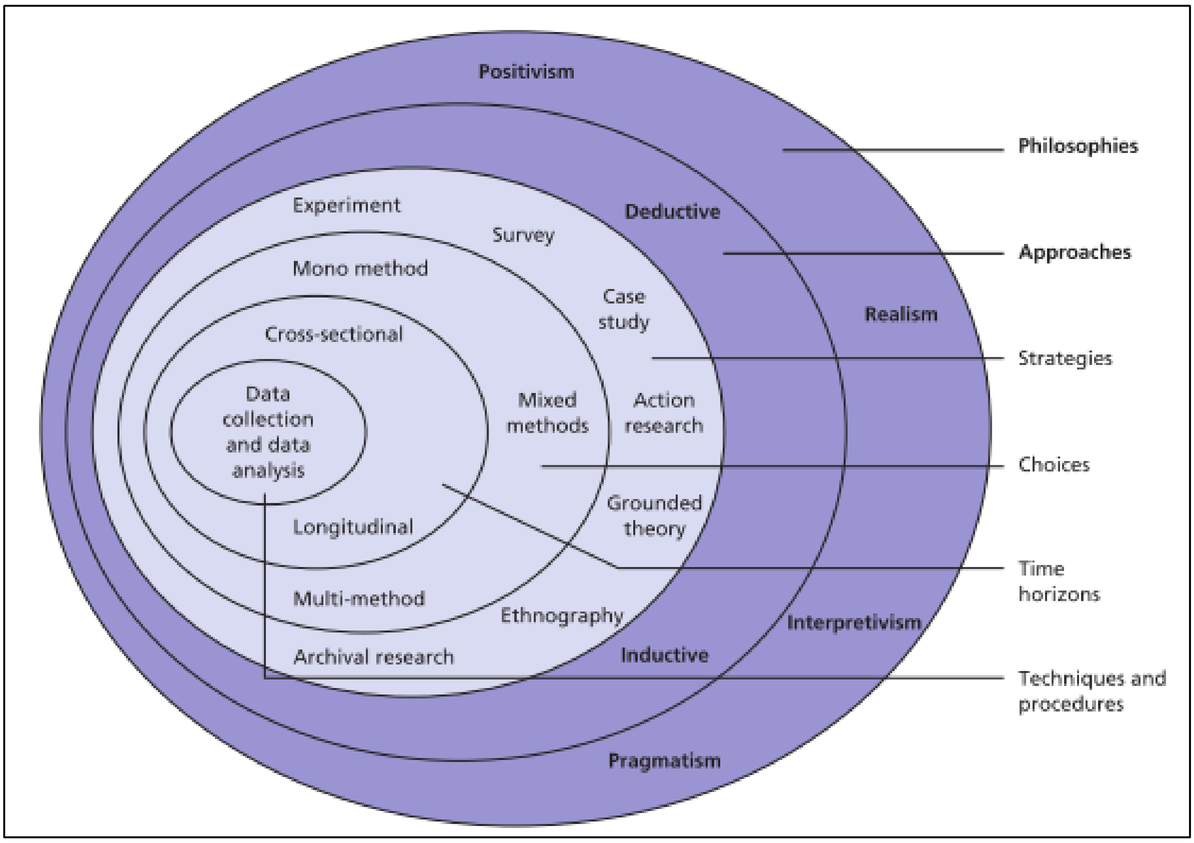


Figure 2-1: The research 'onion' [Source: Saunders et al. (2009)]

The research onion essentially represents the research design process, where one could proceed to the inner layers of the onion by peeling away the outer layers. The outer layer represents several research philosophies, where the researcher selects the most appropriate philosophy for the nature of the research being conducted (Section 2.2). Once an appropriate philosophy is chosen in the outer layer, the researcher considers the approaches to be used in the research in the second layer and the research strategies in the third layer (Section 2.3). An overview of the possible data collection and data analysis techniques to be used in this study is provided (Section 2.4). There are several techniques used to establish the validity and reliability of data (Section 2.5).

The DSR methodology is applied to this research and allows for researchers to produce different types of artefacts on both a theoretical and practical level (Section 2.6). The DSR methodology has two main approaches to search and construct a suitable solution to the identified problem. The first approach is the application of an iterative process consisting of six activities, which serves as a framework for conducting research (Section 2.7). The alternative option to conducting DSR is the three cycle approach (Section 2.8). The application of the DSR activities and cycles can be mapped to the structure of the chapters, which are complimented by research strategies (Section 2.9). Attention needs to be given to ethical considerations before participant may be involved in this study (Section 2.10). The main outcomes of the chapter are summarised (Section 2.11).The structure of this chapter is provided with mappings to the DSR activities and strategies in Figure 2-2.

2.2 Research Philosophy

The research philosophy entails the way people think about developing knowledge. More specifically, the philosophy encapsulates the important assumptions about the manner in which the researcher views the research environment and the nature of the developed knowledge (Saunders et al. 2009). The three primary views of philosophy are: positivism, realism and interpretivism.

Positivism has its origins in the natural sciences to study social interactions and concludes that information and knowledge can only be verified by senses (Bryman 2012). Positivism is often viewed as a scientific approach to research where facts about social issues can be observed and measured objectively with no influence of the researcher on the process of data collection (Hennink et al. 2010).

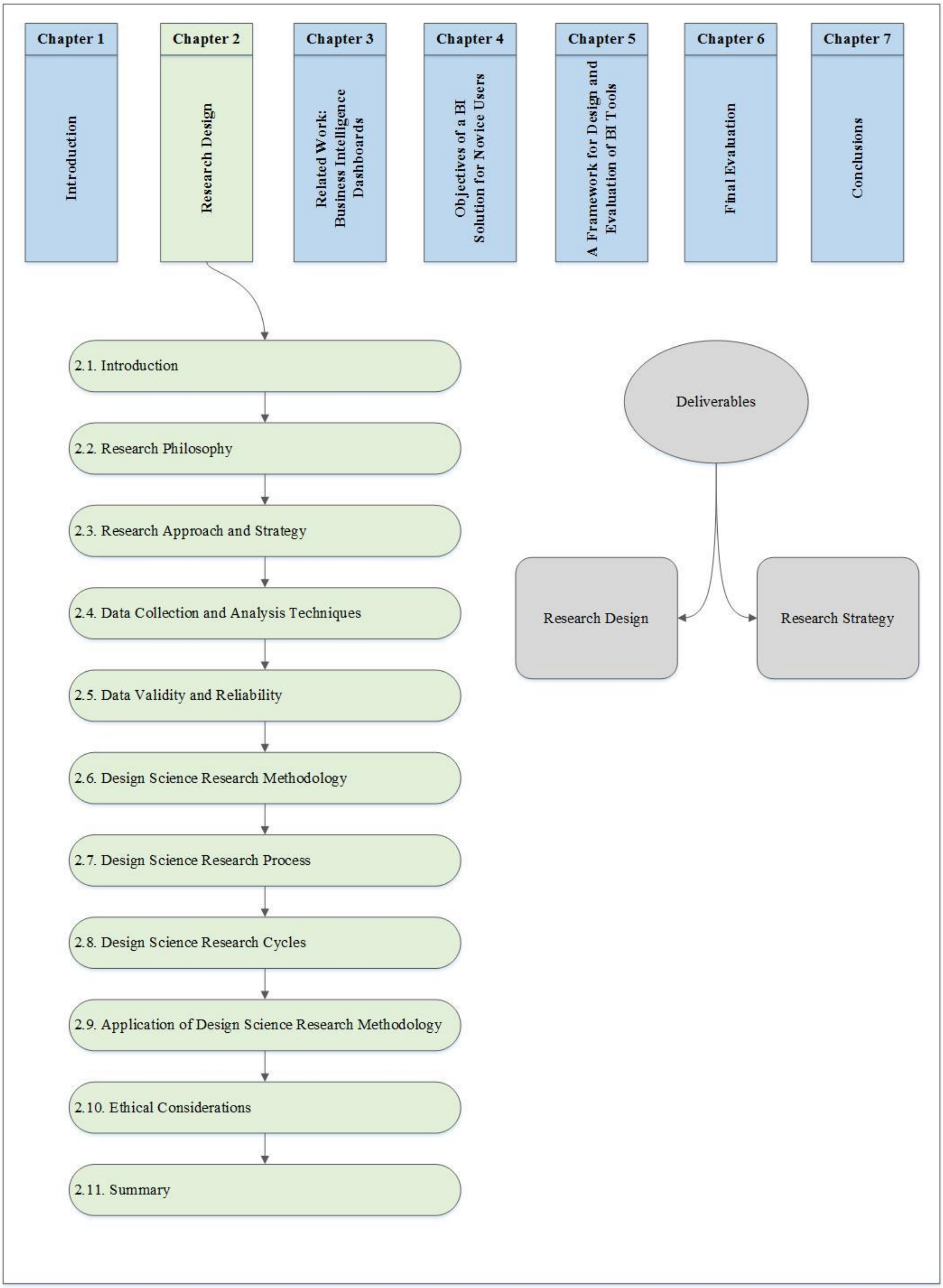


Figure 2-2: Chapter 2 layout

Positivism contends that objective thinking and knowledge are derived by gathering facts, and that existing theoretical concepts and statistical models are used to develop and test hypotheses (Hennink et al. 2010; Saunders et al. 2009). Only once the hypothesis has been tested and confirmed, in whole or part, or refuted, then only will it allow for explanations and understanding of theory which can then lead to additional testing in future research (Bryman 2012; Saunders et al. 2009).

Realism implies that a reality exists where worldly objects are independent of human thoughts and perceptions. Realism has a similar approach to positivism, where a scientific approach is taken to develop knowledge (Saunders et al. 2009). Both realism and positivism posit that natural sciences and social sciences need to be applied by using similar approaches for data collection and explanation, and believe that reality is disconnected from the researcher's understanding of it (Bryman 2012).

Interpretivism refers to the way in which a researcher attempts to understand social interactions of humans in different social contexts (Saunders et al. 2009). Social, cultural, historical, or personal contexts are recognised as influences on human perceptions and interpretations of reality, which is in contrast to positivism's view of a single truth (Hennink et al. 2010). Interpretivism takes into account that social interaction will both influence and be influenced during the research activity (Kelliher 2005). For this reason, the notion of interpretivism is highly subjective, and posits that the background and values of the researcher do influence the collection and generation of knowledge (Hennink et al. 2010). With the focus on conducting research amongst human subjects, interpretivism emphasises the importance of observation and interpretation to understand the world from the subject's point of view, in chnaging their motives, actions and interactions (Saunders et al. 2009). For this reason, interpretivism assumes that researchers rely on their own understanding of social interactions and interpreting information as a product thereof. Qualitative research is often guided by the concepts of interpretivism, whereas quantitative research is mostly conducted by using positivism (Hennink et al. 2010).

Saunders et al. (2009) explain that positivism, realism and interpretivism represent a subarea in the philosophy of science, known as epistemology. Epistemology is concerned with how acceptable knowledge is derived from a field study and how the characteristics of a researcher might have influenced the process of knowledge generation (Saunders et al. 2009). In terms of

DSR, positivism and realism assume that the evaluation of an artefact will yield the same objectives and results, regardless of the individual characteristics of the evaluator (Siau & Rossi 2007). In contrast, interpretivism assumes that the individual characteristics of the evaluator drastically influences the results of an evaluation for an artefact (Siau & Rossi 2007).

2.3 Research Approach and Strategy

The primary approaches typically selected in a research study are ***inductive*** and ***deductive***. ***Inductive*** research follows a bottom-up approach and begins with collecting and analysing data and observing any theoretical themes, which lead to the generation of hypotheses and theories as a result of the data analysis (Saunders et al. 2009). The ***inductive*** process depicts an iterative cycle of working back and forth between themes and the dataset until a comprehensive set of themes are established (Creswell 2013). ***Deductive*** approaches include the development of a theory and hypothesis (or hypotheses) whereby strategies are used to test the hypothesis. ***Deductive*** research is initiated as a top-down approach in which the hypothesis is formulated, based on a theory and is confirmed or refuted through observation (Saunders et al. 2009). ***Deductive*** researchers will therefore revise the collected data from the patterns or themes to determine whether additional evidence will be required to support each theme (Creswell 2013). The adoption of a research approach depends on the extent to which theory is clearly defined at the start of the research study (Saunders et al. 2009). The selected approach also influences the type of strategies to be used in a research study to collect and analyse data.

This study will use both ***inductive*** and ***deductive*** approaches. Problems and solutions will be iteratively identified until a comprehensive set of theoretical themes are established. The collected and analysed data will then be used to formulate hypotheses and theories, which will be tested.

In order to ensure that reliable evidence and useful knowledge is developed and presented in a clear manner, an appropriate research strategy, or collection of research strategies, should be adopted (Johannesson & Perjons 2012). A research strategy is an overall guide to conduct research and assists in answering research questions and objectives (Hennink et al. 2010; Saunders et al. 2009). The choice of research strategies are primarily guided by the research questions and objectives, but can also be influenced by the study's time horizon, available resources and existing knowledge of the research area (Saunders et al. 2009). According to

Johannesson and Perjons (2012), research strategies are complemented by research methods, which assist in the collection and analysis of data. Some popular research strategies are:

- Action research;
- Case studies;
- Ethnography;
- Experiments;
- Grounded theory;
- Surveys; and
- Theoretical analysis.

2.4 Data Collection and Analysis Techniques

The selection of data collection techniques and analysis procedures depend on the data collection approach that can best help to answer the research questions. The three approaches are either qualitative, quantitative or mixed methods approaches (Saunders et al. 2009; Creswell 2013). Quantitative approaches collect data which are quantifiable and can be reduced to numerical values. Quantitative research works best for testing relationships and trends in data to prove or disprove theories and hypotheses, where variables are measured and analysed using mathematical or statistical techniques (Saunders et al. 2009; Creswell 2013). Researchers often use these statistical techniques to aid in the exploration, visualisation and description of identified relationships in the data. Quantitative research is particularly useful when it is required to produce quantifiable, reliable data that can be generalised to a larger population. Popular data collection techniques for quantitative data include structured questionnaires and surveys (Johannesson & Perjons 2012).

In contrast to quantitative research, qualitative research generates or uses non-numerical data (Saunders et al. 2009). Qualitative research methods allow for identifying issues from the perspective of the study's participants and the contextual influences of these issues. Additionally, researchers gain better understanding behind the participants' behaviours and interpretations of events, processes, actions or objects (Hennink et al. 2010; Saunders et al. 2009). The use of qualitative data works best when researchers are aiming to establish different view of phenomena and are less concerned with the need of generalising results to the larger population (Saunders et al. 2009). Some qualitative data collection techniques are semistructured interviews, open-ended questionnaires, observation studies, group discussions and focus groups (Johannesson & Perjons 2012).

Qualitative and quantitative techniques do not have to be used in isolation. Mixed method approaches enable researchers to use a combination of both qualitative and quantitative techniques either at the same time (parallel), or one after another (sequential order). The benefit of mixed methods approaches is the two forms of data can be integrated and distinct design can be used to derive philosophical assumptions and theoretical frameworks (Creswell 2013). Mixed method approaches can also be used as a means to validate quantitative findings (Saunders et al. 2009).

A mixed method approach to data collection will be used in this study and will consist of online questionnaires administered to study participants, where data will be captured and exported to a Microsoft Excel spreadsheet. Mixed method approaches offer the benefits of data triangulation, which is the validation of research findings from two or more independent source of data or data collection methods (Saunders et al. 2009).

The questionnaires to be used in this study will be adapted from standardised measurement materials that primarily consist of Likert rating scales to capture quantitative data. Additionally, the questionnaires incorporate open-ended questions to capture qualitative data, which can be used to validate the findings of the qualitative data. Literature will also be used to compare the findings of this study with the findings of similar studies.

Separate methods exist for analysing quantitative and qualitative data respectively. Quantitative data are analysed through statistical techniques. Qualitative data are analysed by following an appropriate data analysis procedure to categorise data into themes. Thematic analysis will be used to analyse qualitative data collected in the post-test questionnaires. Thematic analysis is used to establish patterns or reoccurring themes in data (Creswell 2013).

Statistical techniques will be performed on the quantitative data collected from the field studies and final evaluation during this research. The two primary subsections of statistics are descriptive statistics and inferential statistics. Descriptive statistics support methods of arranging, comparing, summarising and presenting data in a simpler manner to identify and interpret patterns (Saunders et al. 2009). Descriptive statics can be presented graphically or numerically and are used as a simpler way to describe data for the whole population. Results derived from descriptive statistical techniques do not enable the researcher to make conclusions beyond the data being analysed or a hypothesis formed. The two most popular methods used in descriptive statistics are central tendency (means or averages) and central dispersion (standard deviations and quartile ranges), which are often referred to as parameters.

Inferential statistics are used when it is impractical to measure the entire population. Results derived from inferential statistical techniques can be used to make conclusions or generalisations about the population based on data collected and analysed from a sample. Inferential statistics are used for testing significant differences (t-tests) and measuring the relationship between two or more variables (correlation and regression). Both inferential and descriptive statistics will be used in this study to analyse results and draw conclusions.

2.5 Data Validity and Reliability

Creswell (2013) motivates the importance of being objective throughout a research study and posits that standard validity and reliability need to be established for the research study. In a general sense, reliability refers to the extent in which data collection techniques produce consistent findings (Saunders et al. 2009). In terms of quantitative data, reliability refers to consistency and is concerned with the robustness of the data collection material, such as a questionnaire. Reliability ensures that the questionnaire will produce consistent findings irrespective of the conditions under which the questionnaire was completed. In terms of qualitative data, reliability is concerned with eliminating bias and whether alternative researchers would derive similar results and conclusions if similar techniques were used (Saunders et al. 2009).

In addition to triangulation, three common approaches can be followed to assess reliability namely, test re-test, internal consistency, and alternative form (Saunders et al. 2009). Test re-test involves the correlation of data collected with that from the same questionnaire when a re-test is conducted under as near equivalent conditions as possible. In such an approach, the same questionnaire needs to be administered twice to the same participants, which can become difficult as they might not want to answer the same questionnaire again (Saunders et al. 2009). Internal consistency requires responses to be correlated with each question is the questionnaire. The objective is to measure the consistency of responses across either all questions or only a specific group of questions in the questionnaire. Various methods can be used to determine internal consistency, however, the Cronbach's alpha method is used most frequently (Gravetter

& Wallnau 2009). The third approach to measure reliability is through alternative form, where responses are compared to alternative forms of the same question or groups of questions. The problem, however, is to ensure that alternative questions are equivalent and are interpreted similarly (Saunders et al. 2009). Due to the difficulties associated with alternative form and test re-test, the reliability of questionnaires in this study will by established using internal consistency methods, such as Cronbach's alpha.

Validity refers to the extent to which data collection techniques accurately measure what they intend to measure (Saunders et al. 2009). Validity can be established through pilot testing where the questionnaires are refined to ensure that respondents will have no problems in following instructions and answering the questions, and that there will be no problems in recording data. The objective of establishing validity through pilot testing is to investigate whether the data collected will be sufficient to answer the research questions and to preliminary assess the reliability of data. Initially, experts need to be consulted to receive feedback on the representativeness and suitability of the questions (Saunders et al. 2009). In this study, experts will be consulted and pilot tests will be conducted to refine questionnaires and other research materials to establish validity.

2.6 Design Science Research Methodology

According to Vaishnavi and Kuechler (2007), various disciplines are centred in Information Systems (IS) and differ from other research fields that have established significant paradigms with a dominant set of research questions, exploration methods, and outlets for disseminating new knowledge. The use of IS can be described as multi-paradigmatic and an applied research discipline, since the theory of various different disciplines, such as economics, computer science, behavioural sciences and social sciences are frequently applied to solve issues that exist between the interactions of IS and organisations (Gregor & Jones 2007; Peffers et al. 2007). The paradigms can be used for the design-based research, however, they often lack a thorough validation process that is often emphasised in the development and design of IS, human-computer interaction (HCI) and other branches of software engineering (Kuechler & Vaishnavi 2008).

DSR has its origins in the area of IS research; therefore, the paradigm aims to help people fulfil their needs, overcome their problems and grasp new opportunities. Moreover, DSR is applicable to ICT as the methodology assists in answering questions that occur naturally in the field of HCI. DSR has established itself as an important and legitimate IS research paradigm (Gregor & Hevner, 2013; Hevner et al., 2004; Winter, 2008). DSR does this by identifying problems and associated stakeholders with the aim to design and develop novel artefacts, create knowledge about these artefacts, and their utility in the intended environment as solutions to the problems (Johannesson & Perjons 2012). Depending on the identified problems, artefacts are iteratively developed either as ideas, constructs, models, methods or instantiations that support people in the development, use and maintenance of ICT solutions.

The main reason why DSR is suitable for this study is that ICT is typically complex and grounded in various disciplines where theoretical backgrounds are not always mature enough to support the identified problem (Kuechler & Vaishnavi 2008). DSR may appear similar to disciplines that emphasise the use of "design" in the research process. Vaishnavi and Kuechler (2015) motivate that useful and highly valued artefacts are often designed with sparse or non-existent theoretical backgrounds. Producing artefacts without sufficient theoretical backgrounds prevents the understanding of underlying design principles, which should be used to enable methodical and consistent performance improvement (Vaishnavi & Kuechler 2015). DSR assists in bridging the gap between the physical artefact and the accompanying theory. DSR aims at produce and communicate knowledge that is relevant to a global interest and not only to a secluded group of individuals, which is often the focus on design-intensive projects (Johannesson & Perjons 2012). The DSR methodology enables the exploration and building of artefacts in a series of iterations and assists to answer complex research questions. Research questions need to be developed on a theoretical basis, which will direct the research project's experimentations (Vaishnavi & Kuechler 2015). When DSR is applied to ICT research, a body of knowledge is established about artificial objects (human produced) and phenomena to meet specific needs and goals.

Kuechler and Vaishnavi (2012) describe a framework with three possible outputs from DSR projects: (1) an artefact, (2) an IS design theory, and (3) design relevant explanatory/predictive theory. An artefact can consist of software, composite systems of software, users and processes, and IS-related organisational methodologies and interventions. Knowledge can be presented in different forms from DSR. The most common form is theory, which formalises knowledge in DSR and is referred to "design theory" (Gregor & Hevner 2013). Design theory prescribes principles for design and action, which serves as an expository instantiation for two purposes (Kuechler & Vaishnavi 2012). The first purpose is to serve as a proof of concept of the IS design theory. The second purpose is to serve as a comprehensible illustration of the IS design theory. Design relevant explanatory/predictive theory explains how and why an artefact functions as it does and describes how novel artefact design features have the effects they do.

Gregor and Hevner (2013) support a similar knowledge-contribution framework as Kuechler and Vaishnavi (2012). The framework distinguishes between different DSR outputs as research deliverables with three maturity levels of DSR artefact types and examples at each level (Table 2-1). A DSR project can produce artefacts on one or more of the three levels. Additionally, each maturity level is coupled to a level of abstraction and provides the degree to which the knowledge has advanced in terms of the characteristics of a well-developed body of knowledge.

Table 2-1: DSR contribution types [Source: Gregor and Hevner (2013)]

Design Science Research Contribution Types		
	Contribution Types	**Example Artefacts**
More abstract, complete, and mature knowledge	Level 3. Well-developed design theory about embedded phenomena	Design theories (mid-range and grand theories)
↕ ↕ ↕ ↕	Level 2. Nascent design theory – knowledge as operational principles/architecture	Constructs, methods, models, design principles, technological rules
More specific, limited, and less mature knowledge	Level 1. Situated implementation of artefact	Instantiations (software products or implemented processes)

Artefacts produced at Level 1 are generally more specific, limited and less mature knowledge that are typically presented as instantiations in the form of software products or implemented processes. Artefacts can also be more general or abstract contributions of knowledge at Level 2, which take the form of promising design theory used as operational principles or architectures. Examples of artefacts on Level 2 include: constructs, design principles, models, methods or technological rules. Level 3 relates to artefacts that have well-developed design theories about the phenomena under investigation (Gregor & Hevner 2013).

The development of "strong" theory is one form that a DSR contribution can take (Gregor & Hevner 2013; Kuechler & Vaishnavi 2012). Moreover, contributions from DSR can be partial theory, incomplete theory, or even some particularly interesting, and perhaps unanticipated empirical generalisation in the form of a new design artefact (Gregor & Hevner 2013). In order to communicate the knowledge gained from this study, contributions will be made to theory. For this reason, DSR will be used to produce a theoretical artefact to enhance the understanding of how the design of BI systems can be improved and evaluated for adoption. In order to produce artefacts that add to the body of knowledge, three general activities for theory development can be followed in any DSR project relating to IS (Kuechler & Vaishnavi 2012):

1. Construction of an artefact where construction is informed either by practice-based insight or theory;
2. Gathering of data on the functional performance of the artefact; and
3. Reflection on the construction process and on the implications the gathered data have on the artefact informing insights or theories.

2.7 Design Science Research Process

The researcher does not have to perform the activities in sequence, but can move back and forth iteratively as data is collected and analysed (Peffers et al. 2006). The activities that need to be performed in the DSR process are demonstrated in Figure 2-3.

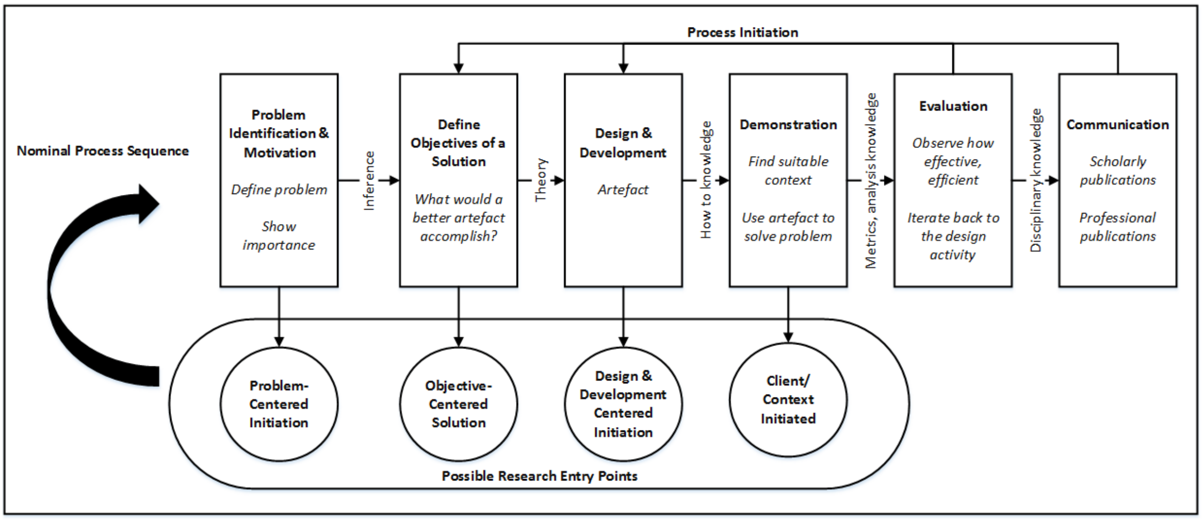


Figure 2-3: DSR methodology process model [Source: Peffers et al. (2007)]

- **Activity 1 - Problem Identification and Motivation:**
  The identified research problem is defined in the first activity of DSR and the importance of the solution is motivated. Defining the different dimensions of the problem and its solution is an important activity. Firstly, the definition communicates the complexities of the problem and informs the audience the reason why the research needs to be pursued.

Secondly, the definition of the problem assists the researcher and audience to formulate an improved understanding of the problem (Peffers et al., 2007).

- **Activity 2 - Define Objectives of a Solution:**
  An appropriate artefact has to be selected as a solution. Given the problem definition (Activity 1), this activity requires the formulation of requirements and objectives for its proposed solution. The objectives and requirements are formulated after gaining knowledge of current solutions and the state of the problem (Peffers et al., 2007).
- **Activity 3 - Design and Development:**
  This activity involves the construction of the selected artefact by considering possible solutions and alternative designs that best satisfy the identified requirements. This activity entails the creation of several prototypes that will be formulated (Peffers et al., 2007).
- **Activity 4 - Demonstration:**
  In this activity, the artefact's feasibility and utility are demonstrated involving the use of the developed artefact to solve one or more instances of the identified problem (Peffers et al., 2007). Demonstrating the artefact should allow participants to interact with the created prototype or system and will provide valuable feedback on any aspects that are unclear or require attention. The feedback is used to modify the prototype's design and functionality before advanced evaluations are conducted. This activity can be executed repeatedly along with the *Design and Development* activity to verify and validate requirements.
- **Activity 5 - Evaluation:**
  This activity is concerned with measures of how well the artefact solves the defined problem and satisfies the identified requirements and objectives. The *Define Objectives of the Solution* (Activity 2) are compared with the recorded results obtained from the *Demonstration* activity (Activity 4). When the evaluation is complete a decision will be made to either go back to Activity 3 to improve the artefact or proceed to Activity 6 (Peffers et al., 2007).
- **Activity 6 - Communication:**
  Communication is essential throughout the entire study using the DSR process. All aspects of the study need to be communicated to other researchers and relevant audiences including: the importance of the problem, the artefact type (solution), its utility and novelty, the rigor of its design, and its effectiveness. Communication typically takes the form of reporting on the results and findings of the study and may also be used to for

research publications, which can be submitted to journals and conferences (Peffers et al., 2007).

2.8 Design Science Research Cycles

In addition to the DSR activities, Hevner (2007) motivates that key insights can be gathered from three distinct research cycles in a DSR study (Figure 2-4). The three cycles include the Relevance Cycle (Section 2.8.1), Design Cycle (Section 2.8.2) and the Rigor Cycle (Section 2.8.3).

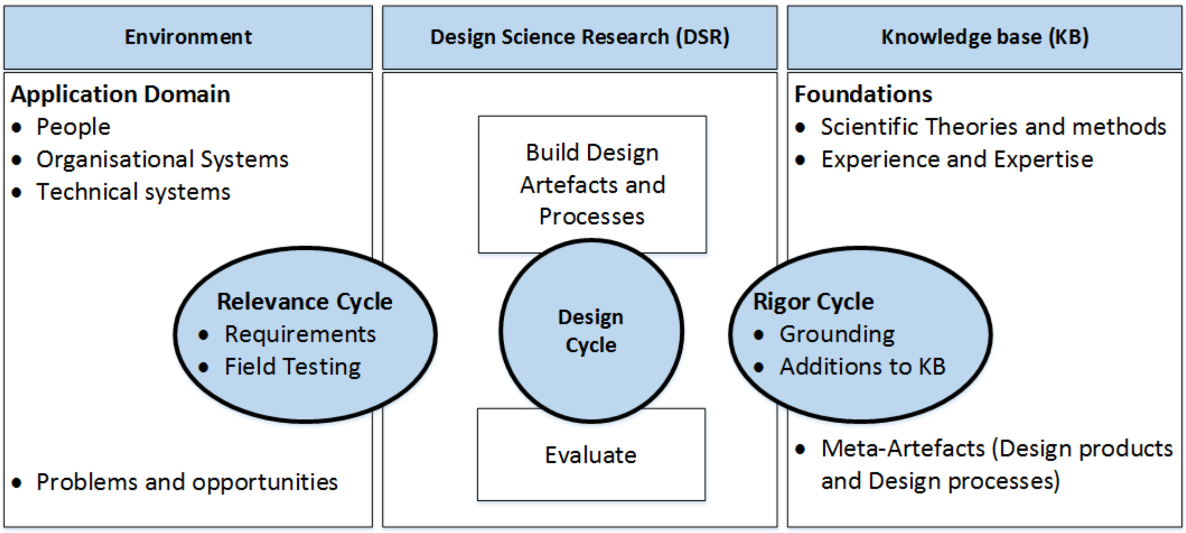


Figure 2-4: The three research cycles for DSR methodology [Source: Hevner (2007)]

2.8.1 The Relevance Cycle

The Relevance Cycle links the contextual environment of a research study with the DSR activities (Hevner 2007). The Relevance Cycle acknowledges that people, organisational systems and technical systems interact with one another in the application environment to achieve a common goal. The Relevance Cycle initiates the DSR where the researcher investigates the problems and opportunities in a particular application environment as inputs (Hevner & Chatterjee 2010). The requirements and acceptance criteria are also established for the research study in the Relevance Cycle, as the evaluation results of the final artefact need to solve the identified problems and satisfy the requirements (Hevner 2007).

The output of the DSR project must be ultimately returned into the application environment, which can be further studied and evaluated in future. However, the results from empirical field testing of the DSR process determine whether additional iterations of the Relevance Cycle are necessary in the DSR study. The problems identified in the Relevance Cycle do not necessarily translate into objectives and requirements, as design and evaluation activities can occur in iterations and allow for requirements to be restated as new discoveries are made (Hevner 2007). According to Peffers et al. (2006), the Relevance Cycle can be mapped to the first two activities of DSR process, namely *Problem Identification and Motivation* and *Define Objectives of a Solution*.

2.8.2 The Design Cycle

The Design Cycle is described as the heart of any DSR study (Hevner 2007). The Design Cycle encapsulates the activities for the construction of the artefact, its evaluation, and subsequent feedback to improve or refine the design further. The activities involved in the Design Cycle iterate rapidly, where the development and evaluation process continues to receive inputs from the Relevance Cycle and evaluation theories and methods from the Rigor Cycle. These activities will iterate until a suitable solution is developed and requirements are met. Hevner (2007) advises that an optimum balance should be found between the development and evaluation activities. Rationale for both the development and evaluation activities needs to be established through the Relevance and Rigor cycles, as the development of a convincing artefact could be regarded as insufficient when the evaluation process is weak.

Hevner (2007) further motivates that the developed artefact needs to be tested extensively in experimental situations and laboratories before releasing the artefact into field testing along with the Relevance Cycle. Therefore, the artefact is refined through a series of iterations where the artefact is demonstrated to prove that the design works, to formal evaluations of the developed artefact before contributions are eventually made to the relevance and Rigor Cycles (Peffers et al. 2006). The DSR activities related to the Design Cycle include *Design and Development* and *Evaluation*, respectively.

2.8.3 The Rigor Cycle

The Rigor Cycle requires the researcher to reference past knowledge and draw existing ideas from the domain knowledge base in order to guarantee that design produced are novel and innovative, and are not routine designs based on the application of known design processes (Hevner & Chatterjee 2010). The researcher is responsible to select and apply appropriate theories and methods for developing and evaluating the artefact. Hevner (2007) emphasises the need for sufficient grounding in design science where the researcher consults several different sources to identify ideas for the research study, including opportunities and problems gathered from the Relevance Cycle, existing artefacts, analogies and theories. The Rigor Cycle requires additions to the knowledge base through clear demonstration of the artefact and required the findings to be communicated clearly after rigorous evaluations have been conducted and empirical research generated.

The additions to the knowledge base include any extensions to the original theories and methods made during a DSR study, as well as the new meta-artefacts such as newly developed products or processes. Additionally, all the recorded experiences may be added to the knowledge as a result of the conducted research and field testing of the artefact in the application environment (Hevner 2007). Peffers et al. (2006) describes that the Rigor Cycle forms part of *Demonstration* (Activity 4) and the final DSR activity, *Communication* (Activity 6), where the resulting knowledge and rigor of the research design is explained and its effectiveness is motivated to researchers.

2.9 Application of Design Science Research Methodology

The DSR methodology has been followed in a number of studies focussing on BI and dashboards. As discussed earlier (Section 2.8), two approaches can be used in the DSR methodology. The first approach is the three cycles of DSR proposed by Hevner (2007) and the second approach is the six activities by Peffers et al. (2006). The approaches are similar and each of the activities can be mapped to the three cycles of the DSR methodology (Figure 2-5).

The process of the DSR methodology is followed throughout this study (Figure 2-6). The first DSR activity of the process, *Identify the Problem and Motivate*, will be reported on in Chapter 3, where the problems relating to BI and dashboard creation will be identified by using literature. The first activity continues in Chapter 4, where a field study is conducted to investigate the problems users experience with dashboard creation in a real world setting. The second activity of the process, *Define Objectives of a Solution*, will then be initiated in Chapter 4, where a possible solution to the problem will be identified to satisfy the identified requirements and objectives.

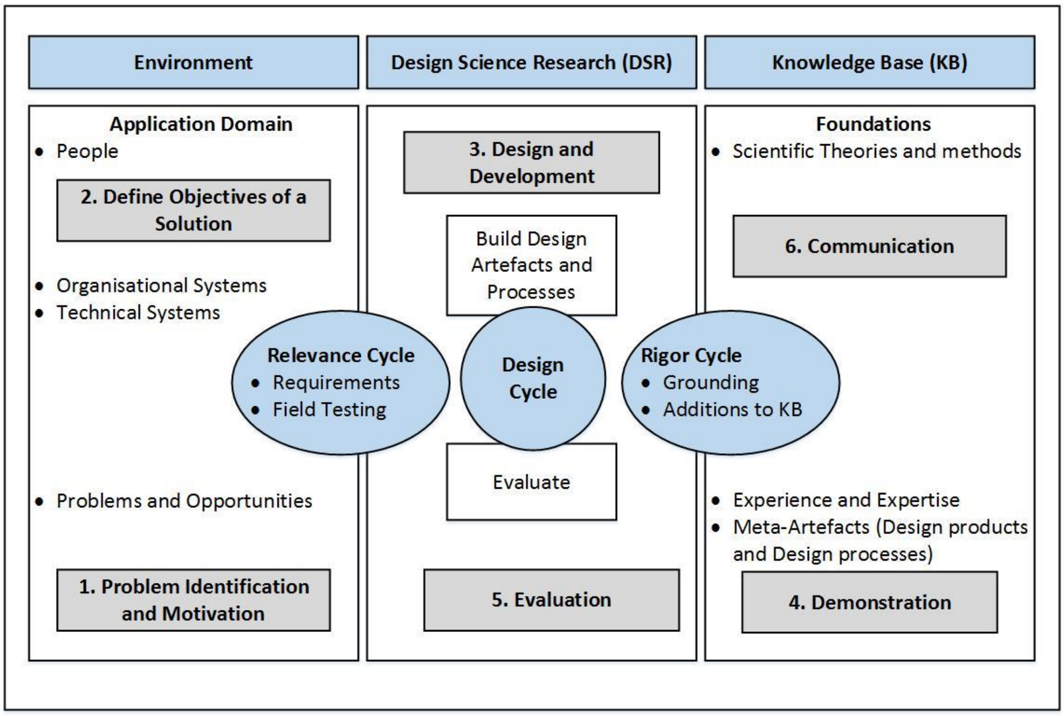


Figure 2-5: DSR activities mapped to cycles [Source: Adapted from Hevner (2007) and Peffers et al. (2006)]

The third activity, *Design* and *Development*, will be discussed in Chapter 5 where the design and development of the proposed BI Framework will be explored in detail. The BI Framework will consist of a number of design guidelines, which can be expanded into a scorecard and features to evaluate and selecting a BI tool. The DSR methodology is iterative and allows for a number of refinements of the designed artefact. For this reason, the fourth activity and fifth activity in the DSR process, *Demonstration* and *Evaluation*, is reported on in Chapter 5. Demonstration will commence as a means of showing the BI Framework's validity as a solution to the identified problem where several BI tools will be evaluated and selected. The DSR requires rigorous evaluation methods to prove that an artefact can solve the problem. A second field study is therefore conducted with users and reported on in Chapter 5, but will incorporate rigorous evaluation methods to determine the usability of the selected tool and validity of the proposed framework.

Once the BI Framework has proven its validity as a possible solution to the identified problem, Chapter 6 will continue with the *Evaluation* activity where the final evaluation of this study will be conducted. The final evaluation will include rigorous evaluation methods to determine the BI Framework's ability to select and evaluate appropriate BI tools for novice users to create dashboards. The final activity, *Communication*, will be reported on in Chapter 7, where the findings of this research are communicated and conclusions are made as additions to the knowledge base.

A number of research strategies and data collection techniques will be used in this study. These include literature reviews, observations and post-test questionnaires. The following data collection techniques with research strategies:

- Theoretical analysis (literature reviews);
- Field studies;
- Case studies;
- Extant systems analysis;
- Usability evaluations; and
- Grounded theory.

Literature reviews are a form of a theoretical analysis strategy that will be used throughout the entire research study to identify the purpose, benefits and problems relating to BI dashboards. Moreover, literature reviews will be used to identify objectives and requirements for a BI Framework, as well as, to identify objectives and requirements for BI tools.

An ***extant systems analysis*** will be performed by the researcher. The objective of the extant systems analysis is to informally evaluate a number of popular BI tools based on the BI Scorecard. Tools selected based on the BI Scorecard will be used in upcoming evaluations.

Field studies will be used as an experiment by using IS students from the Department of Computing Sciences at the NMMU. The focus of the field study is to collect data through observation and questionnaires. Two field studies will be conducted serving different purposes. The first field study, namely Field Study 1, will be conducted as a user evaluation on a popular BI tool and a post-test questionnaire will be answered by the students to collect data regarding the usability of the tool. The focus of Field Study 1 will be to determine the requirements for a BI tool for users and to analyse problems that they face during the creation of BI dashboards. These problems will be combined with those identified in literature and the results will be reported on.

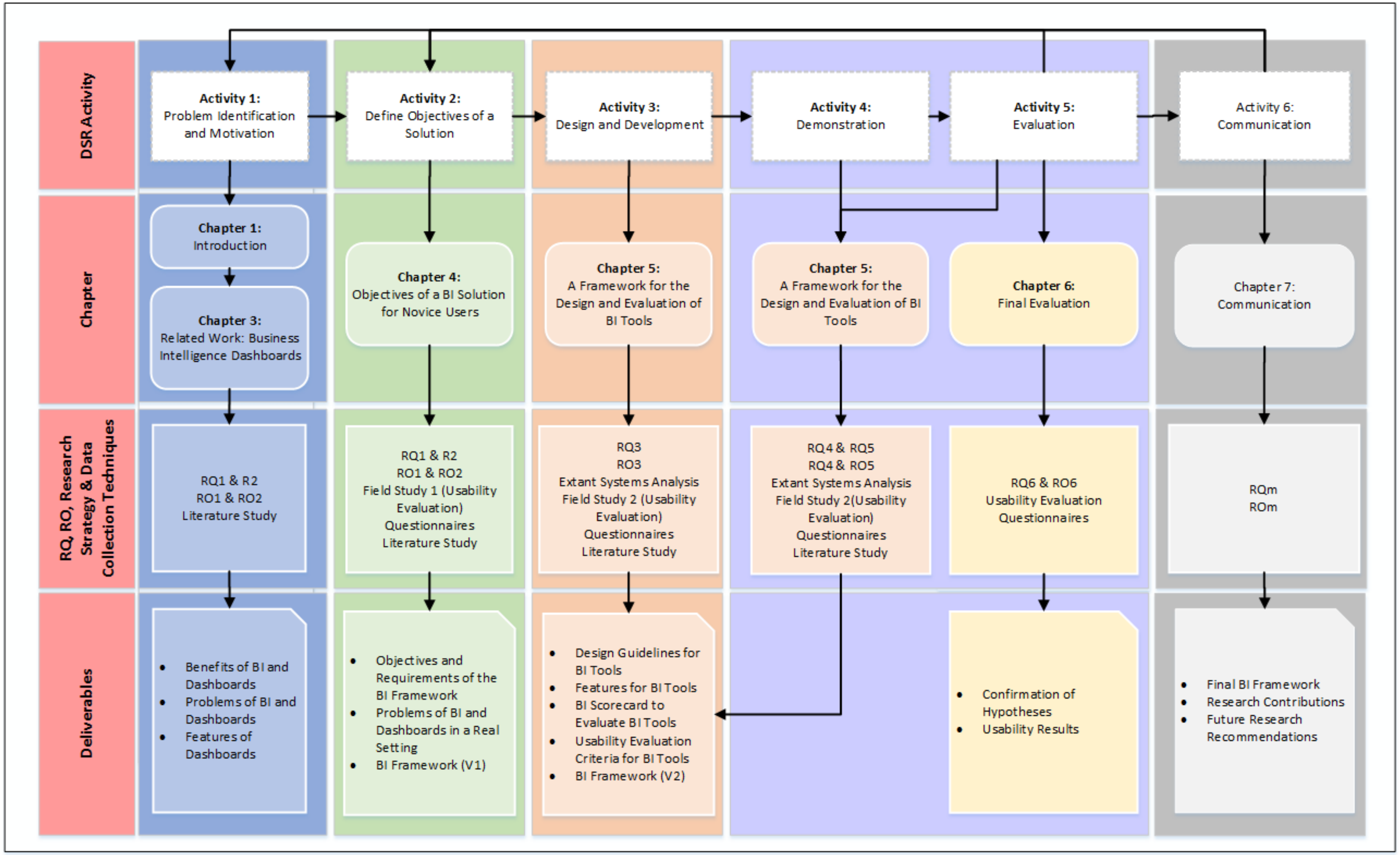


Figure 2-6: Updated dissertation structure

Once the BI tools are selected from the BI Scorecard, a second field study will be conducted as a user evaluation using students at the NMMU. The second field study will be referred to as Field Study 2. The objective of Field Study 2 will be to collect feedback on the usability of the tool, identify additional requirements, and to verify the components of the BI Framework. Field Study 1 is conducted for problem investigation purposes and the second field study is to demonstrate the proposed artefact, which is the BI Framework.

Case studies allow researchers to collect information about a group of individuals, policies, organisations, events, actions or other systems at a specific time and place (Yin, 2013). Case studies may produce both qualitative and quantitative research. Researchers report on the behaviour of the group as a whole and only in that specific context. The goal of case studies are not to focus on the discovery of a universal, generalisable, truth, but to rather emphasise exploration and description of specific problem areas. A case study will be used in conjunction with Field Study 1, where a group of novice users, such as IS students at the NMMU, will be studied to investigate the problem areas of dashboard development.

A ***usability evaluation*** is another form of an experiment to be conducted with IS students in the Department of Computing Sciences with another popular BI tool, which is selected based on the BI Framework. The usability evaluation will require students to complete a post-test questionnaire regarding the usability of the tool. The objective of the user evaluation is to determine the usability of the BI tool and whether the tool satisfies the requirements of the users. Additionally, hypotheses will be formulated and tested. The hypotheses will be developed to test whether differences exist between users' education level and the usability ratings of BI tools. The questionnaires will comprise of several Likert rating scale questions and open-ended questions. All of the data collected from the questionnaires will be statistically analysed and the results reported on.

2.10 Ethical Considerations

The study requires students from NMMU to participate in the evaluation of BI tools. Participants will be required to complete a task-list and answer questionnaires. The participation in this study is voluntary and all participants are to be informed of the aim of this study, as well as the objectives of the relevant activity being participated in. All participants are required to provide their consent before any activity is initiated and are able to withdraw their participation at any time. The results of the study are to be made available to participants upon enquiry. Ethical clearance was approved by the NMMU Human Research Ethics Clearance Committee (REC-H) and the ethics clearance number for this study is H14-SCI-CSS-007 (Appendix A). All consent forms distributed to participants made reference to the ethics clearance number.

2.11 Summary

The purpose of this chapter was to determine the research design of this study. The research design will be used as a general plan of how the research will be conducted in this study. The first part of the chapter follows the research onion, which is an analogy introduced by Saunders et al. (2009). The research onion resembles a research process where layers of the onion are peeled off as part of the research design. The chapter continues with a discussion of the first layer of the onion, which relates to three research philosophies: positivism, interpretivism and realism. This is followed by a discussion on research approaches. The two main research approaches were inductive and deductive. The strategies used in this study that are relevant to this study are field studies, extant systems analysis and usability evaluations. The motivation for adopting the DSR methodology was also presented.

The data collection techniques to be used in this study are primarily questionnaires consisting of qualitative and quantitative questions. Quantitative data will be analysed using statistical techniques and qualitative data will be analysed through thematic analysis. Techniques for data reliability and validity were established and the chapter was concluded by considering ethical considerations.

The next chapter will focus on the first DSR activity, namely *Problem Identification and Motivation*. Moreover, the *Relevance Cycle* will be applied by considering the purpose, benefits and problems associated with dashboard creation.

Chapter 3. Related Work: Business Intelligence Dashboards

3.1 Introduction

The first activity of the DSR methodology, namely *Problem Identification and Motivation*, is reported on in this chapter to investigate the problem in more detail and to justify its importance (Peffers et al. 2006; Johannesson & Perjons 2012). In order to examine the problem in more detail and clearly motivate the research, literature will be reviewed in terms of BI and dashboards and the challenges which users face when creating dashboards. The two research questions partially answered in this chapter are:

> ***RQ1:*** *"What are the problems that novice users experience when using BI tools to create dashboards?"*
>
> ***RQ2:*** *"What are the objectives and requirements of a framework that can guide the design, evaluation and selection of BI tools for novice users?"*

The layout of the chapter, as well as the research objectives and deliverables, is presented (Figure 3-1). EPM has become a key driver in organisational strategy and is often regarded as a component of BI systems (Section 3.2). Enterprise systems are fundamental data sources for BI systems from which data is transformed into valuable insights for decision making (Section 3.3). The complexity of enterprise systems differ across organisations, however, these systems typically form part of a large BI architecture that consists of different layers that function together to transform and present information (Section 3.4). A variety of IV techniques are available to view data, however, the steps in the main process to create visualisations remain consistent (Section 3.5). Considering that dashboards are a type of IV technique, it is important to discuss their purpose in more detail so as to determine their associated features and benefits (Section 3.6). A number of software tools have been developed in the BI and IV market focusing on dashboards and provide different features to support users (Section 3.7). Finally, conclusions are drawn from the literature discussed in this study chapter (Section 3.8).

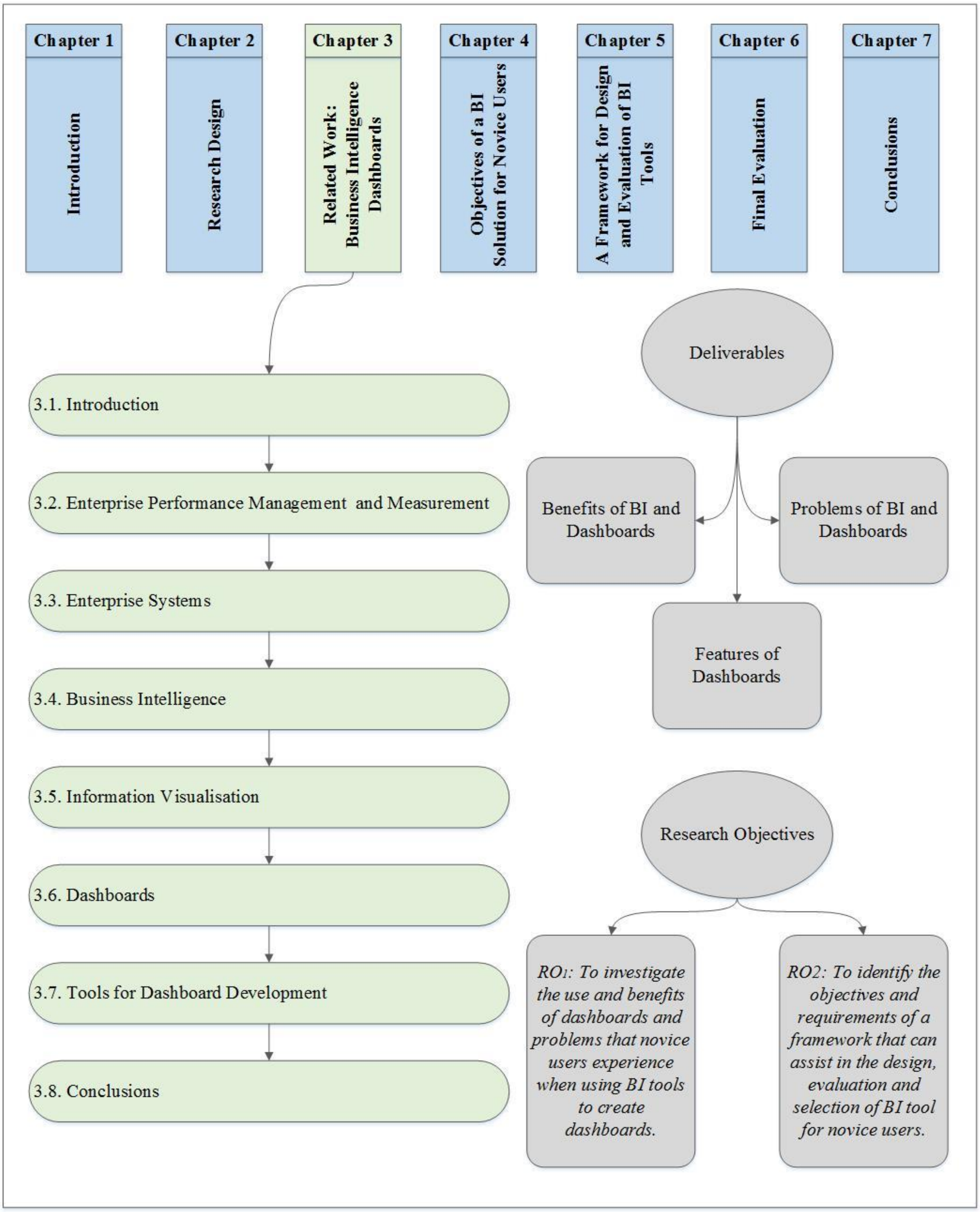


Figure 3-1: Chapter 3 layout

3.2 Enterprise Performance Management and Measurement

The main goal of BI is to support the strategic, tactical and operational objectives of an organisation by providing current, historical and predictive views of various business operations for decision making. Since organisations often struggle to map strategy to execution, BI is often used to incorporate EPM to analyse and visualise performance metrics and has been incorporated by leading BI vendors such as Microsoft, IBM, Oracle and SAP (Bogdana et al. 2009; Botan et al. 2010; Chen & Storey 2012). An EPM system essentially consists of architecture that encapsulates a combination of metrics, processes and technologies designed to optimise both the development and execution of organisational strategies (Franco-Santos et al. 2007; Frolick & Ariyachandra 2006). BI is regarded as the key enabler of EPM initiatives that enable organisations to plan, execute and evaluate organisational strategy and processes using BI tools (Hawking 2013).

BI is changing the way organisations are managed, decisions are made and people perform their tasks. BI is also becoming more pervasive as it provides users with real-time and easy-to-understand information. Interest in performance measurement and management, collectively known as EPM, has notably increased in the last 20 years (Taticchi et al. 2010). EPM uses scorecards and dashboards to help analyse and visualise a variety of performance metrics (Chen & Storey, 2012). The importance of dashboards and other visualisation techniques are the main contributors for effective performance monitoring and management (Watson & Wixom 2007). EPM is not only evident in organisations operating in private sectors, but is increasingly evident in organisations operating in public sectors such as governments, schools, hospitals, universities and local authorities (Taticchi et al. 2012; Heinrich & Marschke 2010).

In order to stay competitive in continuously changing environments, performance information in organisations needs to aid in fast decision making to support a pro-active management style that promotes agility and responsiveness (Nudurupati et al. 2011). EPM is recognised as a critical component, as bottlenecks and anomalies can be detected in real-time to improve organisational performance (Palpanas et al. 2007) and serves as a useful tool to drive organisational change (Aguinis et al. 2011). Bogdana et al. (2009) claim that EPM is not only a technological solution, but includes processes, methodologies, metrics and tools to monitor, measure and manage an organisation.

Furthermore, EPM involves the formulation of metrics, KPIs and benchmark values that are used to assess the state (effectiveness or efficiency) of a business activity or event and to prescribe a course of action (Ranjan 2009; Heinrich & Marschke 2010). Examples of these can include: performance figures on production, quality, markets and customers. Decision makers can proactively act upon these types of indicators to control business processes and to manage performance targets (Nudurupati et al. 2011).

Several frameworks have been proposed for organisations to develop and maintain processes for EPM that link organisational strategy to execution (Nudurupati et al. 2011). Therefore, EPM frameworks are increasingly integrated within BI initiatives, as BI allows organisations to enforce execution, monitoring and measurement from strategic to operational activities. A popular EPM framework recognised by Frolick and Ariyachandra (2006) and Turban, Aronson, Liang and Sharda (2007) consists of a four-step "closed-loop" cycle (Figure 3-2) for the design, implementation and management of EPM. The EPM framework resembles a continuous improvement process. Consequently, any EPM solution and supporting technology must be flexible and configurable to easily apply critical modifications, updates and maintenance (SYSPRO 2010).

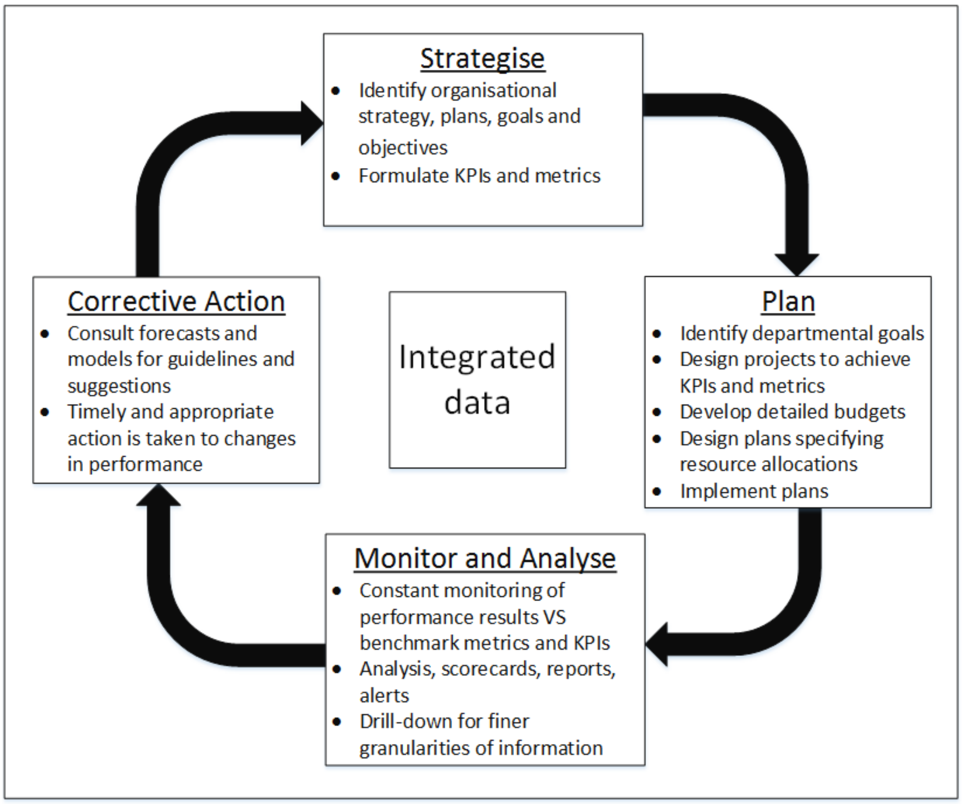


Figure 3-2: CPM framework consisting of four key processes [Source: Bogdana et al. (2009)]

3.3 Enterprise Systems

Massive amounts of transactional information are produced by an organisation's enterprise systems, such as Enterprise Resource Planning (ERP), Business intelligence (BI), Customer

Relationship Management (CRM), and Supply Chain Management (SCM) systems (Ghazanfari et al. 2011). These enterprise systems require integration and manipulation with data from non-transactional systems (Baltzan & Phillips 2012). Data from non-transactional systems can include emails, web logs, customer interaction records, images, videos, spreadsheets and other documents produced by office tools (Chaudhuri et al. 2011). Conventional office tools, such as Microsoft Excel, are not meant to handle all of these different types of data. However, organisational information is most commonly stored in spreadsheets where various manual tasks are required to transform data into a presentable format (Jansen & Dragicevic 2013).

ERP systems are increasingly deployed as the predominant source of data for BI since they are ideal for coordinating enterprise-wide business processes and transactional data across functional departments into a single, integrated system (Nofal & Yusof 2013). ERP systems enable organisations to improve the efficiency of their core business processes and transactions by using an integrated database and shared management reporting tools (Monk & Wagner, 2009). The problem, however, is that traditional ERP systems lack data performance analysis (Søilen & Hasslinger 2012). For this reason, organisations typically customise their ERP systems to communicate with third-party BI applications (Nofal & Yusof 2013). These individual systems are customised to convert, store and integrate data with other transactional and non-transactional systems into a data warehouse to support decision making and to explore relevant knowledge (Ghazanfari et al. 2011). These types of customisations are typically an organisation's attempt to implement an EPM system.

Despite the efforts from organisations to integrate their ERP solutions with third-party vendors, two major problems are still evident across traditional enterprise systems. The first problem relates to organisations that experience a lack of data analysis and BI functionality in their decision making processes when implementing enterprise systems, such as ERP or CRM systems (Søilen & Hasslinger 2012; Ghazanfari et al. 2011; Ranjan 2009). The second problem relates to the limited amount of criteria to evaluate BI and ERP systems as a whole (Ghazanfari et al. 2011). As a result, BI and ERP vendors have realised that organisations must have a thorough strategy to integrate, utilise and evaluate their BI and ERP solutions (Nofal & Yusof 2013).

An ERP system consists of two types of components (Baltzan & Phillips 2012), namely Core ERP components and Extended ERP components (Figure 3-3). Core ERP components are standard ERP functionality and typically include modules for Accounting and Finance, Production and Materials Management, and Human Resources (Hawking 2013; Baltzan & Phillips 2012). Extended ERP components are not typically standard and often reside in a separate system acquired from a third party vendor that requires integration with the ERP system, or they can form part of an integrated ERP solution from a single vendor (Waghmare & Mehta 2014). Extended ERP components include SCM, BI, CRM and E-Business modules (Waghmare & Mehta 2014; Shi 2013; Baltzan & Phillips 2012).

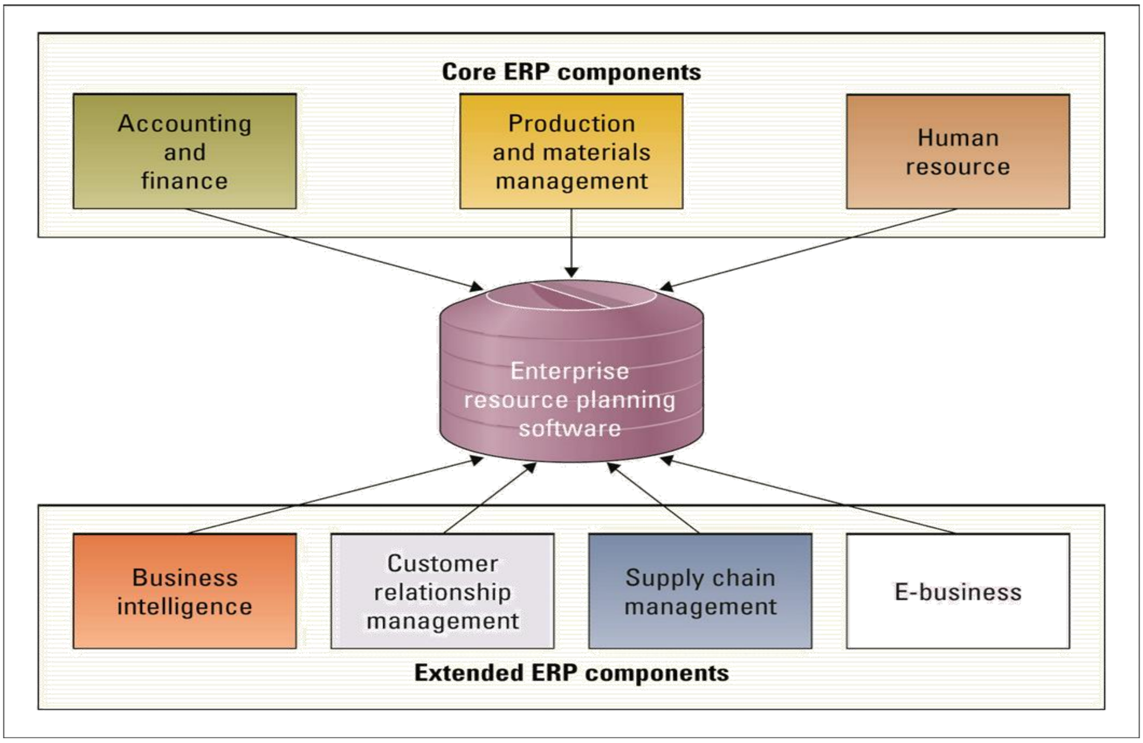


Figure 3-3: ERP components [Source: Baltzan and Phillips (2012)]

SYSPRO is a South African ERP vendor that provides ERP software as a single source solution. The ERP system is constructed using a modular approach, which means that organisations can select and integrate the ERP components to meet their business requirements. The ERP solution does not require external applications to run business operations, however, the solution can be integrated and customised with external applications. SYSPRO also provides a Reporting and Analysis Management solution that offers functionality for reporting, analytics, dashboards and sales analysis that are all important functionality to fulfil the BI and EPM requirements of an organisation. SYSPRO Analytics is a powerful tool within Reporting and Analysis Management solution. SYSPRO Analytics enable users to create multi-dimensional views of financial and operational data to determine patterns and underlying trends, gauge performance through the provision of KPIs, leverage opportunities and attain competitive intelligence (SYSPRO 2014). The problem identified within the SYSPRO Reporting and Analysis Management solution is its limited support for dashboard development. Users are often required to construct dashboards within numerous third party applications, which are technically challenging and inefficient.

3.4 Business Intelligence

BI is an umbrella term that is used to describe a set of concepts and methods to improve business decision making by using fact-based, computerised support systems (Ghazanfari et al. 2011). BI deals with a collection of processes through which an organisation retrieves, analyses and distributes information and knowledge (Sabherwal & Becerra-Fernandez 2011). BI supports organisations in understanding critical business data about their business and market (Chen & Storey, 2012). More specifically, BI can be understood as a set of methodologies, techniques, architectures and software technologies that transform raw data into meaningful and useful information to enable more effective strategic tactical, and operational insights and decision making (Sabherwal & Becerra-Fernandez 2011). The effectiveness of BI is attributed to its ability to present timely, reliable and easy to use business information (Mcbride 2014; Ramakrishnan et al. 2012; Rouhani & Asgari 2012). This information is typically obtained by leveraging a variety of data sources, including those that collect structured and unstructured information (Sabherwal 2007; Lönnqvist & Pirttimäki 2006).

BI has evolved over a number of years and has given rise to a number of related technologies ant terms. In order to understand how BI has evolved and how the needs of users have changes, an overview of BI will be provided in terms of its evolution (Section 3.4.1). The components of a BI architecture are discussed in greater detail to indicate how they work together to analyse and present valuable information (Section 3.4.2). Various benefits and problems are associated with the implementation of BI solutions and may differ across organisations and individual departments. Understanding these benefits and problems can assist in determining whether a BI solution is suited for the goals and objectives of the organisation (Section 3.4.3).

3.4.1 Variants of Business Intelligence

The rate at which organisations collect digital data is growing incredibly. The increasing volume and detail of information collected by organisations are creating new opportunities and challenges in the foreseeable future (Chen & Storey, 2012). Organisations might not only face challenges in data management, but also in data analysis where new approaches are needed to generate insights from highly detailed and contextualised information (Chen & Storey, 2012). Eckerson and Hammond (2011) motivate that the field of BI is gradually shifting toward a more analytic, data-driven culture where users are empowered to explore large data sets through numerous graphical mediums rather than tabular reports. Therefore, data analysis has become a core business objective to uncover trends and behaviours in large data sets, as well as to optimise business decisions and processes for enhanced performance (Chiang et al. 2012; Gartner 2015).

Lim, Chen and Chen (2013) motivate that BI has become a data-centric approach with major objectives to enable interactive and easy access to diverse data, and to enable manipulation and transformation of this data to give target audiences, such as managers and business analysts, the ability to conduct appropriate analyses and perform actions. Organisations are also increasingly encouraging data analysis on varying levels of the organisation to generate insights, and not just managers and analysts who are often the target group of BI systems (Heer et al. 2012; Elias 2012; Watson 2009). A major challenge for organisations is to select an appropriate BI solution to suit the problem space or decision environment within the organisation (Işik et al. 2013). Selecting an appropriate BI solution is thus critical to BI success and a number of factors influence the decision.

The BI field has experienced a number of trends since the term was introduced in the late 1980's (Ariyachandra & Watson 2010). BI systems have evolved from traditional Decision Support Systems (DSS) and Executive Information Systems (EIS). These systems were primarily implemented to suit a specific departmental need or role, such as querying historical data to provide periodic reports for marketing directors (Rouhani & Asgari 2012; Watson 2009). Organisations quickly started to shift their focus from large qualitative reports to simple analysis dashboard systems, which provided a consolidated view of information (Watson 2009). Additionally, the term Business Analytics (BA) was introduced as an essential analytical component in BI systems in the late 2000's. In more recent advancements, the term *big data* and *big data analytics* was introduced. Big data refers to the datasets and analytical techniques that are used in applications requiring their own unique and advanced data storage, management, analysis, and visualisation technologies.

BI techniques and tools assist organisations to turn data into information, which is then turned into knowledge and plans that are used to drive business activity (Eckerson 2011). BI initiatives need to support strategic, tactical and operational objectives along with the integration of EPM, enterprise analytics, and operational BI to manage the organisation effectively (Bogdana et al. 2009).

BI can be understood in two different ways. BI can refer to a process by which an organisation collects, analyses and distributes information and knowledge. BI can also be refered to as a product of this process, as the information and knowledge that can be used for decision making and other business activities (Sabherwal & Becerra-Fernandez 2011). Ghazanfari et al. (2011) identified a “division” between technical and managerial viewpoints regarding BI. Managerial audiences view BI as a process to develop an informational environment in which operational data, gathered from Transaction Processing Systems (TPS) and external sources, can be analysed to support strategic decision making. The analysis of strategic business knowledge is critical for the support of unstructured-decision management, which is evident in fast changing operating environments. Managerial audiences focus on the formulation of strategic outputs from the BI process, such as the implementation and evaluation of organisational vision, mission goals and objectives. Technical audiences approach BI as a set of tools, technologies and algorithms that enable the storage, recovery, analysis and manipulation of data and information. Technical audiences emphasise the technology that supports the gathering, analysis and distribution of information within the BI process and are concerned with operational decisions that enable day-to-day management and execution.

Literature often provides variants of BI such as strategic, tactical and operational BI (Nelson et al. 2010). These terms can be differentiated based on their currency and scope of data (Nelson et al. 2010). Strategic BI and tactical BI focus on medium to long-term planning and utilise BI to formulate business plans, strategies and goals by using historical data (Botan et al. 2010). Operational BI focusses on the management and optimisation of current data for daily business operations, rather than planning or generating insights over the long-term (Botan et al. 2010; Sabherwal & Becerra-Fernandez 2011). Operational BI aims to provide analytical tools from back-office to front-office and customer-facing employees, enabling them to operate as knowledge workers. Operational BI provides a more flexible, transparent and cost effective approach to BI, by tightly integrating it with constantly evolving organisational processes (Marjanovic 2010).

Organisations have a critical need to process transactions and business events at a low latency, since day-to-day activities are dependent on real-time or near real-time data access (Schneider 2007; Seibold et al. 2013). According to Plattner (2009) operational BI must be able to process analytical queries and business transactions at the same time and on the same current data. This type of scenario results in mixed workloads, which is a big challenge for current Database Management Systems (DBMS) that aim to handle operational BI (Seibold et al. 2013). Literature also distinguishes between Big Data and self-service BI(Sridhar & Dharmaji 2013; Chen & Storey 2012), real-time BI, Business Analytics (or simply Analytics), and.

Big Data refers to enormous amounts of unstructured data produced by high-performance applications that are combined with structured data. Big Data does not only focus on the volume, but also on the variety, velocity and veracity of data that is gathered internally and externally (Sridhar & Dharmaji 2013; Fan & Bifet 2013). Data gathered for so-called Big Data falls in a wide category of sources, ranging from enterprise systems, cloud storage, office tools, web systems, scientific computing repositories, social networks, sensor and stream databases, e-government applications to medical IS, and so forth (Letouzé 2012; Wixom & Goul 2014).

Real-time BI is the kind of BI that aims to provide decision makers with access to the correct information when they need it, so that business processes are not significantly slowed down due to waiting for information and knowledge from the BI solution (Sabherwal & Becerra-Fernandez 2011). Moreover, real-time BI is required to react quickly to new opportunities and technological problems that arise (Sridhar & Dharmaji 2013). Much of the BI literature adopted the term "real-time" to be synonymous with "right time" as suggested by White (2004). Although some literature perceive "real-time" to be synonymous with "instantaneous", White (2004) argues that data can only be as fresh as the business requirements and therefore the term "right time" is a more accurate description. For simplicity, this study assumes that all BI is "real-time" in nature, unless otherwise stated.

Business Analytics (BA) involves the design and implementation of sophisticated algorithms for filtering and analysing data. Where BI has developed along with data integration and visualisation technology to present historic and current performance, trends and patterns, BA includes prediction and optimisation (Sridhar & Dharmaji 2013). In order to utilise Big Data, real-time BI and BA need to be carefully incorporated in organisational processes and solutions. BA can be split into three main types, namely descriptive, predictive and prescriptive analytics (Sridhar & Dharmaji 2013; Sabherwal & Becerra-Fernandez 2011). Descriptive analytics uses mathematical models and algorithms to sum or count past occurrences, patterns and trends to take corrective action or optimise business activities. Predictive analytics use mathematical models and algorithms to test hypotheses, predict possible future outcomes, or to stop repeating patterns before they occur. Predictive analytics does not only anticipate future outcomes, but also helps to anticipate when something will happen. Furthermore, predictive analytics provides insights based on future opportunities or to mitigate risks at a predicted time. For simplicity, this study assumes that BI solutions and tools include BA, unless otherwise stated.

Self-Service BI is a BI environment that enables users to become more self-reliant and less dependent on the IT organisation. Self-service BI aims to provide an environment which supports easy access, analysis and sharing of data with less IT dependency, and enables users to perform better analysis. The target audience of self-service BI is business users who have little experience with IT or related knowledge. Moreover, self-service BI provides an easier tool with more flexible configurations and easier administration by means of a predefined package. Organisations that require BI solutions for highly customisable and advanced business requirements will typically use traditional BI, involving IT and business users. However, self-service BI allows business users to have direct access to data sources, which enables faster analysis and dashboard creation than traditional methods of BI.

3.4.2 Business Intelligence Architecture

Sabherwal and Becerra-Fernandez (2011) distinguish between BI tools and BI solutions. BI tools are individual components, developed by vendors, which form part of larger architecture known as a BI solution. A typical BI architecture consists of five layers (Figure 3-4). These layers are: Data Sources, Data Movement, Data Warehouse, Metadata (or Mid-tier), and front-end (or end-user) layers (Chaudhuri et al. 2011; Ong et al. 2011).

The first layer, Data Sources, consists of internal and external data sources to which the organisation has access. Internal data is collected from operational data sources such as ERP, CRM, SCM and traditional legacy systems that mainly record day-to-day transactional data

(Chaudhuri et al. 2011; Shi 2013). External data is often accessed from sources that exceed the boundaries of the organisation and include data collected from the internet, business partners, government sources or market research (Ong et al. 2011; Ranjan 2009). Data Sources can also consist of a combination of structured and unstructured data (Sabherwal & Becerra-Fernandez 2011).

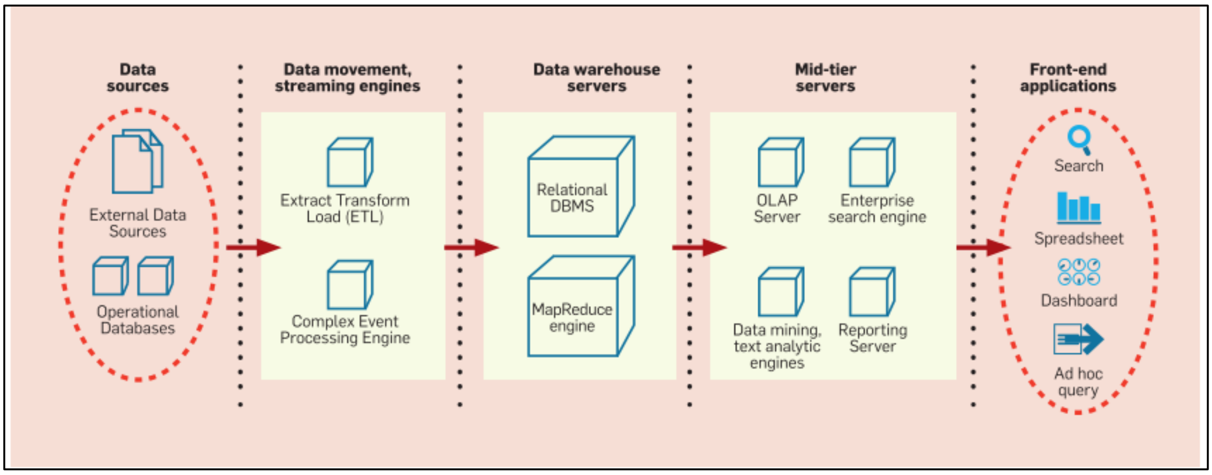


Figure 3-4: Business intelligence architecture [Source: Chaudhuri et al. (2011)]

The objective of operational data sources is to perform simple query processing (Baltzan & Phillips 2012). Operational sources are combined with external sources of information to conduct analyses to derive insights for trends and patterns. Performing analyses directly from operational data may, however, cause several problems. These problems relate to inconsistencies in data, poor data quality, and the lack of data standards. In order to overcome these problems associated with operational data sources, organisations implement the use of data warehouses (Shi 2013; Baltzan & Phillips 2012). A data warehouse is large data repository that is specially prepared to support decision making (Ariyachandra & Watson 2010).

Shi (2013) explains that the key driver of BI is its ability to extract and cleanse useful data from many disparate enterprise systems. The process of cleaning and preparing data in a consistent format is referred to as scrubbing and is an essential part of implementing and maintaining a BI solution (Baltzan & Phillips 2012). The second layer, Data Movement, includes the process of Extraction, Transformation and Load (ETL) which is applied to ensure that accurate and non-redundant data. The process of ETL extracts and merges data from internal and external sources into a central repository such as a data warehouse, which contains the third layer of a BI architecture, known as the Data Warehouse or Data Warehouse Servers layer (Shi 2013; Chaudhuri et al. 2011; Baltzan & Phillips 2012).

The data warehouse may consist of independent data marts. Data marts contain a subset of the data warehouse based on the data requirements of specific business units and are usually confined to a specific subject of information such as finance, production or marketing (Baltzan & Phillips 2012; Shi 2013). The data warehouse is typically managed by one or more data warehouse servers (Chaudhuri et al. 2011; Shi 2013), which allow organisations to perform multi-dimensional data analysis from the independent data marts (Shi 2013).

Before analysis is applied to data, the data warehouse needs to be queried for information by using either a Relational Database Management System (RDBMS) server for structured data, or an equivalent server that processes large and unstructured data in parallel, such as a MapReduce server. MapReduce is one example of a programming paradigms that allow for optimal scaling of processing power of servers in large data sets (IBM 2015). Alternatively, MapReduce is a programming model that allows analytical procedures to be optimised as execution engines can analyse data sets with a parallel, distributed algorithm on a cluster (Ullman 2012). Given the rate at which data volumes are increasing, organisations are seeking cost-effective methods to manage structured and unstructured data sources, and deploy RDBMS that can execute SQL queries in parallel with low latency. Traditional RDBMS servers cannot necessarily handle the large volumes of unstructured data, therefore, MapReduce technologies assist organisations to execute complex SQL queries to a data warehouse in parallel with RDBMS (Chaudhuri et al. 2011).

Data warehouse servers are complemented by a set of servers that reside in the Mid-tier Servers layer, which is the fourth layer of a BI architecture. Mid-tier servers provide specialised functionality that assists a specific BI reporting task and optimises data for presentations in the front-end application. Mid-tier servers function as the “bridge” between the stored data in the data warehouse (third layer) and the front-end applications to view data (fifth layer) (Chaudhuri et al. 2011).

Mid-tier servers include: OLAP servers, enterprise search engines, data mining and text mining engines, reporting servers and web analytics (Chaudhuri et al. 2011). OLAP servers enable users to interactively analyse multi-dimensional data with varying levels of aggregation (Elias & Bezerianos 2012; Sabherwal & Becerra-Fernandez 2011). OLAP enables functionality such as slice-and-dice, filtering, drill-down, aggregation and pivoting to view data from different perspectives (Chaudhuri et al. 2011; Sabherwal & Becerra-Fernandez 2011).

Organisations need to make decisions near real-time and use in-memory BI engines in conjunction with OLAP servers to optimise the memory capacity of its BI solution. Using in-memory servers improves the performance of multi-dimensional queries. Reporting servers assist users to define, execute and render reports in an efficient manner. Enterprise search engines query a data warehouse based on a keyword entered by the user. The keyword method handles text and structured data in the data warehouse to find insights on a specific subject of information such as customers, emails, documents or call logs (Chaudhuri et al. 2011).

Text mining and data mining engines enable in-depth analysis of data, which cannot be attained by OLAP, reporting servers or enterprise search engines (Chaudhuri et al. 2011; Sabherwal & Becerra-Fernandez 2011). Data mining applies advanced algorithms to extract hidden patterns and relationships among variables, which can be used to build predictive models (Chaudhuri et al. 2011; Sabherwal & Becerra-Fernandez 2011). Text analytic engines are used to perform text mining to collect insights from unstructured data, by automatically reading large documents of text written in natural language (Sabherwal & Becerra-Fernandez 2011). Text analytics differs from enterprise search engines as they analyse large amounts of text data, such as surveys, to extract valuable information which generally requires substantial manual effort. Web analytics assist organisations to understand how visitors interact with the business website, navigation patterns and most persuasive pages for purchases (Chaudhuri et al. 2011; Sabherwal & Becerra-Fernandez 2011).

The fifth layer of a BI architecture includes the front-end applications that are used to support a large number of BI users (Watson 2009). Users can query the data to create and view dashboards, visualisations, reports, spreadsheets, perform searches on enterprise portals and conduct multi-dimensional analysis (Watson 2009; Chaudhuri et al. 2011). The front-end layer is typically equipped with performance management applications that enable users to monitor KPIs and to execute ad-hoc queries (Sabherwal & Becerra-Fernandez 2011; Shi 2013). Most front-end applications also include trend and scenario analysis through the use of predictive analytics (Watson 2009).

3.4.3 Benefits and Problems of Business Intelligence

A correctly implemented BI solution can assist an organisation to realise a number of benefits. Before a BI implementation can be conducted it must be justified by the potential benefits (Hočevar & Jaklič 2010). Measuring the benefits as a result of an implemented BI solution is an important task, but benefits are difficult to quantify (Rouhani & Asgari 2012; Hočevar & Jaklič 2010). Some benefits of BI have a local impact, such as on a specific department. Benefits such as return on investment and cost saving are then relatively easy to calculate. However, benefits associated with BI often have a global or company-wide impact, which are often intangible and do not translate to financial measures, such as attainment of strategic objectives or communication between departments (Watson 2009).

A number of BI benefits have been identified from literature (Table 3-1). BI enables an organisation to make informed business decisions and can be a source of attaining a competitive advantage (Seibold et al. 2013; Ranjan 2009). Mungree and Morien (2013) motivated that a need exists for a comprehensive, strategic approach to BI that addresses human resources, knowledge processes and organisational culture. BI solutions provide decision makers with access to both real-time and historical data and information on various levels of the organisation (Sabherwal & Becerra-Fernandez 2011; Eckerson 2011). Timely information access on various aspects of the organisation lead to *improved operational performance* through *improved decision making*, *increased process visibility*, *increased productivity, increased response rates, decreased operational costs and increased efficiency* (Sabherwal & Becerra-Fernandez 2011; Ranjan 2009; Eckerson & Hammond 2011).

Managers can make use of analytical capabilities to monitor, detect and predict events and problems within business processes to take quick corrective action or optimise decision making (Eckerson & Hammond 2011). Alternatively, managers can focus on their core tasks as the visual presentation and exploration functions enable them to get insights into problems within seconds, without having to work through vast amounts of data to extract key information (Eckerson & Hammond 2011; Sabherwal & Becerra-Fernandez 2011). BI solutions can identify and present internal and external trends, as well as automatically optimise and allocate available resources to process activities (Ranjan 2009; Sabherwal & Becerra-Fernandez 2011).

Table 3-1: Benefits of BI

Benefit	Reference
Improved operational performance	Ranjan (2009) Sabherwal & Becerra-Fernandez (2011)
Faster and easier access to information	Hočevar and Jaklič (2010) Watson (2009)
Improved customer service (including customer retention and service)	Hočevar and Jaklič (2010) Ranjan (2009) Sabherwal & Becerra-Fernandez (2011)
Savings in IT and operational costs	Hočevar and Jaklič (2010)(Watson 2009)
Improved competitiveness/ opportunities/ response rate	Hočevar and Jaklič (2010) Olbrich, Poppelbuß and Niehaves (2012)
Improved decision making capabilities	Dawson and Van Belle (2013) Watson (2009)
Improved business processes visibility/ communication	Ranjan (2009) Watson (2009)
Support for attainment strategic objectives	Dawson and Van Belle (2013) Watson (2009)

Organisations using BI solutions enjoy the benefit of *improved customer service* (Ranjan 2009; Sabherwal & Becerra-Fernandez 2011). Providing customer-facing employees with timely access to customer information enables them to be more responsive and anticipative when dealing with customer requests. Benefits such as *improved customer retention* and *improved customer service quality* are often leveraged when using BI solutions (Sabherwal & Becerra-Fernandez 2011). Frequent problems with products are more easily identified along with possible solutions. Customer-loyalty programmes are easier to manage and monitor as website usage, spending patterns and other behaviour are analysed to target those customers who are most likely to take their business to a competitor or identify their most profitable customers (Ranjan 2009).

BI facilitates the creation of new insight and knowledge through the discovery of patterns, correlations, and trends. Providing decision makers with access to new insights and knowledge allows them to anticipate opportunities in the market, such as new distribution channels, products and customers (Sabherwal & Becerra-Fernandez 2011; Olbrich et al. 2012). Thus, benefits relating to the accomplishment of organisational strategies are produced, such as market transparency, increased innovation, and increased effectiveness (Sabherwal & Becerra-Fernandez 2011; Watson 2009).

The importance and benefits of BI and dashboards have been identified; however, some problems have also been reported. Some common problems related to BI have been summarised (Table 3-2). One of the biggest problems related to the complexity to choose, acquire and implement BI tools as the costs and time required to implement are often expensive (Watson 2009; Sabherwal & Becerra-Fernandez 2011). The complexity of the BI tools make them difficult to use for end users as vast amounts of data are collected, stored and processed from various systems (Muriithi & Kotzé 2013). The complexities often contribute to low adoption rates of BI tools and increase excessive expenditure on support and training (Watson 2009). Training users on BI does not only involve the capabilities of the tool, but also the underlying data, terminology and processes necessary to access the data to perform the tasks (Clavier et al. 2012; Watson 2009). Data quality is another problem associated with BI as data is collected from various sources that store data in different formats and is often incomplete (Clavier et al. 2012; Işik et al. 2013). Using incomplete or inaccurate data in BI analysis can directly affect the overall quality of information from which a managers base their decision making and could might not satisfy the information-centric regulations (Işik et al. 2013).

The implementation of a BI solution requires the support of skilled IT professionals. In order to use BI tools, the user needs to know more than the application or technology. The end-user must be familiar with the data, know how to use the technology, and incorporate business and decision making skills (Clavier et al. 2012). Relying heavily on the IT skills causes a problem for flexibility, since decision makers often do not have the time to learn a new BI tool or request access to data from the IT department (Yu et al. 2013; Işik et al. 2013). Appointing skilled analysts and BI professionals is essential to any BI initiative as to provide support in planning, implementing and maintaining the BI solution is needed. For this reason, the benefits of BI need to be understood and the BI strategy needs to be aligned with the business objectives (Işik et al. 2013). Organisations often experience problems in the alignment of their BI solution and organisational goals, which inevitably leads to inaccurate measures and decisions (Clavier et al. 2012).

Table 3-2: Problems of BI

Problem Description	Reference
Complexity to choose, acquire and implement BI tools	Muriithi and Kotzé (2013) Sabherwal & Becerra-Fernandez (2011) Watson (2009)
Time and cost of implementing BI tools/solution	Clavier et al. (2012) Muriithi and Kotzé (2013) Sabherwal & Becerra-Fernandez (2011) Watson (2009)
Time and cost of training and supporting users	Clavier et al. (2012) Watson (2009)
Complexity of BI tools (usability)	Clavier et al. (2012) Işik et al. (2013) Jooste et al. (2014) Watson (2009)
Data quality	Clavier et al. (2012) Işik et al. (2013) Watson (2009)
In-house IT support/skills	Clavier et al. (2012) Muriithi and Kotzé (2013) Yu, Lapouchnian and Deng (2013)
Organisational alignment	Clavier et al. (2012) Işik et al. (2013)

3.5 Information Visualisation

Information Visualisation (IV) is essential for supporting data analysis and summarising the main characteristics of data. IV uses graphical representations to enhance the reader's understanding of large data sets. IV draws its contents from various interdisciplinary fields concerned with the visual representation of complex information. These fields typically include computer science, computer graphics, visual design, psychology, mathematics, and business (Patterson et al. 2014). An IV system consists of two main components, namely: representation and interaction (Yi et al. 2007; Yigitbasioglu & Velcu 2012). Representation stems from computer graphics and is concerned with transforming data into an illustration and ultimately rendering the data on a display. Interaction originates from the field of Human-Computer Interaction (HCI) and deals with the communication between the user and the system as the user explores the dataset to uncover insights.

Various definitions have been proposed for IV in literature. Ward, Grinstein and Keim (2010) describe IV as the process of representing data, information, and knowledge in a visual form to support the user in exploration, cognitive reasoning, confirmation, presentation, and understanding. Shiravi, Shiravi and Ghorbani (2012) define IV as a research area where users visually explore, understand, and analyse data through a series of progressive iterations. The definition of Card, Mackinlay and Shneiderman (1999) is considered to be the most widely accepted definition of IV and describe the concept as follows: "*the use of computer-supported, interactive, visual representations of abstract data to amplify cognition.*"

The underlying concept of IV is that it increases user cognition through the use of the visual perceptual system (Patterson et al. 2014; Ward et al. 2010; Card et al. 1999) to enable the user to analyse and extract relevant and useful information effectively for both high-level and low-level tasks (Patterson et al. 2014; Carpendale 2008). From the definitions, it can be deduced that IV involves a *process* where users *iteratively* engage in data analysis through a set of *interactions* and *visual representations*. Moreover, there are three major goals of IV, namely: presentation, confirmatory analysis, and exploratory analysis.

Often IV techniques are used interchangeably with the concept of Visual Analytics (VA). Although both IV and VA are closely correlated and are not mutually exclusive, they remain different concepts. VA can be described as the science of analytical reasoning supported by means of highly interactive visual interfaces (Thomas & Cook, 2006). VA combines interactive visualisation, human factors and automated data analysis methods for decision making (Keim et al. 2006). Automated data analysis methods relate to those of data cleaning and data mining, whereas human factors include such as cognition, perception and collaboration (Keim et al. 2006). The biggest differentiator between the two concepts is that VA relies heavily on methodologies from statistical algorithms, machine learning, knowledge discovery, and data management to automate analysis (Keim et al. 2006). On the other hand, IV mainly focuses on presenting data and providing appropriate interaction techniques. Nonetheless, VA tools are used to derive insights from complex and large data sets to synthesise information into knowledge.

There is a demand for more interactive and easy-to-use VA and IV tools in different application areas where large information spaces need to be analysed. For many years the focus of VA has been to support areas such as science, industry and government which are data intensive. The use of VA is becoming increasingly widespread to the point where people interact with visual representations in everyday life, such as blogs, websites, mobile applications and so on (Huron et al., 2014a).

Elias (2012) motivates that a challenging problem appears when multi-dimensional data needs to be visualised, as the human perceptual system typically processes data presented in a maximum of three dimensions. The use of IV and VA has changed in recent years and a wider range of audiences is demanding access to easy-to-use and interactive software tools. Dashboards have been motivated as the most popular form of IV techniques to view business data, especially when used in IV and BI tools (Card et al. 1999). However, several problems have been identified with the process to develop dashboards as several software tools and expertise are necessary to develop dashboards.

Users create a mental model of the specific steps that need to be followed to create visualisations of their data (Liu et al. 2014). If the creation process is moderately complex, users often struggle to map their data to visualisation techniques (Grammel et al. 2010a; Huron et al. 2014a). As a result, users need assistance from experts to extract the required data from various software applications, where they apply statistical techniques and present data accordingly (Elias 2012). Many reference models and processes have been proposed to depict the steps that users take to create and customise visualisations to gain insights. A popular reference model for an IV process has been proposed by Card et al. (1999). The reference model was refined by Chi (2000), Tobiasz, Isenberg and Carpendale (2009) and Jansen and Dragicevic (2013).

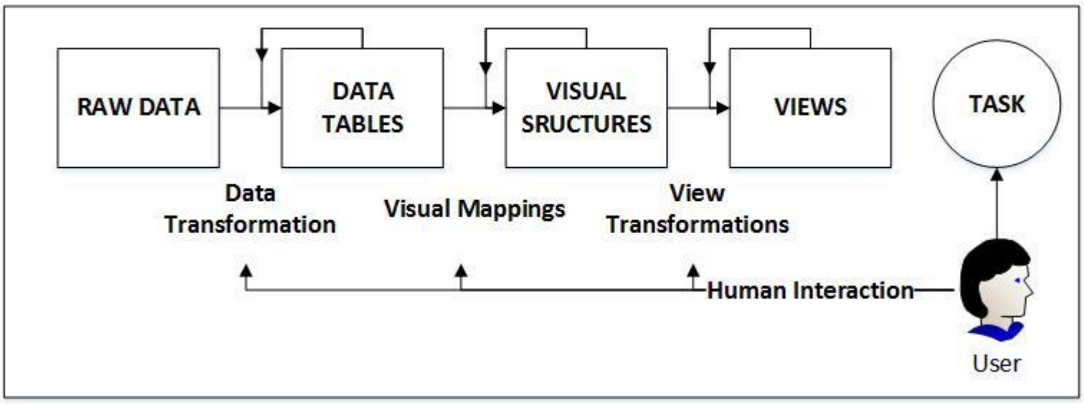


Figure 3-5: Reference model of the process for visualisation creation [Source: Card et al. (1999)]

The reference model describes three steps for how users interpret and interact with visualisations, namely*: data transformations*, *visual mappings* and *view transformations.* The first activity involves selecting the raw data set, from which data tables are processed and transformed from raw data (Data transformation). Data tables can be further transformed by adding calculations and merging tables. Visual structures are then mapped to data tables (Visual mappings), which typically take the form of generic visualisation features such as bar graphs or line charts with their corresponding properties. Specific views are typically rendered and displayed from the visual structures. Views display different parts of the visual structures at varying levels of abstraction (View transformations). Selecting different views do not change the visual structure of the selected visualisation, but allow users to observe the data from different perspectives. Operations that can be applied to transform a view are typically filters, highlighting, zooming on a map, or zooming out or drilling down on different granularity levels. Finally, users interpret the views with a particular goal or task in mind, thereby interacting with the visualisation in an iterative process of data transformation, visual mapping and changing current views. Since dashboards are classified as a specific IV technique, the process applied to dashboard creation.

3.6 Dashboards

The following section provides a formal definition of dashboards (Section 3.6.1). Dashboards are used for various purposes and are deployed on different levels of the organisation (Section 3.6.2). Although dashboards are used for different purposes, a number of common features can be associated with dashboards and need to be included in a BI tool (Section 3.6.3). Additionally, various benefits can be derived from dashboards if they are developed correctly and provide the necessary features to their users (Section 3.6.4).

3.6.1 Defining Dashboards

Dashboards have become increasingly popular in recent years and are regarded as the most prominent technique for BI systems. Organisations need to manage the overwhelming amounts of data collected on a daily basis. Dashboards are an effective solution for overcoming the information overload problem by providing busy managers the opportunity not only to monitor performance, but also to communicate and rationalise decisions (Velcu-Laitinen & Yigitbasioglu 2012). A profound researcher in the field of visualisation, Stephan Few (2007, p. 1) defines a dashboard as *"a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance.*"

Dashboards reveal performance insights into a particular business area, and are typically contextualised through goals and KPIs (Velcu-Laitinen & Yigitbasioglu 2012). Dashboards enable users to quickly recognise critical changes in KPIs and metrics. The effectiveness of dashboards can be attributed to their ability to first provide a consolidated view of the most critical information on a single screen, before initiating exploration into finer details of information. Dashboards enhance ease of use by engaging users through a variety of visualisation techniques and interactions (Bremser & Wagner 2013). These include intuitive charts, buttons, dials, sliders, gauges and "traffic lights" that provide visual cues of information (Few 2007a).

Dashboards leverage an organisation's BI infrastructure and help them achieve strategic goals that are defined by their EPM process (Eckerson 2011). Dashboards have become a mainstream visualisation method for executives, managers and employees to monitor KPIs at a glance and rapidly sift through layers of organisational data for better analysis, insight and discoveries (Eckerson 2011; Muntean et al. 2010). Dashboards have the ability to measure performance on a number of different levels including: corporate levels, business units, functional levels and process levels (Muntean et al. 2010).

The multi-layered nature of dashboards typically allows interactive drill-down and slice-and-dice capabilities that enable users to move from higher levels of synthesised information to lower levels of detailed data (Eckerson 2011). A dashboard provides the support of extensible features, existing from a range of additional widgets, such as metrics, capacity gauges, charts, graphical trend analysis, stop lights and tables (Negash & Gray 2008; Muntean et al. 2010).

3.6.2 Dashboard Purpose and Use

Dashboards are developed to suit a specific requirement and objective, which may differ across individual organisations and departments. The design of dashboards is often influenced by the particular role, internal performance measures and other organisational aspects. Yigitbasioglu and Velcu (2012) motivate that dashboards are expected to collect summarise and present information from multiple sources such as legacy, ERP and BI systems so that the user can view various performance indicators at once.

The focus of many literature sources typically relates to the effect that dashboards have on organisational readiness, change management, and employee adoption (Few 2007a). Pauwels et al. (2009) describe that dashboards are used for the purposes of consistency, monitoring, planning and communication. Consistency refers to the similar measures and measurement procedure that are used across departments, which in turn improve communication. A dashboard serves as a communication tool for performance metrics and the values of the organisation. Planning can be improved through predictive simulations (what-if analysis) of various business events and scenarios. Lastly, dashboards are ideal for monitoring the day-to-day execution of business processes to identify those metrics that need corrective action.

The focus of this study is HCI and usability aspects in terms of dashboards development tools, rather than their organisational deployment. Despite the focus of this study, it is important to recognise the different roles that dashboards can fulfil in organisations, as each type has its unique implications on dashboard requirements and usage. Numerous classification schemes exist to classify dashboards. The most common classification scheme relates to the role of dashboards. These include strategic, analytical or tactical, and operational dashboards (Velcu-Laitinen & Yigitbasioglu 2012; Few 2006; Eckerson 2011).

Strategic dashboards are the most popular form of dashboards and provide decision makers with a general overview of the opportunities and overall health of the organisation. The content displayed takes the form of high-level measures of performance such as forecasts, comparisons to targets, and brief histories with simple performance evaluations (Few 2006). The emphasis of strategic dashboards is not to provide strategic decision makers with immediate or real-time information, but rather with periodical snapshots to monitor organisational performance on a monthly, weekly, or daily basis (Few 2006; Eckerson 2011). Attention is specifically given to critical trends, possible investment opportunities, and alerts for performance deficiencies to guide decision makers in clarifying their future priorities (Allio 2012). Therefore, the goal of strategic dashboards is to track progress toward achieving a long-term goal, and dashboards are anticipated to communicate and review strategic performance to enable effective management across the organisation (Eckerson 2011). Few (2006) motivates that strategic dashboards are rarely designed to be highly interactive and explorative, but should rather be simple and unidirectional displays of information to prevent busy strategic managers from getting side-tracked from their immediate goals.

Analytical or *tactical* dashboards are mainly used by mid-level managers for data or business analysis. Managers use analytical dashboards to monitor operational processes, events, and other activities of interest as they occur on a daily or hourly basis (Eckerson 2011). Analytical dashboards require a richer context of information compared to strategic dashboards. Analytical dashboards require both historic and current data where extensive comparisons, subtler performance evaluations, and performance histories can be monitored (Few 2006; Abdelfattah 2013). As with strategic dashboards, users of analytical dashboards also benefit from periodical snapshots of data that does not constantly change(Few 2006). However, analytical dashboards emphasise on analysis more than monitoring or management, and provide sophisticated visual analysis capabilities to examine relationships in data (Eckerson 2011). Users benefit from highly interactive capabilities and visualisations, such as drilling-down into finer details of information, to enable the exploration needed to make sense of data. From a monitoring perspective, the dashboard informs the user what to investigate, and should support all the necessary analysis capabilities and interactions to link the high-level performance data to the underlying causes (Few 2006).

Operational dashboards are used for monitoring purposes on departmental levels, which need real-time and immediate attention (Eckerson 2011). Front-line workers are the most common set of users of operational dashboards and they are intended to support the management and control of the day-to-day operational processes (Eckerson 2011; Velcu-Laitinen & Yigitbasioglu 2012). Operational dashboards are not designed for statistical or data analysis, but rather to inform users by simple alerts and clear presentations of the appropriate response to emergency events (Few 2006). The level of detail is often more specific in operational dashboards, such as whether an operation has dropped below an acceptable threshold (Eckerson 2011; Few 2006). Access to specific details of information is critical and appropriate interactions need to be in place to move from high-level statistics to finer granularities. These interactions may also be realised by using drill-down or hovering capabilities to provide deeper levels of details on demand (Few 2006; Abdelfattah 2013).

The three different categories of dashboards are not mutually exclusive, since successful organisations generally implement all three categories. The application and functionality of the three types of dashboards correspond to the needs of users and cannot be strictly defined according to their use for each group of users. A dashboard does not need to satisfy a particular category, as long as the dashboard's visual design effectively suits the role it needs to fulfil in the business. The dashboards provide clear and timely information to support the role of the decision maker. This study does not focus on a particular category of dashboards, since BI users may have different requirements in terms of analysing data.

3.6.3 Features of Dashboards

Few (2007b) describes four characteristics of well-designed dashboards that should be evident in any BI tool incorporating the use of dashboards. The first characteristic is that the information in dashboards should be well-structured and help people to immediately recognise those indicators that need attention. Secondly, dashboards should be condensed, showing summaries and exceptions of data. Summaries are described as a set of numbers that is aggregated through summations or averages. Exceptions represent events that either do or do not meet a specific benchmark value that could be problematic, or an opportunity from which the organisation can benefit. Condensed dashboards make it unnecessary for users to work through hundreds of values, when they need only need to focus on a few values. The third characteristic relates to precision, where dashboards need to be customised to present that data that is relevant to the end-users' tasks, data questions, and objectives. The fourth characteristic of dashboards is that they need to be concise and require small mediums to communicate data clearly and in the most direct way possible.

Dashboards should have a number of important functional features and visual features (Yigitbasioglu & Velcu 2012; Eckerson 2011; Few 2007b). Visual features improve visualisation and information encoding, whereas functional features cognitively fit with different types of users and describe what the dashboard is capable of doing. Popular features that need to be included as functional features for dashboards are:

- A variety of presentation formats (graphs versus tables);
- Flexible presentation formats with predefined settings;
- Scenario analysis;
- Drill-down and drill-up;
- Theory guided visualisation and view selection; and
- Automated alerts of any outliers or unusual results.

The effectiveness and efficiency in which dashboards display information depend on visual features and design principles. Some of the visual features that can be incorporated into dashboards include (Yigitbasioglu & Velcu 2012; Few 2007a):

- Integrating individual components on a single page;
- Making effective use of colours to highlight different aspects of the data; and

- Displaying information using a high data-ink ratio.

Although the software market lacks a consensus of the most necessary features required for dashboard development, these features are typically evident in most BI tools. Interactive drill-down and drill-up allows for viewing multi-dimensional data, thus moving from aggregated levels to finer details of data granularity. Flexible presentation formats with predefined customisation settings, such as colours, sizes and labels enable users to highlight those data points that are of particular interest to them and allow for alerts. Other functional features may include filtering, where specific categories of information can be displayed. However, Elias and Bezerianos (2011) stated that half of their participants did not understand the concept of drill-down and got confused between global filters and local filters. Global filters apply filters to all visualisations in the dashboards, where as local filters are only applied to a single dashboard (Elias & Bezerianos 2011; Schröter 2015). Moreover, guidance needs to be provided for the selection of data, and how that data is mapped to the visualisations and dashboards. Grammel et al. (2010a) explains that visual mappings are the most difficult task for users as they do not have experience with appropriate IV. Therefore, automatic visualisations with predefined settings need to be used, which are based on theory (Heer et al. 2008a; Yigitbasioglu & Velcu 2012).

3.6.4 Benefits and Problems of Dashboards

In addition to the general benefits of BI solutions (Section 3.4.3), Pauwels et al. (2009) and Eckerson and Hammond (2011) describe six potential benefits that organisations can attain when implementing effective dashboards:

- **Improved organisational culture:** The sharing of key metrics across the organisation can strengthen an analytic culture when aiming to create consistent, creative and holistic solutions to business problems. This is due to the cross-disciplinary input during the development of dashboards as they are changing the behaviour of people towards management approaches.
- **Performance framework:** Dashboards must be implemented according to a business plan/strategy, which can provide a framework for recognising excellent performance. The dashboard should indicate the current position compared to expected targets, and forecast or simulate "what-if" scenarios for remedial actions when targets are not met.

- **Source of organisational learning:** There is no direct correlation between the use of metrics and current performance. In contrast, metrics do enhance learning (Pauwels et al. 2009). Learning to stress those questions which dashboards are trying to answer drives future performance (Eckerson & Hammond 2011).
- **Increased profitability:** Dashboards provide a greater ability to calculate productivity (return on investment) on marketing and sales projects, and especially in terms of budgeting and finance activities (Pauwels et al. 2009; Eckerson & Hammond 2011).
- **Improved decision making:** Traditional reporting systems typically provide the shortfall or attainment of targets without providing transparency. Dashboards assist in the analysis of time-series data. The cross-functional nature of data combines outliners, solutions, trends, comparisons and other indicators to enable a consensus amongst users (Eckerson & Hammond 2011; Pauwels et al. 2009).
- **Improved Communication:** Dashboards offer a consistent method for viewing and interpreting information across an organisation.

These benefits can only be realised if dashboards are created properly and can be efficiently customised to adapt to organisational needs. Allio (2012) explains that well designed, developed and deployed dashboards enable decision makers to condense clutter and provide strategic insights, improve decision making, accelerate response time and enhance the organisation's performance alignment and implementation. According to Eckerson and Hammond (2011) one of the greatest problems associated with dashboard development and implementation is user adoption that drives positive change in the organisation. Users often do not trust data from dashboards due to a lack of understanding of data or its source (Eckerson & Hammond 2011; Clavier et al. 2012).

Dashboards depend heavily on context, user role and organisational culture (Eckerson & Hammond 2011). Elias and Bezerianos (2011) and Grammel et al. (2010a) revealed how users attempt to develop visualisations. Considering that novice users have limited IT skills, a human mediator is required to create the visual interface of dashboards and connect underlying data sources. Grammel et al. (2010a) also revealed the problems associated with the process to create dashboard and described three major barriers that users face: selecting correct data attributes, choosing appropriate visual mappings, and interpreting the visual results.

The greatest challenge identified in literature is the challenge of developing dashboards in a distributed environment. Reporting and dashboards often need to be combined with third-party solutions and often require two separate tools, thus increasing administration costs and reducing flexibility (SAP, 2011). Organisations often use third-party commercial BI dashboards to support dashboard use and development (Elias 2012). Additionally, Pantazos et al. (2013) motivate that users struggle to follow a development process when the development environment is complex and involves various tools. This problem is especially relevant when the tool does not provide interactive visual objects and immediate visual feedback, as users often struggle to map written code to visualisations.

Eckerson and Hammond (2011) and Lofvinga (2013) identified that users are too comfortable with office tools, such as Microsoft Excel, and prefer storing and analysing information in spreadsheets rather than learning to operate with dashboards. The study by Eckerson and Hammond (2011) indicated that participants spend almost two thirds (65%) of their time analysing data in tables and text, where only 12% of the respondents ranked tables analysis as highly useful. This indicates the need for tools that can assist users to create dashboards efficiently and effectively that benefit from users' visual perception capabilities (Patterson et al. 2014).

Another two problems identified were poor visual design and visual overload (Eckerson & Hammond 2011). These two problems are associated with users who are not familiar with the new dashboard environment. Users need to gradually learn how to view more data over time, cluttering a dashboard with functions and tables of information from various sources leads to a poor design and information overload. A dashboard that has a poor design causes users to work harder to find information. Development tools should allow users to expose data and functionality on demand. This scenario emphasises the need for dashboard functions that enable users to view performance information at a high-level, and provide access to selected drill-down paths when insights are required.

3.7 Tools for Dashboard Development

A number of BI tools are offered in the market (Section 3.7.1). A distinction can be made in terms of the focus for which a BI tool is produced. In this study, a distinction is made between two main categories, namely, commercial tools (Section 3.7.2) and custom visualisation toolkits (Section 3.7.3).

3.7.1 The BI Market

According to Gartner, a renowned research company in the field of information technology, the market for BI and analytics platforms is undergoing a fundamental shift as new competitors and products emerge, and the needs of customers continuously change (Sallam et al. 2015). New software products are enabling organisations to rely less on the traditional, centralised IT department to generate reports and dashboards. A wider range of business users are demanding access to interactive analysis tools to derive at insights, without requiring them to have IT or data analysis skills (Sallam et al. 2015). As a result, a new trend of software products has emerged and is marketed as "*data discovery*" tools, which have become a significant component of self-service BI where various tasks are automated to support the users to easily connect to data sources, transfer data, and create and customise dashboards accordingly.

Figure 3-6: Gartner magic quadrant 2015 [Source: Sallam et al. (2015)]

The leaders in the BI market are depicted in an annual Gartner Magic quadrant that also shows the challengers, visionaries and niche market players (Figure 3-6). Although the BI market has been dominated by leaders, such as Tableau (Tableau 2015) and QlikView, traditional BI vendors are quickly catching up to the trend and are launching visualisation modules on their existing products.

Various IV techniques are designed and selected for specific purposes and typically rely on software tools that support particular features. For this reason, one should consider the purpose for which a BI tool will be used before evaluating it, since no single BI tool will support all purposes equally (Few 2012). BI tools can be used for either exploratory data analysis, descriptive or narrative statistics, monitoring and prediction (Few 2012; Heer et al. 2012; Zhang et al. 2012). A number of taxonomies have also been developed in recent years to categorise IV and BI tools according to their features and the level of expertise required (Few 2012; Zhang et al. 2012; Kuhail et al. 2012; Satyanarayan & Heer 2014; Heer et al. 2008a). Victor (2013) distinguishes software tools based on three fundamental paradigms that either support programming, pre-defined templates or free-hand drawing.

3.7.2 Commercial Tools for Dashboards

The increasing need to support users is reflected in the increasing focus of research communities and commercial vendors of IV and BI (Elias & Bezerianos 2011; Sallam et al. 2015; Huron et al. 2014a). Commercial tools have become the focus of self-service BI, generally offering a type of software suite that functions as a stand-alone system, or integrates it as add-ons into an existing data infrastructure (Zhang et al. 2012). Commercial tools assume that from the end-user perspective the dashboard design remains consistent, and emphasises on features for easy report generation (Elias 2012). Some of these features include sophisticated typologies with visualisation templates, drag-and-drop interactions, design pallets, predefined calculations, data connection wizards, filters, visualisation comparisons and direct manipulation of dashboards.

Users benefit from commercial tools since they require no, or limited, programming configurations to become operational (Zhang et al. 2012). Vendors of commercial tools focus on ease of use and attempt to facilitate the entire IV process in a single environment, thus allowing users to view the immediate visual output of their actions. Users have the flexibility to connect to various data sources and are guided by wizards to connect to databases, CSV files, spreadsheets, web services and so on. Chart or visualisation typologies enable rapid data exploration by selecting variables, a predefined visualisation type, and configuring the parameters such as colour, size, and text labels with a limited number of clicks (Bostock & Heer 2009). Visualisation typologies incorporate design functionality into predefined templates, which assist the user in selecting an appropriate visualisation based on their selected data (Satyanarayan & Heer 2014). Since dashboards aim to provide a synthesised view of information, many commercial tools support the creation of coordinated and multiple views.

Multiple coordinated views represent highly interactive visualisation environments that enable users to view a data set (or combination of data sets) from multiple perspectives, to manipulate the visual presentation in different ways, and also to coordinate the interaction between different views (Elias & Bezerianos 2011). Moreover, some vendors have incorporated advanced functionality to integrate data sources, setup drill-down hierarchies, allow for easy data manipulation and smart data discovery, and pattern detection capabilities (Sallam et al. 2015).

Commercial tools do not offer the opportunity for novel visualisation designs, but focus on easy and rapid dashboard creation (Elias 2012; Huron et al. 2014a; Satyanarayan & Heer 2014). The benefit of commercial tools is that they offer great flexibility for operating on various devices, making dashboards and data analysis more accessible to users from decentralised locations (Sallam et al. 2015). Some noticeable examples of popular commercial tools include the popular (a) Tableau, (b) Microsoft PowerBI integrated with PowerPivot, (c) SAP Lumira, (d) TIBCO Spotfire, (e) QlikSense is part of the Qlik software range and (f) SAS Visual Analytics (Figure 3-7).

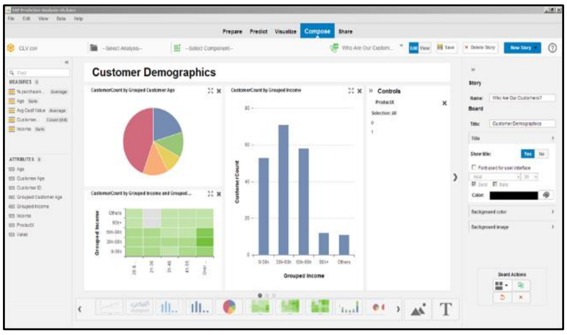
3.7.3 Custom Visualisation Toolkits

In order to enable custom visualisations, many programming toolkits have been developed for IV (Lauesen et al. 2013; Satyanarayan & Heer 2014). The toolkits are highly flexible for developing novel visualisations and unique BI solutions. However, they are not tailored towards users and are often limited to software engineers (Zhang et al. 2012; Heer et al. 2012). These tools offer open-source environments to create unique visualisation applications, and have strong capabilities of displaying data on various devices (Elias & Bezerianos 2011; Zhang et al. 2012; Satyanarayan & Heer 2014). Creating visualisations is not easy and requires a large amount of programming expertise and effort to synchronise components into an existing system, or to feed data back into an existing data source. Multiple individual visualisations need to be linked together and this can be a tedious process to configure navigation and interaction features between them. Custom toolkits also generally require high setup costs and have a steep learning curve (Huron et al. 2014a). A number of these toolkits incorporate their own declarative grammars that consists of high-level languages to specify how data should be mapped to visual elements (Pantazos et al. 2013; Liu et al. 2014).

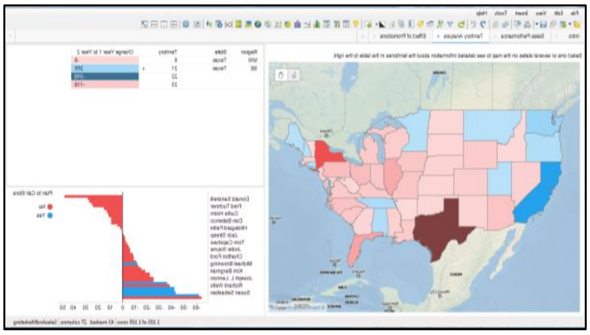
a) Tableau

b) Microsoft PowerBI incroporating PowerPivot

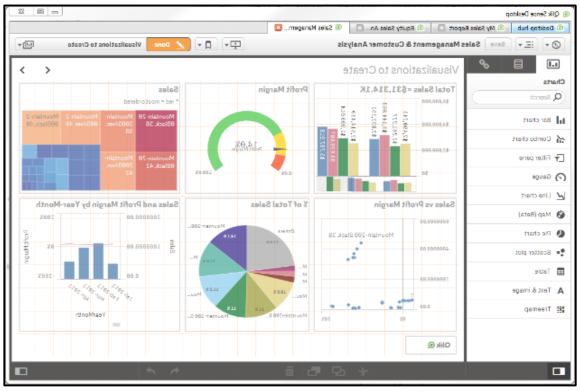
c) SAP Lumira



d) TIBCO Spotfire



e) QlikSense



f) SAS Visual Analytics

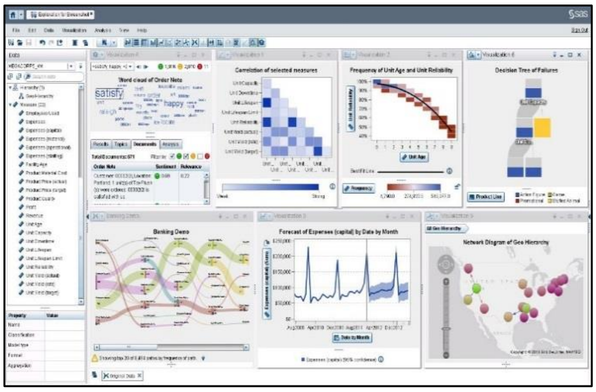


Figure 3-7: Commercial tools for BI dashboards

A number of lightweight programming toolkits have been developed to target programmers using web services (HTML5, CSS, SQL, AJAX, Flash, J2E and JavaScript libraries) to manipulate elements in webpages (Chen & Storey 2012; Elias & Bezerianos 2011; Satyanarayan & Heer 2014; Liu et al. 2014). Some of the most popular custom toolkits are

D3(Bostock, Ogievetsky, & Heer 2011), Prefuse (Satyanarayan & Heer 2014), The InfoVis toolkit (Belmonte 2009) and Google Charts (Google Inc. 2015).

3.8 Conclusions

The chapter provided an extensive literature view in the fields of EPM, BI, dashboards and IV. Some benefits of dashboards were improved *communication*, improved *decision making* and improved *organisational culture*. The benefits of dashboards also contribute toward the benefits of BI, such as *improved customer service and performance*, *improved visibility in business process*, and *support for the attainment strategic objectives*. Whilst there are several benefits, there are also many problems. These include the technical expertise often necessary to create dashboards, which often require users to consult with experts before dashboards can be used. A review of the dashboard creation process revealed that users often struggle to transform data without assistance from a human mediator. Additionally, users often experience difficulties when mapping their data to visual structures.

The benefits for BI were also reviewed; however, not all of them are relevant to dashboard development and are more organisational strategy related. The focus of this study rather falls on improving the usability and user interaction of dashboards for BI analysis. For this reason, some initial features were revised in this chapter that are necessary for BI dashboard tools. Lastly, an overview was provided on two different categories of software tools, namely commercial BI tools and IV customisation toolkits.

The first two research objectives were therefore partially achieved and further investigation will be conducted in the next chapter. These objectives were ***RO1*** *"To investigate the use and benefits of dashboards and problems that novice users experience when using BI tools to create dashboards." and* ***RO2*** *"To identify the objectives and requirements of a framework that can assist in the design, evaluation and selection of BI tool for novice users".* The following research questions were partially answered in this chapter:

> ***RQ1:*** *"What are the problems that novice users experience when using BI tools to create dashboards?"*
>
> ***RQ2:*** *"What are the objectives and requirements of a framework that can guide the design, evaluation and selection of BI tools for novice users?"*

In order to fully answer these research questions, Chapter 4 will conduct a field study to investigate the problem in more detail and to derive at a comprehensive set of objectives and requirements for a BI Framework, as well as a BI tool that can support users in creating dashboards.

Chapter 4. Objectives of a BI Solution for Novice Users

4.1 Introduction

The previous chapter reviewed a number of benefits and problems relating to BI and dashboards. However, dashboards play an important role in any BI project and organisations need to determine their specific purpose and the potential benefits and problems associated with their implementation. The process to create dashboards is not easy and BI tools supporting dashboard creation need to provide specific features to make them more accessible to users. This chapter continues with the investigation of the problems users experience when using BI tools to create dashboards.

Two DSR activities are reported on in this chapter. The first activity is a continuation of the *Problem Identification and Motivation* activity to understand the problem in more detail. The second activity of the DSR methodology, *Define Objectives of a Solution,* elicits the specific requirements and objectives of a BI Framework. Identifying objectives and requirements in the second activity can be viewed as an extended problem explication activity (Johannesson & Perjons 2012). Both these activities form part of the second cycle in the DSR methodology, namely the Relevance Cycle.

A large majority of problems associated with BI tools relate to usability. Usability is a major concern for BI tools as they need to support dashboards that are used to provide valuable insights and decision support. In order for users to become proficient in dashboard development, usability should be a high priority when selecting a BI tool in order to enhance HCI and the user experience.

The primary artefact that this study contributes is the BI Framework. In order to construct a BI Framework, the problems associated with identifying an appropriate BI tool need to be identified. Moreover, the problems that users experience during dashboard development need to be analysed in more detail and the relevant usability aspects for a BI tool have to be identified. A thorough understanding of the functional requirements is essential, as the BI tool has to offer the necessary features to support users with the creation and general use of dashboards. This chapter attempts to further answer two research questions to assist with these requirements and are addressed in this chapter:

RQ1: *"What are the problems that novice users experience when using BI tools to create dashboards?"*

RQ2: *"What are the objectives and requirements of a framework that can guide the design, evaluation and selection of BI tools for novice users?"*

As part of *Problem Identification and Motivation* activity, Field Study 1 was conducted to further investigate the problems with a popular dashboard tool used by IS student at the NMMU (Section 4.2). High-level objectives were formulated for a BI Framework (Section 4.3). Although the BI Framework is developed incrementally throughout this study, an initial version of the BI Framework is proposed (Section 4.4) and the chapter is concluded (Section 4.5). The chapter layout is presented in Figure 4-1.

4.2 Field Study 1: Dashboard Development Problems

Field Study 1 consisted of a usability evaluation, where post-test questionnaires were administered to participants to receive valuable feedback on the usability of the software. Additionally, the researcher recorded notes of interesting observed behaviours and remarks voiced by the participants. A field study is a method similar to a usability evaluation in that careful observation of participants is involved (Lam et al. 2012). The main difference between the two evaluation methods is their goals. The main goal of a field study is to understand how users interact with a software tool in a real-world setting and to extract useful information, such as emerging patterns, to develop suggestions for new designs and improvements (Lam et al. 2012). The goal of a usability evaluation is to identify major problems and deficiencies in existing software tools, and to elicit overlooked requirements (Greenberg & Buxton 2008). Another differentiating factor is the extent to which task-lists and feedback materials are carefully prepared for usability evaluations (Lam et al. 2012). The researcher typically defines a set of tasks to evaluate only a subset of features deemed important for the project, which also forms part of the project's scope.

As part of the *Problem Identification and Motivation* activity, Field Study 1 was conducted with IS students at the NMMU to evaluate a BI tool. The students were those registered for an ERP course, which primarily focusses on teaching them the skills to operate an ERP system such as entering transactional data, configuring the UI, and creating input screens for customised reports. Students are also trained to create BI dashboards by using an ERP system, known as SYSPRO, and a popular dashboard tool known as SAP Xcelsius. The development environment facilitated by these tools can become complex and students need to follow a stringent development process to create a dashboard.

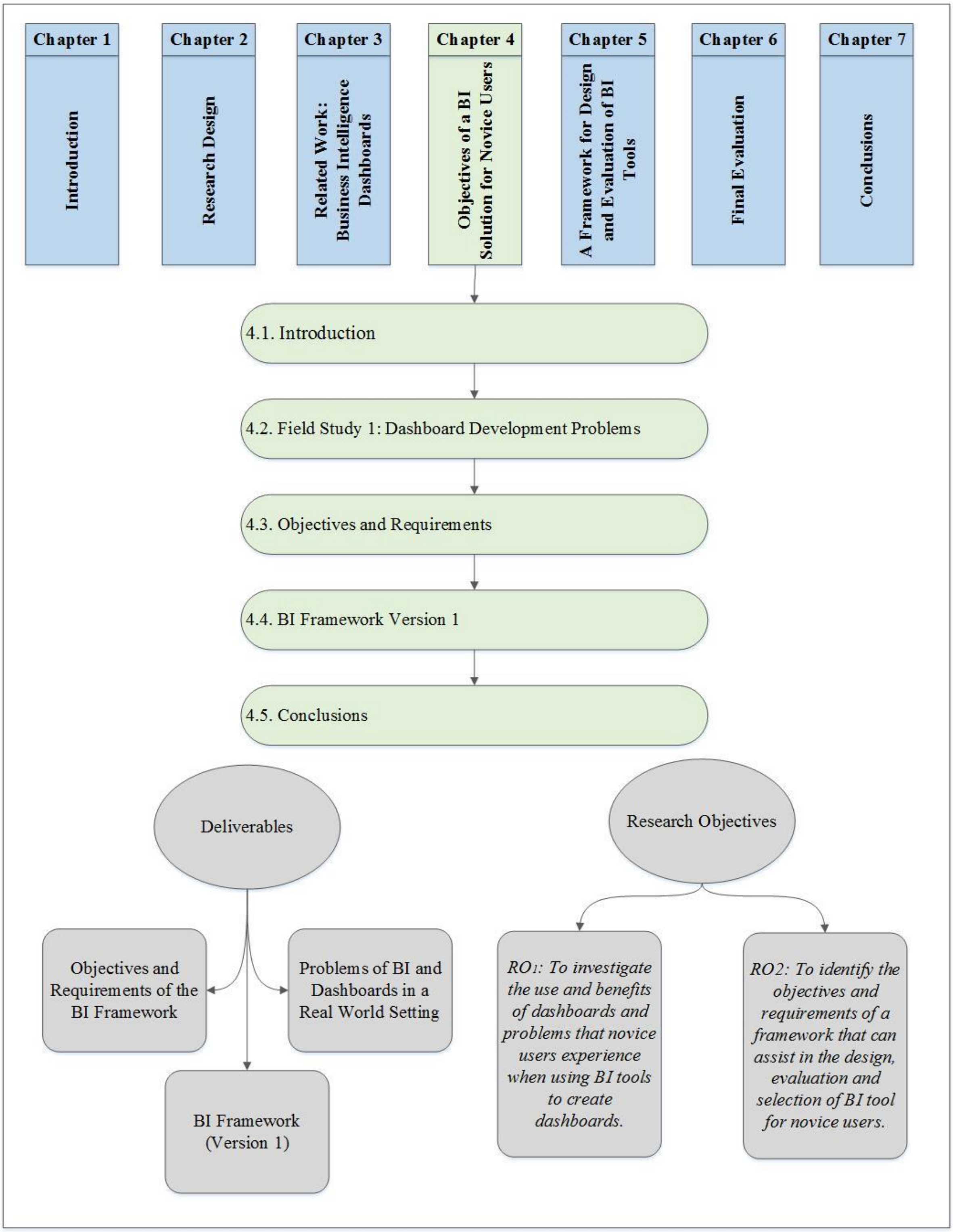


Figure 4-1: Chapter 4 layout

The objective of Field Study 1 was investigate how easily students could follow the development process and utilise the features of the software to develop a dashboard. Other goals were to determine the usability of the software, positive or negative features of software, and any other aspects for the elicitation of requirements. A number of steps and software tools are involved in the processes to create dashboards for the SYSPRO ERP system (Section 4.2.1). Before Field Study 1 could be conducted, the research approach had to be planned properly to ensure that the evaluation could be executed with minimal problems (Section 4.2.2). The participants that were selected for the field study were all third year IS undergraduates (Section 4.2.3). A number of research materials were used in the field study, which mainly consisted of task-lists and questionnaires (Section 4.2.4). The validity and reliability of questionnaires were confirmed by using pilot studies (Section 4.2.5) and the results of the field study were analysed (Section 4.2.6).

4.2.1 The SYSPRO Dashboard Development Process

The current dashboard creation process in SYSPRO requires the use of various disparate software tools that are not integrated. These software tools include the SYSPRO ERP system, Microsoft SQL Server Management Studio, Microsoft Excel and SAP SAP Xcelsius (Xcelsius). The problem in the current process is that users need to follow a strict step-by-step process to develop dashboards that require technical knowledge. Users find themselves working in disparate development environments where they need to switch from one software tool to the next. The various tools do not provide a single environment where students can simply interact with dashboards through intuitive visual objects and link underlying data in a single workspace. Instead, the distributed environment requires users to have thorough querying skills and knowledge of the tools involved.

The example used in this field study is to develop as dashboard displaying inventory information about a fictitious company, known as the Outdoors Company. The Outdoors Company database was obtained from SYSPRO as a training database for clients and was installed at the NMMU computer laboratories. A number of software tools are required to create a dashboard for the SYSPRO ERP system. The activities that are required to be performed in the process to create dashboards for the SYSPRO ERP system consist of five main activities. The five activities are categorised according to the different software tools involved in the process and are depicted in (Figure 4-2).

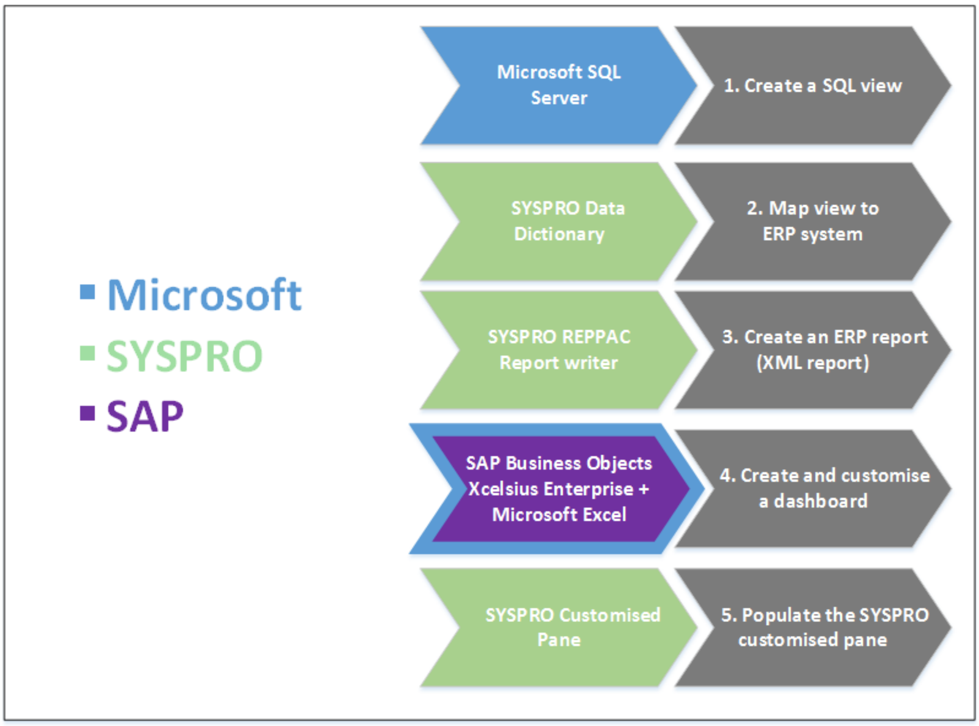


Figure 4-2: Activities and software tools required to create dashboards for the SYSPRO ERP system

Create a SQL view (using SQL Server): The Outdoors Company is training database was installed on a Database Management System (DBMS), known as Microsoft SQL Server Management Studio 2014 (or referred to SQL server). Dashboards are intended to only depict the information of interest to the end user. In order to select the most relevant information, a database view or SQL view needs to be created. A database view is a set of results from a stored database query. Users observe the data, selected in the view data as a virtual table, which is computed or ordered dynamically from existing database tables when access to that view is requested. Database views provide users with access to a particular set of data, which is optimised from other tables. Depending on the database administrator, a view is typically set to read-only. The first activity, therefore, requires the user to create a database view using SQL and saved into the database dictionary. This activity can be a time-consuming and difficult task for users who do not have experience with SQL or who are not familiar with the schema of a database.

Map view to ERP system (Using SYSPRO ERP system): This activity is not mutually exclusive from the next activity, *Create an ERP report*. The inventory data was selected in the DBMS using a SQL view. In order to obtain access to the data from the ERP system, a connection needs to be made. This connection is made by mapping the exact table and column names selected in the SQL view (in SQL server) to the SYSPRO Data Dictionary (in the SYSPRO ERP system). This is necessary as the SQL view is created to provide access to a specific set of data. Mapping the SQL view to the SYSPRO Data Dictionary is an important step, as a reporting service will be generated from the SYSPRO ERP system to retrieve the data from the DMBS. Special attention is required when entering the names of the columns and tables in the data dictionary as ordering and case sensitivity applies.

Create an ERP report: The SYSPRO REPPAC Report Writer is used to generate a report from the mapped view and data dictionary entry. The user has to select all the necessary columns that need to be displayed from the created, data dictionary entries. Once the columns are selected, a new report is created by using the report wizard. This activity is particularly important since the report needs to be exported to a local directory as an XML file, which contains all the data that was selected from the data dictionary.

Create and Customise a dashboard: SAP Xcelsius is used to create the visual structure of the dashboard. Upon importing the XML file into SAP Xcelsius, the file is converted to an Excel spreadsheet file where data and columns can be edited. For example, adding additional calculations, renaming columns, or changing data formats. One particular requirement is that the Developer tab needs to be activated within Excel before viewing the data in SAP Xcelsius. Once the data is visible in the spreadsheet, it can be manipulated and linked to the dashboard. The dashboard can be customised using a variety of functions such as alerts, filters and refresh functions. Once the dashboard is completed, it needs to be saved and exported into two different types of file formats, namely a SWF and XLF file. The SWF (small web format) file is an Adobe Flash file format used for multimedia, vector graphics and ActionScripts to enable varying degrees of interactivity and functions. XLF (XML Localisation Interchange File Format) is an XML-based format used as a standardised way of passing data between tools during a localisation process. These files need to be stored in a local directly where the SYSPRO ERP systems can easily access them.

Populate the SYSPRO Customised Pane: SYSPRO offers users the functionality to customise sections of the UI to view synthesised information they are interested in. These sections are known as customised panes, where dashboards, browsers and other forms of information can be accessed quickly. Customised panes also enable users to view relevant information at a glance and are intended to refresh the information regularly. Once the two separate dashboards files are saved in a local directory, the developed dashboard should be loaded into a customised pane. This information is typically standardised and defined according to the role of the user. The position of the dashboard is manipulated within the customised pane using a text file written in Visual Basic (VB). The text file is generally not generic and requires the developer to have a thorough background of VB. The file must be saved in the same local directory as the dashboard files.

4.2.2 Research Approach

The application of field studies and usability evaluations have been motivated as sufficient research methods to identify problems and elicit requirements in the field of BI and IV, especially when the focus is on users (Elias & Bezerianos 2011; Schröter 2015; Grammel et al. 2010a; Heer et al. 2008a). The evaluation was conducted with a group of 14 students from an ERP course and where scheduled during a usual practical session in the computer laboratories. The environment consisted of a typical computer laboratory with desktop PCs and the evaluation was facilitated by the main researcher and two student assistants.

Before the usability evaluation was initiated, informed consent was obtained from each participant. A brief summary of the study's goals and procedures was explained to each participant, and any questions were answered. Participants were also required to fill out a consent form affirming that they are participating voluntarily and can withdraw at any time without penalty. Each participant was provided with a unique participant number to ensure that anonymity was maintained throughout the evaluation. Once the consent forms were addressed, each participant was provided a printed task-list with instructions and was given three hours to complete the tasks. Participants were encouraged to take notes of any problems that were encountered at specific tasks.

Participants were allowed to seek the assistance from the facilitators when problems were encountered and student assistants were instructed to take note of such observations. For example, they had to record the number of the task where the problem was encountered, how the problem was solved, and whether a facilitator provided assistance. Recording whether a facilitator was asked for assistance was important, as various studies have identified that users cannot develop dashboards without the assistance of a human mediator (Grammel et al. 2010a; Elias & Bezerianos 2011). A post-test questionnaire was administered to participants to receive feedback about the usability of the software tools and development process. Upon completion of the tasks, participants were required to answer the post-test questionnaire and submit their task-lists to the facilitators.

4.2.3 Participant Selection

The participant sample was identified by using a non-probability sampling method, namely convenience sampling. In this sampling method, participants were selected because of their convenient accessibility and proximity to the researcher (Saunders et al. 2009). However, the participants must be representatives of the population of interest and are expected to serve the objectives of the research study (Saunders et al. 2009). In order to conduct Field Study 1, the evaluation was required to commence in a real setting where the participants are a representation of the actual users of the system under investigation. For this reason, the participants selected were registered students of the Enterprise Resource Planning third year module (WRER302) at NMMU in 2014. The participant sample consisted of 14 undergraduate students and were equally split between males (n=7) and females (n=7). None of the participants had prior experience of ERP systems outside of the registered module, meaning they have only been working with ERP system for less than one year. Only one participant (n=1) indicated that he had prior experience with dashboards using pre-defined templates, where the rest (n=13) indicated that they had no prior experience with dashboards. The majority of the participants were between the ages of 21-28 (Table 4-1).

Table 4-1: Demographic profile of selected participants

	Total sample size (n)	***Percentage (%)***
Gender		
Male	7	50
Female	7	50
Total	**14**	**100**
Age groups		
18 – 20 years	1	0.07
21-28 years	12	86
28 + years	1	0.07
Total	**14**	**100**
Prior experience		
External ERP experience	0	0
Experience with dashboards	1	0.07

4.2.4 Research Materials

Two research materials were used during the evaluations. The first research material was provided as a printed task-list (Section 4.2.4.1). The second research material was administered as an online, post-test questionnaire (Section 4.2.4.2).

4.2.4.1 Task-list

The first material consisted of a printed task-list document, which required the participants to perform the five main tasks as per the SYSPRO dashboard development process (Section 4.2.1). The goal of the task-list was to develop an executive dashboard displaying inventory information in a customised pane within the SYSPRO ERP system. The dashboard consisted of an inventory scorecard, which displayed data from a SYSPRO database with inventory levels, inventory values, and potential gross profit values (Figure 4-3). Each participant had to record the total task times (start and end times) on the printed document and take notes of any problems encountered (Appendix B). The time recordings were important to identify which task the participants spent the most time on. The recorded times for each task were captured by the researcher in a spreadsheet to calculate the mean times.

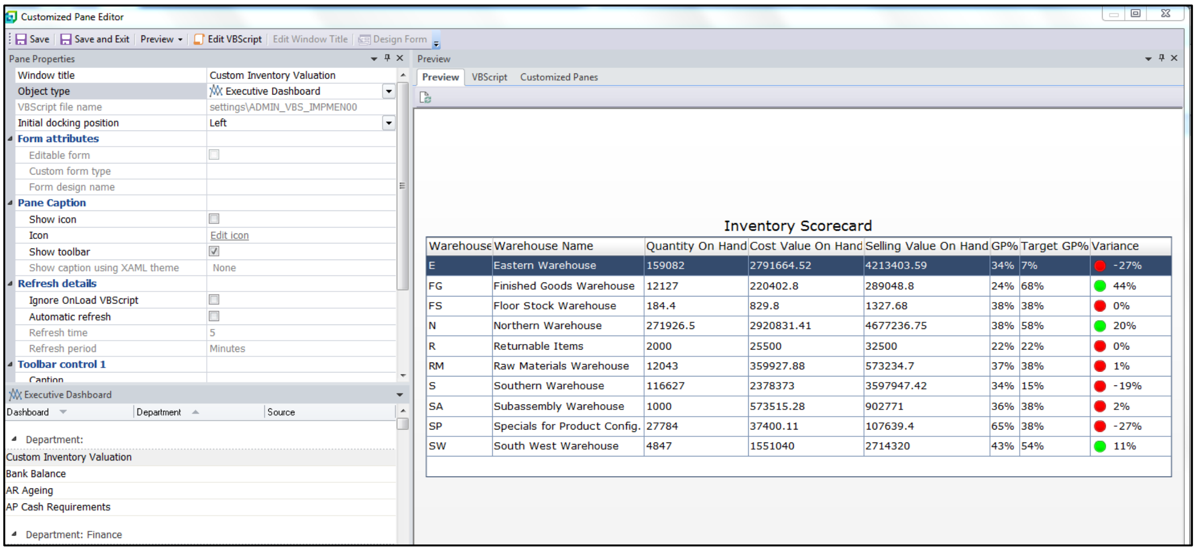


Figure 4-3: A screenshot of the final dashboard in SYSPRO

4.2.4.2 Post-test Questionnaire

Questionnaires were used as the second research materials as they are often combined with usability evaluations to collect more information regarding subjective opinions and reactions to the tested software and visualisations (Lam et al. 2012). The post-test questionnaire consisted of three main sections (Appendix C) out of five sections in total. The structure of the questionnaire is depicted in Figure 4-4. Although the questionnaire was administered to collect both qualitative and quantitative data, the focus was to analyse the subjective feedback and observations qualitatively rather than quantitatively to explore the problem in more detail.

The first section, Section A, included questions regarding demographic information such as gender, age, and experience with ERP systems and dashboards. The second section, Section B, evaluated the cognitive load of participants and was adapted from a separate post-test questionnaire namely, the National Aeronautics and Space Administration Task Load Index scale (NASA-TLX). The third section, Section C, related to user satisfaction and was adapted from the Computer System Usability Questionnaire (CSUQ). The fourth, and final, section involved two open-ended questions regarding the positive and negative aspects software tools and the development process. The fourth, and final, Section D of the questionnaires included consent forms that were designed using an online survey tool known as Google Forms.

Measuring cognitive load during a usability evaluation is important, since difficult tasks are likely to increase cognitive load and may cause users to forget some of steps required to create dashboards (Toker et al. 2013). As participants develop dashboards and other visualisations, they typically form their own mental models which in turn also increases their cognitive load (Liu et al. 2014). For this reason, it is important to identify how strenuous the process is to develop dashboards on a participant's cognitive load. Several questions were adapted from the NASA-TLX post-test questionnaire, which was first developed by Hart and Staveland (1988) and later revised by Hart (2006). The NASA-TLX measures factors that impact cognitive workload with three subscales: task-related, behavioural-related, and subject-related scales.

The task related subscale measures were factors surrounding the participant's mental demand (MD), physical demand (PD) and temporal demand (TD). Behavioural-related aspects refer to subscales measuring perceived level of effort (EF) and personal performance (PP). The subject-related subscale measures the perceived level of frustration (FR) during the evaluation (Hart 2006). The participants are required to rate each of these factors based on a five-point Likert scale (1= *strongly disagree* and 5 = s*trongly agree*). The overall workload score is calculated based on a weighted average of each subscale and presented as an overall score out of 100.

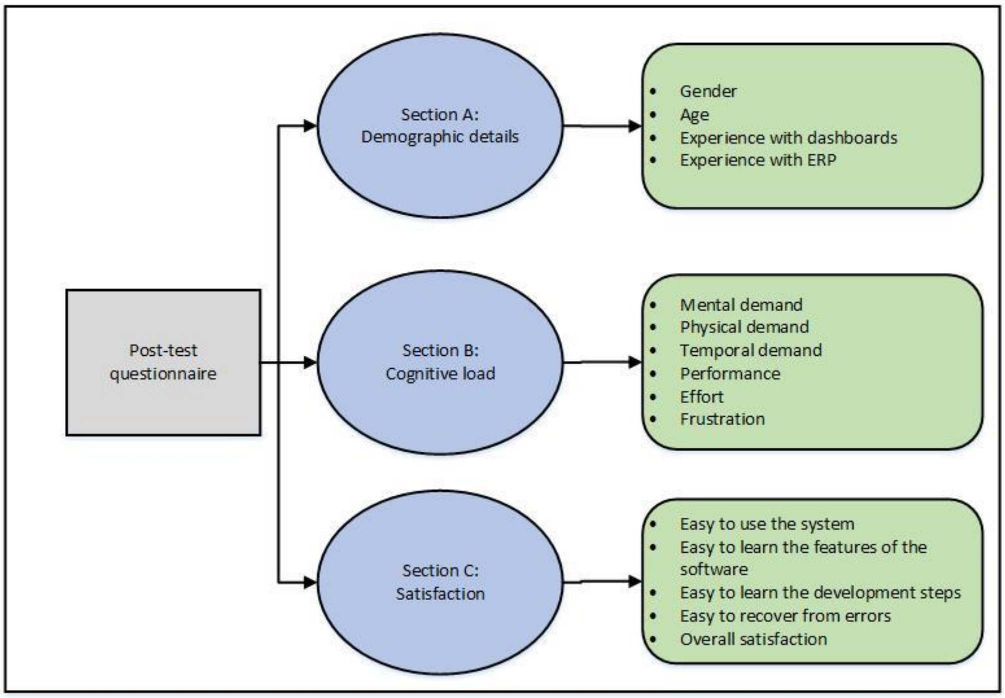


Figure 4-4: Structure of the post-test questionnaire for Field Study 1

Although the factors had to be weighted during the computation of the overall workload score, there is no clear instruction on which factors require specific weightings. This is due to the fact that each process or system requires activities of a different nature and could cause each factor to contribute differently towards the overall workload. According to Hart (2006) the factors representing more important contributions to the overall workload require a greater weighting and can be tailored towards individual workload definitions. For the purposes of this study each of the subscales was weighted equally.

Satisfaction is an important measurement of usability, as users will not utilise a tool if they are not satisfied with the way it operates. The questions relating to the overall satisfaction were adapted from the CSUQ, which was firstly introduced by Lewis (1995). The questions used in the CSUQ were developed to evaluate the psychometric properties for usability in scenario-based computer system evaluations. The CSUQ offers 19 unique questions in total. Only five questions were used and reported in the questionnaire for two reasons. The first reason was that the focus of the field study was to explore the problems of the development process and to receive qualitative feedback from users in open-ended questions and on the notes made on the task list. The second reason was due to time constraints on participants. The questions used from the CSUQ are worded positively and evaluated four broad criteria: *ease of use*, *learnability*, *overall satisfaction*, and *information quality*. The participants were required to rate each of these criteria on a five-point Likert scale (1= *strongly disagree* and 5 = *strongly agree*).

4.2.5 Validity and Reliability of Field Study Research Materials

Face validity ensures that the instructions, questions, scales and criteria accurately reflect what it is intended to measure by those participants under examination (Saunders et al. 2009). Participants need to perceive the relevance of the questions being asked in the questionnaire and be able to map them to the purpose of the study. Face validity was established for questions as they were adapted from literature sources. The questionnaire was refined and validated during consultations with experts to ensure that questions appear transparent and relevant. Additionally, pilot tests were conducted with three experts to ensure that the task-list and questionnaire were unambiguous.

Content validity refers to the extent to which the questionnaire provides adequate coverage of a study's objectives and research questions (Saunders et al. 2009). Content validity was achieved as criteria were derived from similar studies in the field of BI and IV. Once again, content validity was confirmed during consultations with experts to ensure that the questions and criteria are aligned with the objectives of the study.

4.2.6 Results [1]

The task-list was successfully completed by all 14 participants. The mean time to complete the task-list was confirmed at 121 minutes, with the quickest time being 82 minutes and the slowest time being 143 minutes. The mean times were acceptable as compared to the expert's task time in the pilot studies. The mean for each closed-ended Likert-scale item in the NASA-TLX and CSUQ sections was classified according to the following ranges:

- *Strongly disagree* [$1.0 \geq \mu < 1.8$);
- *Disagree* [$1.8 \geq \mu < 2.6$);
- *Neutral* [$2.6 \geq \mu \leq 3.4$);
- *Agree* [$3.4 > \mu \leq 4.2$); and
- *Strongly agree* [$4.2 > \mu \leq 5.0$).

[1] The paper "Usability Guidelines for Designing Information Visualisation Tools for Novice Users" was accepted and published in the proceedings of the IDIA 2015 Conference based on this section of the study (Appendix D).

Since the NASA-TLX measures workload, higher scores for factors represent a *negative* rating. For this reason, the ranges for the NASA-TLX Likert-scale items could be further categorised into *positive* ($1.0 \geq \mu < 2.4$), *neutral* ($2.4 \geq \mu < 3.6$), and *negative* ($3.6 \geq \mu \leq 5$) ranges. The participants *agreed* that the development process was mentally challenging (μ=4.07) and required a great deal of effort (μ=4.00) to complete (Figure 4-5). Participants were, however, *neutral* regarding the physical (μ=2.79) and temporal (μ=2.86) demand required to complete the tasks. Although all participants completed the tasks successfully, they perceived their performance with the system to be *neutral* (μ=2.43) and *agreed* that they experienced high-levels of frustration (μ=3.50).

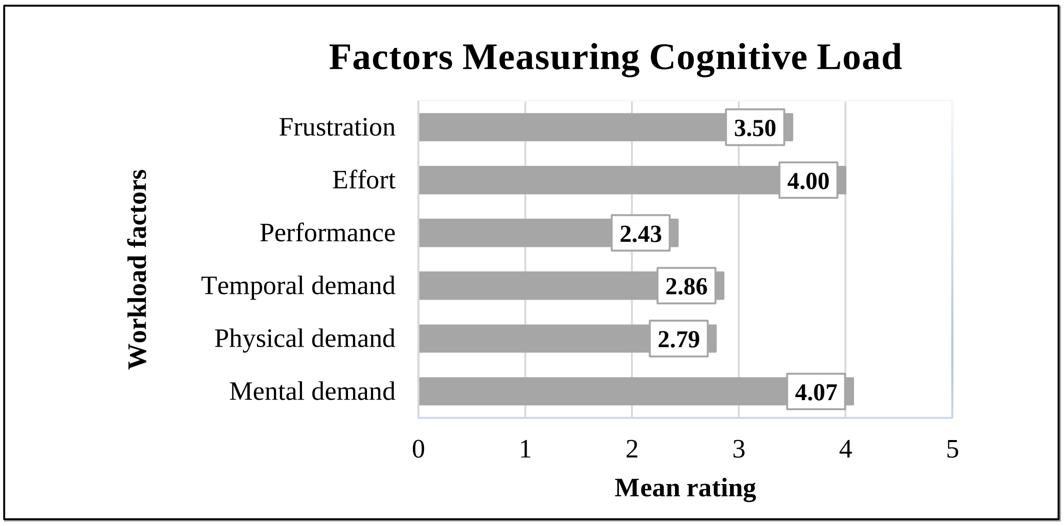


Figure 4-5: Cognitive load factors using a five-point Likert scale (n=14)

The CSUQ Likert-scale items was categorised into *negative* ($1.0 \geq \mu < 2.4$), *neutral* ($2.4 \geq \mu < 3.6$), and *positive* ($3.6 \geq \mu \leq 5$) ranges. The analysis of the CSUQ section revealed that *overall satisfaction* was the criterion that had the highest mean rating and was rated in the *neutral* range (μ=2.86*)*. None of the criteria received a rating in the *positive* range. The criterion with the lowest mean was information quality and was rated *negatively* (μ=1.43). Participants may not have received sufficient assistance from the system when they encountered a problem. Participants further *disagreed* that the software was easy to use (μ=2.43), easy to learn the various development steps (μ=2.50), and easy to learn the different software components (μ=2.57). One reason for this result is that the participants encountered usability problems, which were supported by the irregular ratings of frustration, effort and mental demand (Figure 4-5). Another reason may be that participants struggled to understand how software components integrate and interconnect. Moreover, the reason for the result may be that participants are not knowledgeable of the process and software tools that support dashboard development. Participants were not satisfied with the amount of time they took to complete the task-list (μ=2.36). For this reason, participants regarded the process to be inefficient and stated that the process to develop a single dashboard with only one visualisation takes too long.

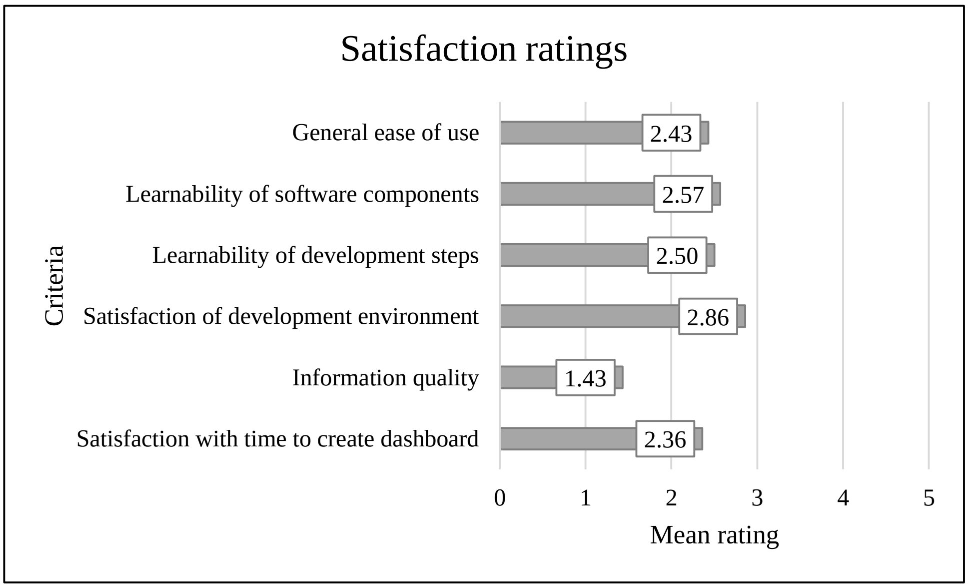


Figure 4-6: Satisfaction criteria adapted from CSUQ

Qualitative data was collected and analysed from the open-ended questions and task-list notes. Since Field Study 1 forms part of *Problem Identification and Motivation* (Activity 1), the qualitative data was coded or categorised into problem themes. Creswell (2013) describes an analysis procedure for qualitative research (Figure 4-7), which will be followed throughout this study to effectively identify themes:

Step 1: Organising and preparing data for analysis. The data will be captured from web-based questionnaires. Captured data will be exported to a spreadsheet and responses will be in column form for each respondent.

Step 2: Review all the captured data to gain a general understanding of the information and to reflect on the overall meaning.

Step 3: Analysis must be conducted on a specific theoretical approach and method. The use of a coding process assists in organising data into different categories. The coding process can be conducted by hand or by the use of software.

Step 4: Themes or descriptions must be generated from the categories. Themes act as the descriptions of people or settings in which the study is performed. The themes will represent the results from the questionnaires.

Step 5: Report on the analysed data in an appropriate manner. This can be done by presenting data in a narrative manner to convey the findings of analysis. The discussion can include a chronology of events, details of individual themes, or a discussion with interconnecting themes.

Step 6: Draw conclusions or lessons learnt from the data and themes to provide more meaning to the information. The interpretation of results can be compared to existing literature or theories to refute or confirm findings. Interpolation can also be done to enhance personal understanding.

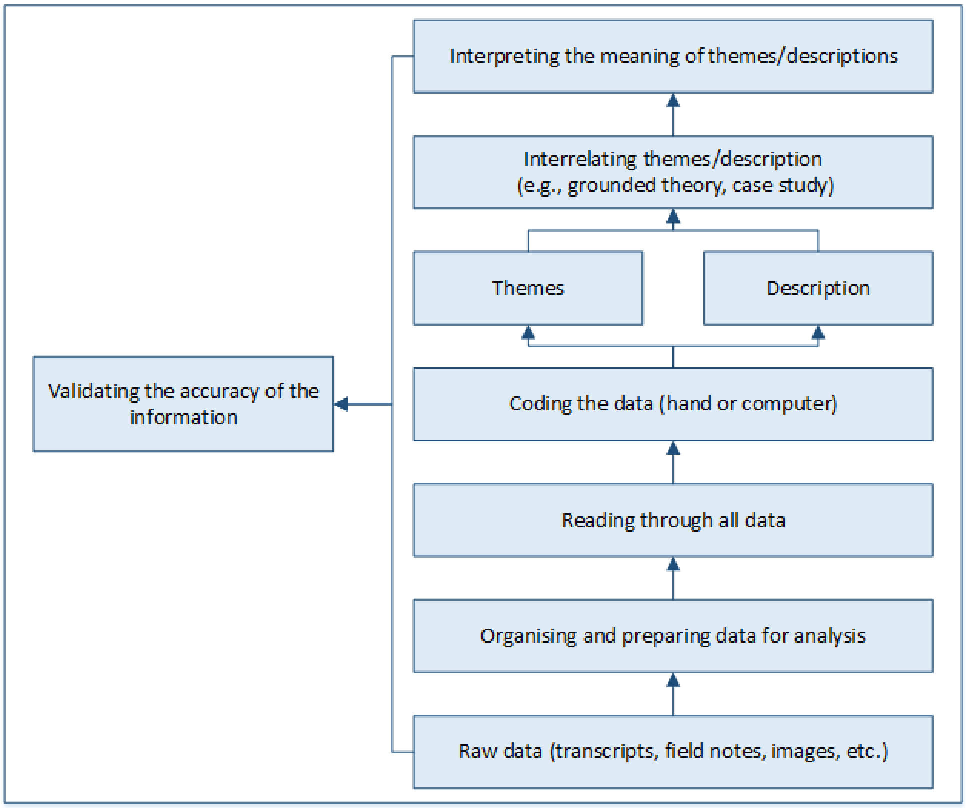


Figure 4-7: Data analysis procedure for qualitative data [Source: Creswell (2013)]

Thematic analysis was used to present the findings and was complemented by frequency counts from both the task-list notes and the open-ended questions from the questionnaire and (Table 4-2). The themes identified for Field Study 1 were not priori themes. Although some problems related to the UI of the SYSPRO ERP system and the Xcelsius BI tool, the focus was to identify problems relating to the overall development environment and dashboard creation process. The highest frequency (*f*) of responses for the open-ended question related to the *information quality* theme (P1). The menu and navigation items were difficult to identify in SYSPRO and Xcelsius, and participants criticised the minimal feedback that these software provided. Some participants mentioned that the software had minimal *assistance or help* (P2) features to easily recover from errors or guide them through the development steps. As a result, many participants had to seek the guidance of facilitators to explain steps and instructions. Some of the negative comments cited in the open-ended questions by participants were: "*no guidance for in-between steps; it's like assuming we know what to do*" and "*menus aren't easy to find*". Two participants also mentioned that they would not have been able to complete the task-list without assistance from the facilitators.

The number of development steps was thought to be too excessive and difficult to learn to create a single dashboard, which made it difficult to keep track of the particular activity they were busy with. The excessive amount of *development steps and the distributed development environment* (P3) make it difficult for users to create dashboards. Some of the comments from participants were that "*the process for creating a dashboard is difficult*", "*was not able to follow a logical sequence*", and "*there are too many steps are involved in the process*". Others stated that the system was not designed with the user in mind and complained about the *complexity of the software* (P4). Some negative comments regarding the development environment were "*the system is not designed with the user in mind*", "*for beginners, this was not well detailed*", and "*too many tools are needed to perform this process*".

A *lack of flexibility* (P5) was experienced by the participants. One comment was "*there are no shortcuts*". The lack of *flexibility* contributed to problems surrounding *data selection* (P6) and *dashboard customisation and visual output* (P7). Since the data attributes needed to be selected by using a query in SQL server and then needed to be mapped manually in the SYSPRO data dictionary, many mistakes were made regarding the syntax and spelling of column names. This resulted in many participants re-doing tasks, as participants were unsure as to where exactly they made a mistake or encountered an error. One participant mentioned that "*it helped me when I saw a picture; I knew what I was doing was correct*".

The final problem theme that was identified, related to the *lack of knowledge* (P8) about the software tools and programming languages such as VB, SQL and XML. Although some students were comfortable using these languages and different software, some students mentioned that they did not have enough experience and did not completely understand the role of the software in the process, nor the programming code. The positive feedback was minimal and some of the comments were "*the formatting features were useful*" and "*interesting to see the interaction between different software packages*".

Table 4-2: Problems identified from Field Study 1

			Open-ended questions	**Task-list notes**
Problem number	**Problem theme**	**Description**	**Frequency (*f*)**	**Frequency (*f*)**
P1	Information quality	• Minimum feedback on successes or errors. • Navigation and menus are not well structured. • No guide for to assist in the development steps.	8	7
P2	Assistance/ help	• Required assistance from a human mediator. • Insufficient help functions.	5	2
P3	Development steps and distributed environment	• Too many steps required for each tool. • Steps are difficult to learn and to remember. • Steps are time consuming.	6	2
P4	Complexity of software	• Too many software tools. • Difficult to understand and learn. • Lack of knowledge of software tools.	6	3
P5	Lack of flexibility	• Lack of undo functions. • Cannot change the data attributes easily. • Cannot change visualisations.	5	4
P6	Data selection	• Querying and mapping of the data is a difficult task since it requires a series of steps across various tools.	4	9
P7	Dashboard customisation and visual output	• Mapping data to a visualisation is difficult. • Needs immediate display of data in selected visualisation. • Exporting dashboards into other software is difficult and tedious.	3	9
P8	Lack of knowledge	• Lack of knowledge of software tools. • Also a lack of SQL and VB languages. • Lack of visualisation types and measures.	4	2

The problem themes identified in Field Study 1 confirmed some the findings in similar studies. The findings of Field Study 1 were consistent those of Elias and Bezerianos (2011), who identified that novice users often rely on human mediators, such as experts, to assist in creating dashboards (P2). Facilitators were often requested to assist participants with some tasks during the field study. The results also confirmed the findings of Pantazos et al. (2013), which showed that participants struggled to follow various steps in the development process when using a distributed environment (P3). Using a distributed environment is often technical and users do not have the knowledge and programming skills to develop dashboards, which increases the level of task complexity (P4) and reduces the level of *flexibility* (P5). The results were also consistent with the findings of Grammel et al. (2010a) and Pantazos et al. (2013), where participants faced major barriers when selecting data attributes (P6) and struggled to map the data to visualisations (P7). This problem supports the need for an integrated development environment that provides immediate viewing of the changes in dashboards. Eliminating the need for programming and providing interactive visual objects can improve the problem of users who often struggle to understand the semantic gap that exists between the written code and the visual outcome of the dashboard.

4.3 Objectives and Requirements

Many problems have been identified from literature regarding BI tools (Table 3-2) and dashboards (Section 3.6.4). Field Study 1 highlighted several usability problems relating to BI dashboard tools in a real setting at the NMMU (Table 4-2). These problems can be used to develop objectives and requirements for a BI solution. Additionally, a number of objectives and requirements could be identified from the features recommended for BI tools focusing on dashboards from literature (Section 3.6.3). Identifying these objectives and requirements for a BI tool can become very specific in nature and may be used to satisfy the need of a particular situation, as indicated at the NMMU. By producing a software tool as an artefact, the focus falls on specific objectives and requirements that suit the specific need of students to create dashboards. However, such an approach is necessary, but may limit the level of maturity (generated knowledge) for the contributed artefact (Table 2-1). The primary contribution of this study is a BI Framework. Producing a theoretical BI Framework will allow this study to contribute artefacts on Level 1 and Level 2 maturity levels. For this reason, the objectives of solution need to be considered in terms of the theoretical framework serving as an artefact on the Level 2 maturity level (Section 4.3.1). The BI Framework will be implemented in this study to identify a BI tool for users at the NMMU, which serves an artefact at the Level 1 maturity level. Therefore, the objectives and requirements of BI tool that suits the specific needs of novice users also need to be considered (Section 4.3.2).

4.3.1 Objectives and Requirements of a BI Framework (Theoretical Artefact)

A number of research outputs have been proposed to guide the evaluation and adoption of a BI tool or solution (Muriithi & Kotzé 2013; Mungree & Morien 2013; Antoniadis et al. 2015; Mcbride 2014; Dawson & Van Belle 2013; Ghazanfari et al. 2011). However, most of the research focuses on the benefits, critical success factors (CSFs), organisational fit and technical viability of the BI tool as motivation, without focussing on the usability aspects of a BI tool. Ghazanfari et al. (2011) and Muriithi and Kotzé (2013) agree that a BI tool needs to be evaluated and considered in terms of the role they would play in the organisation. However, in order to evaluate BI tools, models and approaches need to be developed that consider specific BI criteria, as well as traditional functional and non-functional requirements (Ghazanfari et al. 2011). According to Muriithi and Kotzé (2013) the adoption process of BI is often considered difficult as organisations have minimal guidance for the procurement, installation, configuration and general training on the operability of BI tools. These difficulties can be overcome by proposing a framework to guide organisations in selecting and evaluating an appropriate BI tool (Muriithi & Kotzé 2013).

The BI Framework proposed by Muriithi and Kotzé (2013) consists of three main components with the focus on evaluating and selecting a cloud BI tool. However, the three components can be applied to this study when proposing a theoretical framework for evaluating and adopting a BI tool for users. The three components of the framework are:

- Situational Analysis;
- Suitability Assessment; and
- Implementation.

Situational Analysis: The current situation within the organisation is analysed and opportunities for BI are identified. In this phase, the organisation considers the tasks and associated requirements of users, as well as the current IT infrastructure and how potentially new BI tools could improve tasks or provide improved services to users. The BI tools can be considered from any layer in the general BI architecture (Section 3.4.2), which includes the data layers (ETL, data warehouse or data marts) and the front-end layers (reporting tool, OLAP, or data mining tool). Although the focus of this study falls on BI tools in the front-end layers, the framework still needs to consider that the selected BI tools needs to be compatible with the current IT infrastructure of the organisation.

Suitability Assessment: The opportunities identified in the previous phase need to be considered in more detail to identify potential BI tools. Despite the requirements and objectives of BI tools that are gathered from users, BI tools are subject to a range of evaluation factors such as the potential business value, technical viability, risk exposure and organisational impact. Business value relates to the benefits that can be realised, such as improved service delivery or communication. Technical viability relates to the BI tool's ability to handle large volumes of data and achieve an acceptable performance in terms of response times, security, and allowable latency. Risk exposure is concerned with issues such as vendor lock-in, vendor support, and compliance violations. Organisational impact differs from business value in the sense that the implementation of the BI tool could alter the organisation's culture. Organisational impact is concerned with the effect of the BI tool on the jobs and tasks of employees and other stakeholders. Once these factors are taken into consideration, the organisation must determine which of the prospective BI tools have the capability to best meet the technical, operational and trust requirements of users. The outcome of this phase is essentially to select the best alternatives out of a range of choices against a set of criteria. Evaluation should be based on a multi-criterion analysis as many factors influence the final decision of the BI tool (Muriithi & Kotzé 2013).

Implementation: The BI tools that satisfy the Suitability Assessment must be evaluated so as to determine how well they meet the needs of the users. The Implementation components is typically accompanied by a set of evaluation phases so as to determine whether the core features of the BI tool work properly in the underlying IT infrastructure and whether the tool satisfies the needs of users. The usability of the BI tool should therefore be evaluated with actual users and its conformity to requirements needs to be measured.

The BI Framework proposed in this study will follow a similar structure to the three components recommended by Muriithi and Kotzé (2013). This structure was used to identify the high-level objectives of the BI Framework to evaluate and adopt a BI dashboard tool for users. The high-level objectives of the BI Framework are to:

- Consider the potential risks, benefits and challenges that a BI tool may have an organisation;
- Consider the current IT infrastructure and technical viability of BI tools;
- Provide guidance for analysing users' non-functional and functional requirements by considering their experience and educational backgrounds regarding BI, IV, and general computer use;
- Provide design guidelines for a BI tool supporting dashboards;
- Provide a scorecard that can be used as criteria to evaluate the features of a BI tool;
- Provide usability criteria and allow the BI tool(s) to be iteratively evaluated ; and
- Determine suitability of a BI tool.

4.3.2 Objectives and Requirements of a BI Tool

Several high-level objectives and requirements for a BI tool were identified from Field Study 1, as well as from the problems and recommendations identified in literature. The high-level objectives are:

- The software must provide an integrated environment to facilitate the entire process to create dashboards or similar visualisations (select data, map data to dashboard or visualisation, and apply different views);
- The software must support a guide that allows users to systematically develop dashboards;
- The software must reduce programming to a minimum and automate the majority of tasks; and
- Encourage learning through interactive exploration and explanation.

The initial functional requirements are listed in Table 4-3. The BI tool must provide an integrated development environment for selecting, manipulating and visualising data. An integrated environment should reduce the learning curve of learning different software tools. Immediate visual feedback should be provided when a user selects new data attribute or changes the visualisation type. Providing immediate visual feedback may enhance understanding of what a feature does, where the user is in the creation process, and allows the user to view changes in the visualisation's appearance. The software should have the ability to connect to various data sources, manipulate the data by using built-in calculations, and display the most current information.

Table 4-3: Functional and non-functional requirements of a BI tool

Number	Requirement	Literature	Field Study 1
Functional Requirements			
R1	The software must support immediate visual feedback.	✔	✔
R2	The software must be able to connect to a data source from an integrated development environment.		✔
R3	The software must allow for selecting multiple data attributes and visualisations in an interactive manner.	✔	✔
R4	The software must support sufficient features to easily recover to a previous state.	✔	✔
R5	The software must have built-in features to support data manipulation and calculations.	✔	
R6	The software must provide pre-defined, but flexible settings that automate the creation and customisation of visualisations.	✔	✔
R7	Guides and help should be provided to connect to data sources, select attributes, create visualisations and apply formatting changes.	✔	✔
Non-functional Requirements			
R9	The tool must be effective to use for creating dashboards.	✔	✔
R10	The tool must be efficient to use to create dashboards in a reasonable time.	✔	✔
R11	The tool must be flexible to change any aspects of the dashboard and to recover from errors.	✔	✔
R12	The tool must be helpful to users.	✔	✔
R13	The tool must assist users in learning its features.	✔	
R14	The tool must satisfy the users' dashboard and analysis needs.	✔	✔
R15	The tool must be highly operable to apply a variety of data analysis tasks.	✔	

In addition to functional requirements, several non-functional requirements have been identified. The tool should also be effective in the sense that users can create dashboards that answer the questions they have regarding their data. The user must be able to create dashboards efficiently and in a reasonable amount of time. The software should also encourage learning, not only of its features, but also provide assistance in learning data analysis concepts. The tool should be helpful in terms recovering from error and also guide the user in performing the tasks required in the dashboard creation process. Moreover, *flexibility* is required to restore to a previous state or to make changes to any aspect of the data or dashboard quickly. Furthermore, the tool must be highly operable so that its features are easy to use.

4.4 BI Framework Version 1

The BI Framework proposed in this study is similar to the structure proposed by Muriithi and Kotzé (2013) consisting of three main components. In addition to the three components, the objectives and requirements of a BI Framework were identified (Section 4.3.1). The first component, Situational Analysis, involves the assessment of any opportunities in the current organisation regarding BI tools (Figure 4-8). Opportunities may arise from any problems that users experience with current BI tools or IT infrastructure that hinder the effective creation of dashboards. Since the focus of the BI Framework is to select and evaluate BI tools for novice users, the experience and skills of users are also analysed to determine the level of complexity they can handle. Once these issues have been considered, objectives and requirements can be formulated for a BI tool to support in creation of dashboards.

The second component, Suitability Assessment, helps to identify BI tools that satisfy the needs of the organisation and its users. The opportunities identified in the previous component, Situational Analysis, need to map to evaluation factors such as potential business value, risk exposure and organisational impact. Moreover, the identified opportunities and requirements need to be considered in terms of technical viability to determine whether the organisation's IT infrastructure is compatible with the requested BI tool. Once these factors are approved, specific design guidelines for BI tools need to be established that meet the technical, operational and trust requirements of users. The design guidelines must be accompanied by a sub-set of features that are necessary for users to create and interact with dashboards. Potential BI tools need to be identified, evaluated and selected based on a BI Scorecard. The BI Scorecard can be derived from the design guidelines and its associated features, which should be used to rate the features of BI tools.

The third component, Implementation, is concerned with implementing the BI tool incrementally. This will allow organisations to test the BI tool's compatibility with the existing infrastructure. Users need to evaluate the BI tool for usability so as to determine whether the tool is easy to use and satisfied their needs. Evaluating the BI tool incrementally may also enable organisations to determine the features that users are most likely to struggle with. Depending on the outcome of the evaluations, the BI tool may either be adopted or alternative tools may be implemented and evaluated until a satisfactory solution is achieved.

The BI Framework is the primary artefact produced in this study and will be incrementally developed. For this reason, the components of the BI Framework will be used to select and evaluate BI tools in a real setting (case study) in order to validate the framework and to iteratively improve the framework based on the evaluation results and feedback.

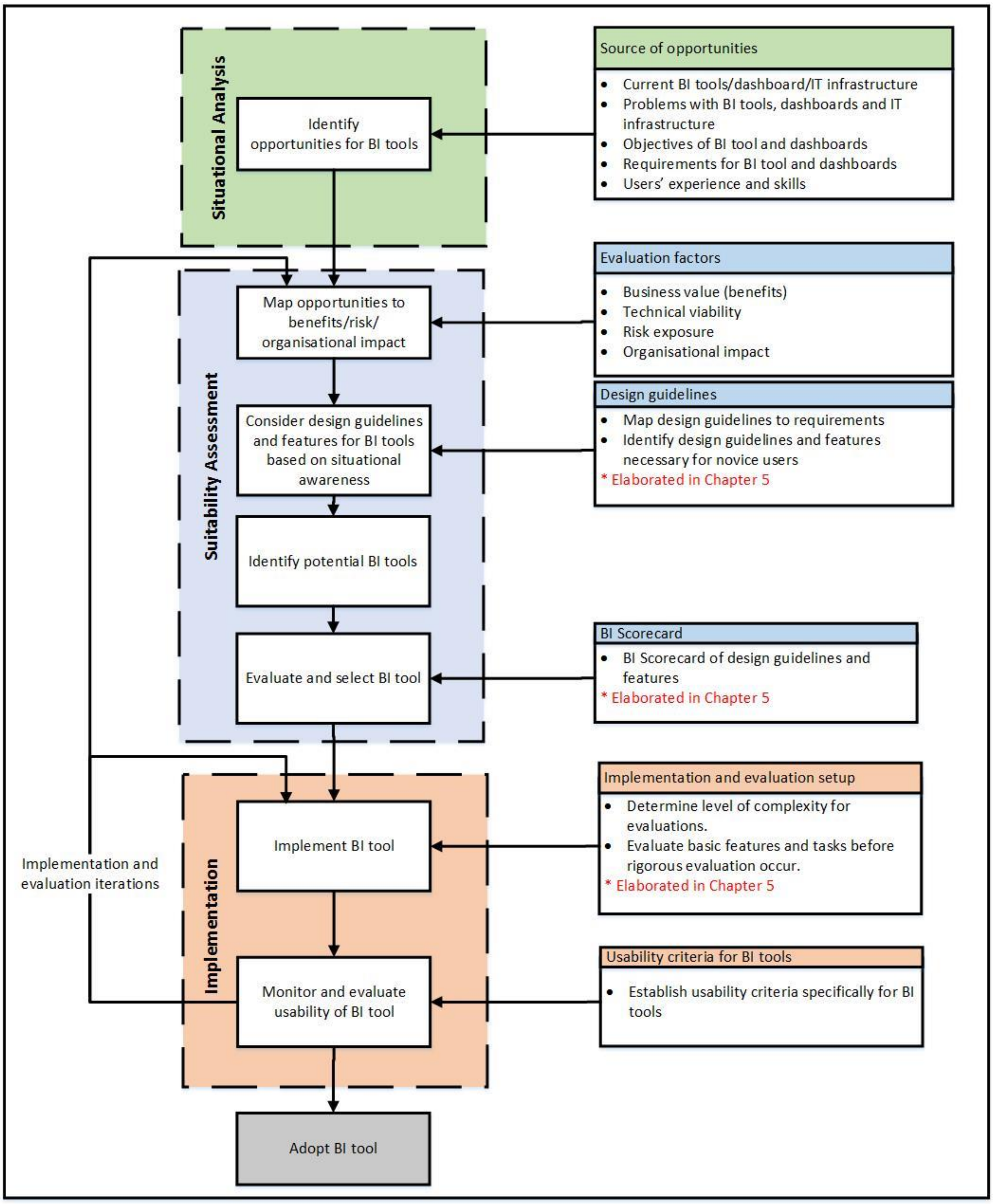


Figure 4-8: Proposed BI Framework for novice users (Version 1)

4.5 Conclusions

The chapter discussed a field study that was conducted as an in-depth problem investigation and was a continuation of the first DSR activity (*Problem Identification and Motivation*). The second DSR activity was reported on in this chapter (*Define Objectives of a Solution*). The problems that users experience during the creation of dashboards were identified and problem themes were documented. The most frequent, identified, problems related to *data selection*, *information quality, flexibility*. Other problems related to a difficult creation process where participants could not view the immediate visual effect of their actions. The identification of problem categories therefore answers the first research (RQ_1): "*What are the problems that novice users experience when using BI tools to create dashboards?*" and satisfied the first research objective (*RO_1*) *"To investigate the use and the benefits of dashboards and problems that novice users experience when using BI tools to create dashboards*".

The primary contribution of this study is the BI Framework, which serves as a solution to the problem. The findings from literature were combined with the field study results to derive an initial set of high-level objectives for a BI Framework. The BI Framework also includes the identification of functional and non-functional requirements for a BI tool. The high-level objectives relate to a single, guided environment where the majority of the tasks are automated and allow users to easily select and transform data, recover to a previous state when an error is made, and apply a wide range of pre-defined settings to customise the appearance of their dashboards. By defining the objectives and requirements, the second research question (RQ_2) was answered "*What are the objectives and requirements of a framework that can guide the design, evaluation and selection of BI tools for novice users?".*

The next chapter will continue to focus on the design, development and evaluation of the BI Framework by considering the objectives and requirements identified in this chapter (Section 4.3). Chapter 5 will also identify design guidelines that can be expanded into the BI Scorecard to evaluate the features of BI tools. The BI Scorecard will be used in an extent systems analysis by the researcher to select BI tools that satisfy the design guidelines. The selected tools will be used in further evaluations where usability criteria will be identified for BI tools. The design guidelines and features will also be verified by means of a second field study (Field Study 2) with one of the selected BI tools.

Chapter 5. A Framework for the Design and Evaluation of BI Tools

5.1 Introduction

The first cycle in the DSR methodology, Relevance Cycle, was reported on in the previous two chapters. The high-level objectives of a BI Framework were defined (Section 4.3.1) and an initial version was proposed that consists of three main components (Section 4.4). One of the framework's objectives is to determine the requirements of users for a BI tool. Field Study 1 was conducted with users and several problem categories associated with dashboard creation were identified (Table 4-2). The results revealed that users experience a number of usability problems when creating dashboards, especially with regard to integrating different software tools and following a development process. The results from the field study were compared with literature and were used to define a number of high-level objectives and requirements for a BI tool that can assist users in dashboard creation (Section 4.3).

The second cycle in the DSR methodology, the Design Cycle, is reported on in this chapter. The Design Cycle allows for multiple iterations of designing and building an artefact. The Design Cycle also allows for evaluating the artefact to receive feedback and refine the artefact. The next activity in the DSR process, namely *Design and Development,* is reported on in this chapter where the main objectives of the BI Framework are addressed and evaluated. This chapter also involves the demonstration of the BI Framework by using an extant systems analysis and a second field study (Field Study 2).

The extant systems analysis is used to demonstrate how the BI Framework assists in evaluating and selecting BI tools. Field Study 2 involves a usability evaluation on a BI tool selected from the BI Framework, where participants are required to complete a task-list and a post-test questionnaire to rate the usability of the tool. Therefore, the fourth and fifth DSR activities are initiated, namely *Demonstration* and *Evaluation*, respectively.

The first component of the BI Framework, Situational Analysis, was discussed in detail in the previous chapter (Section 4.4). This chapter continues to design and develop the second and third component of the framework, Suitability Assessment and Implementation, respectively. A set of 11 design guidelines are proposed for BI tools that may alleviate the identified problems and satisfy the high-level objectives and requirements of a BI tool (Section 5.2). Each of the design guidelines are accompanied by a set of features that can expanded in the BI Scorecard. The BI Scorecard is used as criteria to evaluate the features of a BI tool and to derive at an overall score for each tool's conformity to the design guidelines. A number of popular BI tools are selected from the Suitability Assessment component of the BI Framework and are evaluated in an extant systems analysis using the BI Scorecard (Section 5.3). The extant systems analysis was informally conducted by the researcher where two BI tools were selected for further evaluations.

Usability criteria had to be considered to evaluate the selected BI tools with actual users in a real setting (Section 5.4). Additionally, the design guidelines had to be verified as suitable criteria to select and evaluate BI tools. For this reason an evaluation plan was documented to evaluate the selected BI tools (Section 5.5). Field Study 2 was conducted as a usability evaluation with one of the selected BI tools, namely PowerPivot (Section 5.6). The structure of the chapter is depicted in Figure 5-1.

The main purpose of Field Study 2 is to serve as a demonstration and an initial evaluation of the BI Framework and its components, as required by the fourth and fifth DSR activities (*Demonstration* and *Evaluation*). The objective of Field Study 2 was also to receive feedback from users and to verify the proposed design guidelines. The results were analysed and taken into consideration for improving the BI Framework (Section 5.7) and final conclusions could be made to complete the chapter (Section 5.8). The chapter therefore answers the following three research questions:

> ***RQ3:*** *"What are the design guidelines and features of BI tools for novice users?"*
>
> ***RQ4:*** *"What current BI tools can support novice users in creating dashboards?"*
>
> ***RQ5:*** *"What usability criteria can be used to evaluate BI tools?"*

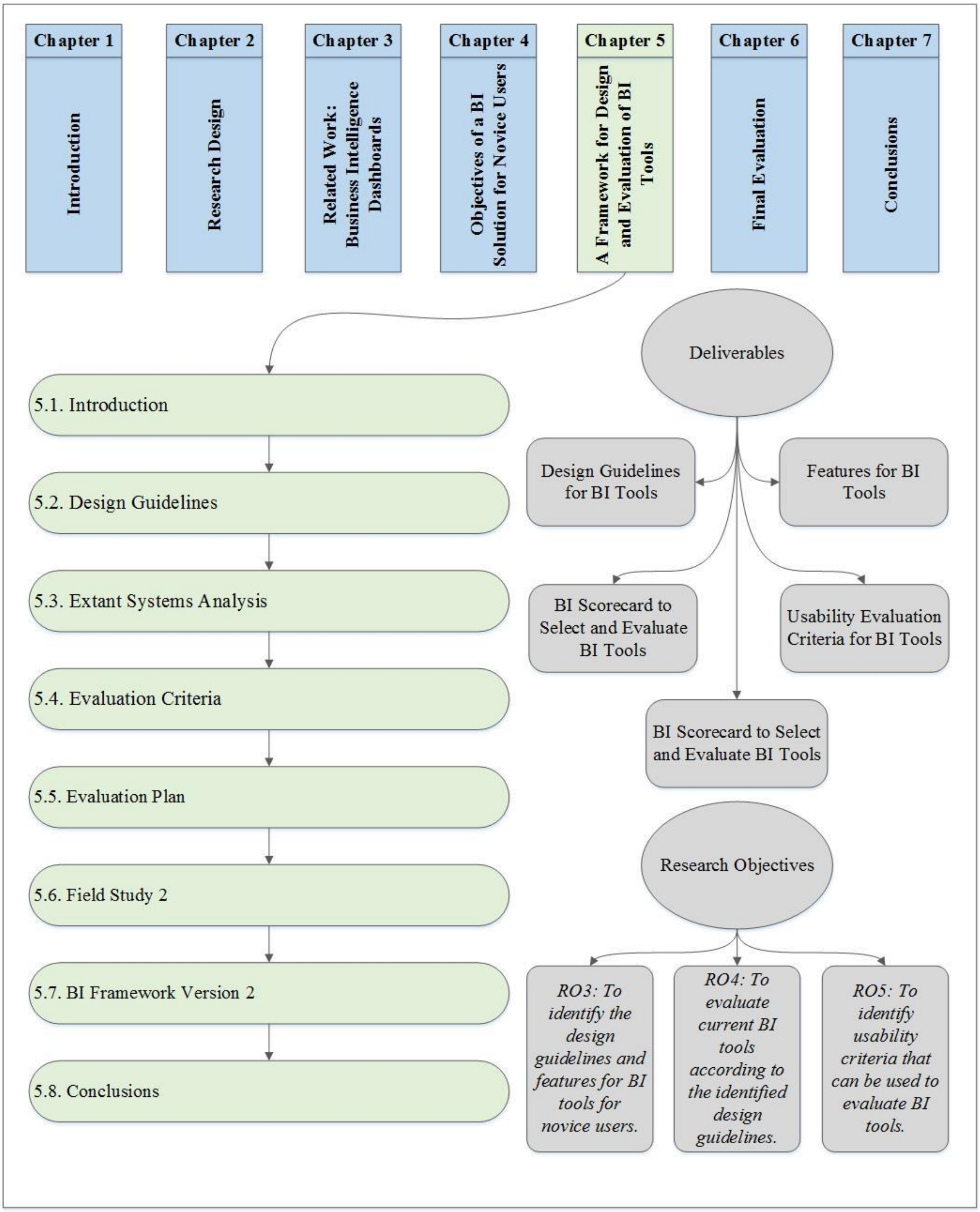


Figure 5-1: Chapter 5 layout

5.2 Design Guidelines [2]

Identifying the requirements of a BI tool is one of the objectives of the BI Framework. By considering the second component of the framework, Suitability Assessment (Figure 4-8), a number of design guidelines and features need to be identified for a BI tool that satisfies the requirements of users. The next activity in the DSR methodology is to design and develop an artefact that solves the identified problem and fulfils the requirements. Considering that the DSR methodology allows for various iterations, new requirements may be identified and solutions can be designed. A number of evaluation criteria, design guidelines and taxonomies of features and capabilities have been proposed for IV and BI tools in literature (Elias & Bezerianos 2011; Grammel et al. 2010a; Heer et al. 2008a; Pantazos et al. 2013; Few 2012; Heer et al. 2012; Eckerson 2009; Yi et al. 2007). By taking the requirements and identified problems (Section 4.2.6) into consideration, a comprehensive set of 11 design guidelines were identified from literature and are synthesised in Table 5-1 and discussed in this section.

Easy Development Process (G1). The first guideline relates to an environment that supports an easy dashboard process where the sequence of steps is simple (Elias & Bezerianos 2011). An integrated environment facilitating the entire dashboard development process may alleviate the complexities of integrating various software tools (Pantazos et al. 2013). Thus, many tasks in the development process need to be automated as far as possible by allowing users to easily connect to data sources, have functions for assisting with the manipulation of data attributes, and be able to create and customise dashboards efficiently with minimal effort.

Guided Development Process (G2). The second guideline complements the first guideline. In order to ensure an easy development process, the BI tool needs to provide sufficient guidance throughout the process to support its users (Heer et al. 2012). One method of supporting an easy development process is to incorporate step-by-step guides through tabs and windows or similar wizards, which enable users to follow a systematic set of common steps. These steps are followed in a workflow type of manner and aid users to keep track of where they are in the development process (Huron et al., 2014a). The user needs to be informed of the exact step

[2] The design guidelines were initially proposed in the paper "Usability Guidelines for Designing Information Visualisation Tools for Novice Users" and were included in the proceedings of the IDIA 2015 conference (Appendix D). However, the design guidelines were empirically evaluated in the paper "Design Guidelines for Business Intelligence Tools for Novice Users", which was presented at SAICSIT 2015 (Appendix E).

they are busy with so as to determine to carry on with the next step or revert back to a previous step in the development process. The user should therefore be guided through the steps to first connect to a data source, select data tables/attributes, conduct calculations if needed, select appropriate visualisation types, and customise the views of the final dashboard.

Table 5-1: Design guidelines for BI tools

Number	Description	Resources	
G1	Easy development process	Eckerson (2009) Elias and Bezerianos (2011) Few (2012)	Grammel et al. (2010a) Heer et al. (2012) Pantazos et al. (2013)
G2	Guided development process	Eckerson (2009) Elias and Bezerianos (2011) Grammel et al. (2010) Heer et al. (2012)	Huron, Carpendale, Thudt and Tansg (2014) Zhang et al. (2012)
G3	Flexible customisation and development process	Elias and Bezerianos (2011) Grammel et al. (2010a) Heer et al. (2012)	Huron et al. (2014a) Kienle and Muller (2007) Kuhail, Pandazo and Lauesen (2012)
G4	Dynamic, interactive and immediate visual feedback	Elias and Bezerianos (2011) Grammel et al. (2010a) Jansen and Dragicevic (2013)	Pantazos et al. (2013) Yigitbasioglu and Velcu (2012)
G5	Search, filter, sort, and navigation for drill-down features	Eckerson (2009) Elias and Bezerianos (2011) Heer, Card and Landay (2005)	Kienle and Muller (2007) Pantazos et al. (2013) Watson (2009)
G6	Multiple coordinated views and dynamic queries	Elias and Bezerianos (2011) Few (2012) Heer et al. (2012)	Macneil and Elmqvist (2013) Tobiasz, Isenberg and Carpendale (2009)
G7	Automatic visualisation creation and suggestions with useful defaults	Elias and Bezerianos (2011) Grammel et al. (2010a)	Heer et al. (2008) Kienle and Muller (2007)
G8	User friendly data input for common data formats and smart data discovery	Elias and Bezerianos (2011) Heer et al. (2008)	Heer et al. (2012)
G9	History tools, storytelling and annotations	Elias (2012) Fekete, Hémery, Baudel and Wood (2012)	Heer et al. (2012) Huron et al. (2014b) Kienle and Muller (2007)
G10	Saving, sharing and collaboration	Elias et al. (2013) Few (2012) Heer et al. (2008)	Heer et al. (2012) Satyanarayan and Heer (2014)
G11	Promote learning through demos and explanations	Elias and Bezerianos (2011) Grammel et al. (2010a)	Heer et al. (2008)

The guided development process should follow a bottom-up approach, where users progressively select data attributes first, and then appropriate visualisations are defined (Huron et al. 2014a). Moreover, consideration has to be given to the fact that users refine their dashboards in a series of iterations, which leads to the third design guideline, namely "a flexible customisation process".

Flexible Customisation and Development Process (G3). Although users require guidance during the development process, they should still have the flexibility to explore the features of the software and have the freedom to assess its capabilities. When users gain more experience and start to progress, they would desire to deviate from the systematic approach and experiment with more advanced features (Heer et al. 2012). Exploratory data analysis may result in a number of hypotheses, leading to multiple rounds of question-answering (Heer et al. 2008b). Keeping in mind that they would still like to keep track of what they have done and where they are in the process.

A flexible customisation process is particularly important for iterative refinements in order to meet the goals of the user (Elias & Bezerianos 2011; Huron et al. 2014a). A high-level of customisability alleviates the problem of consulting with experts to change any aspects of the dashboard, such as its appearance or underlying data (Huron et al. 2014b). This enables users to make changes to the dashboard themselves, which is more satisfying and efficient (Elias 2012). The flexibility does not only relate to moving backward and forward in the development process, but also relates to configuration of the overall UI and the features of the software. These might include positioning menu items and windows, enabling and disabling features, or integrating software with other tools. Thus, a BI tool needs to support an easy, flexible, and guided development process to create dashboards.

Dynamic, Interactive and Immediate Visual Feedback (G4). Users need to see the effects of their changes immediately, promoting exploration and experimentation with the software's features and different visualisations (Elias & Bezerianos 2011). For this reason, the BI tool must support a dynamic UI, which is interactive and provides immediate visual feedback. This guideline is related to flexible customisation and is closely coupled to the visual analytics process. BI tools need to be both visually pleasing and functionally intuitive (Eckerson 2009). To enable users to dynamically create and customise dashboards, BI tools should provide interactive GUI objects (Jansen & Dragicevic 2013; Eckerson 2009).

Interactivity is also important for navigating the dashboard (Eckerson 2009; Kienle & Muller 2007). BI tools need to provide a variety of interactive objects to create, control and navigate dashboards (Yigitbasioglu & Velcu 2012). These objects range from search boxes, expansion tabs, sliders, buttons, radio buttons, and pick lists (Heer et al. 2012). Dynamic environments where users can interactively explore data and visualisations also help them learn and increase their performance (Ritsos & Roberts 2014).

Search, Filter, Sort, and Navigation for Drill-Down Features (G5). The interactive objects are typically used to apply features related to the fifth guideline, which refers to the use of search, sort, filter and navigation features. Occasionally, users would also utilise features for linking, zooming, and aggregating (Heer et al. 2012; Eckerson 2009). Search features are helpful when users know what they are looking for and can range from a specific data source, data table, data attribute, or any information evident in the dashboard (link to multiple views across pages). Searching for features are particularly useful when the user knows the name of the data attribute, for example "Sales" or "Costs". Search facilities are also particularly helpful when users desire to highlight any text or value in the dashboard, for example when annotations are made about a particular data point (Elias & Bezerianos 2011). Moreover, auto-complete functions are highly recommended when searching for particular data from the BI tool (Kuhail et al. 2012).

Filters are useful features to manage so called "clutter" on a dashboard. Since users have specific objectives for the data they would like to view, they would often apply filters to view only those categories of data that are relevant to their task at hand. Dashboards typically have two types of filters, namely local and global filters. Local filters are applied to a single visualisation on a worksheet or dashboard only. Global filters affect all of the visualisations on the dashboard or entire workbook (Schröter 2015).

Sorting enables users to view information in a particular sequence. Sufficient navigation features and interactions, such bread crumbs, minimise icons, double click actions and back buttons, are highly recommended to support users when exploring an interface and moving from different level of data granularity (Guimarães et al., 2011; Heer et al., 2008). Navigation features are especially necessary when following a specific drill-down path through an aggregation hierarchy, as users would like to investigate an interesting data point in more detail (Elias & Bezerianos 2011; Eckerson 2009). Moreover, sufficient hide/show tabs should be used not only for screens, but also to avoid dashboards from being cluttered.

Multiple Coordinated Views and Dynamic Queries (G6). Dashboards typically incorporate the use of multiple coordinated views and dynamic queries. The concept of coordinated views are often demonstrated in dashboards, where multiple individual visualisations are linked to each other and represent a different dimension(s) from the same data set (Macneil & Elmqvist 2013). Moreover, multiple coordinated views can be used as comparison charts to compare those factors that influence performance (Ghazanfari et al. 2011). Essentially, coordinated views rely on features for global linking and filtering, and drill activities. When applied, they could affect the appearance of all the linked visualisations, panels or worksheets with a single click (Eckerson 2009). Elias & Bezerianos (2011) explains that users often get confused between linking, filtering and drill. Linking occurs when data items are selected in one view to highlight (or hide) corresponding data in other views (Heer et al. 2012). Filtering allows for removing unwanted data items from the entire display. Drill-down "navigates" the user from one aggregated level of information in a hierarchy, to more detailed levels of information.

Dynamic queries are especially relevant to multiple coordinated views that will dynamically highlight all data points a particular text search or selection on a visualisation. For example, the user might click on a single bar in a bar chart, which will affect the data displayed across all linked visualisations. (Elias & Bezerianos 2011; Heer et al. 2005). The benefit of dynamic queries is that they are often used as a direct manipulation interaction technique, because they enable users to explore relational data without having to formulate their own queries using complex languages such as SQL (Lee et al. 2012). This helps users to focus on their task at hand as they formulate queries with minimal effort by manipulating interactive widgets, such as check boxes, tick boxes, double range sliders, and text searches to immediately view their query results.

Automatic Visualisation Creation and Suggestions with Useful Defaults (G7). The provision of automatic visualisations using pre-defined typologies has been motivated as a useful feature to assist users in creating visualisations quickly (Elias & Bezerianos 2011; Grammel et al. 2010a; Heer et al. 2008a). The benefits of visualisation typologies are efficiency, simplicity and familiarity since users are better at recognition rather than recall (Heer et al. 2012; Satyanarayan & Heer 2014). Visualisation typologies are designed based on best-practices, which assist users to visually map their data to appropriate visualisations. Furthermore, visualisation typologies inhibit the creation of novel designs to reduce time-consumption and often error-prone visualisations (Satyanarayan & Heer 2014; Bostock & Heer 2009). The typologies often include automatic visualisation generation based on the amount (and type) of the selected data attributes.

Users tend to have a particular visualisation type in mind when viewing data attributes, however, the selected visualisation may not be appropriate for their data. Suggestions (or recommendations) are especially helpful to select an alternative visualisation type that is appropriate for the selected data attributes. The suggestions may offer users automatic previews to discover and learn new visualisation types that they have never used before (Elias & Bezerianos 2011). Providing pre-defined visualisations also require the implementation of useful defaults, which refers to parameters or pre-sets for refining the appearance of the dashboard elements, such as text labels, colours, transparency, size, scales and so on (Heer et al. 2008a).

User Friendly Data Input for Common Data Formats and Smart Data Discovery (G8). Users need to be able to connect to a data source easily and be able to perform manipulations to the data from within the BI tool (Heer et al. 2008a). Before these manipulations can be performed, such as merging data attributes or performing calculations, the software should be able to identify relationships between data tables automatically. The user should be offered previews of the data and an opportunity to merge these data tables through a visual query builder, if not done automatically. Furthermore, the BI tool should also identify the nature of the data attributes and classify them according to "*measures*" and "*dimensions*". Measures are typically quantitative or numerical information that produce axes in a visualisation. Dimensions typically produce headers in a visualisation and are qualitative or categorical information. This concept can be referred to as "smart data discovery" and has become key success factors for vendors' software in the BI and Analytics market (Sallam et al. 2015).

BI tools need to facilitate data transformation (manually or automatically), so that the user does not have to apply calculations prior to importing the data (Heer et al. 2012). User friendly data input is essential for users as they might not be familiar with DBMS where calculations are performed. Thus, users should have access to predefined calculation functions that are able to transform variables (counts, summations, averages, standard deviations etc.) or create new attributes (calculations or merging) in the BI tool, from existing values in the data set (Heer et al. 2008a; Heer et al. 2012; Few 2012).

History Tools, Storytelling and Annotations (G9). Users develop dashboards through iterative refinements and experimentation. During experimentation, users will often want to re-apply or undo changes to revert to a previous state (Kienle & Muller 2007). Therefore, it is important to ensure that the software has the features to keep track of analysis findings (Heer et al. 2012). These mechanism are often referred to as history tools, which remember the previously performed steps of visualisation operations (Heer et al. 2008b). Users should be able to re-view, re-visit or re-apply specific settings and analysis steps (Elias 2012; Huron, et al. 2014b). This is particularly relevant for users who are experimenting with various types of visualisations and are also learning how to operate the features of a tool. History tools do not only allow for undo or redo, but should also keep track arbitrary navigation to return to a preceding navigation step, as well as those features that have been applied (sort, filter, aggregation etc.).

In more recent advancements, IV and BI research has motivated the effect of storytelling and annotations (Huron et al. 2014b; Heer et al. 2012; Elias et al. 2013). Storytelling and annotations enable the transfer of knowledge between people and organisations, as a rationale of key findings, expectations, events and contexts can be synthesised in a single space. Users can create or "tell" a story to support their arguments and analyses of findings that contribute to overall sense-making (Elias et al. 2013; Huron et al. 2014a).

Storytelling and annotation features are useful for quickly revising the situation depicted in the dashboard and allows to logically describe steps that were taken to derive at the results. Storytelling features should support tasks for highlighting, marking, colouring and zooming to make the key findings prominent (Elias et al. 2013; Huron et al. 2014a). Storytelling features can be implemented through the mapping of findings into text frames or scripts, which can be placed in sequential order to simulate a flow chart or map. Elias et al. (2013) explains that during analysis, the software should support the user to convey the complete "BI story" to present a collection of visual representations of the most important data. This should be accompanied by instruction how to read and interpret the visualisations and how to conduct further analysis to view more details. Advanced features for storytelling allow data stories to unfold as a "playback" option, which revises and explains to the user how findings were identified and highlights the most important data points on the dashboard (Heer et al. 2012).

Saving, Sharing and Collaboration (G10). The concept of storytelling is particularly useful for the purposes of saving a dashboard and sharing those findings with peers for collaboration. Users often have the need to share or publish their findings with others for follow-up analysis and to share thoughts of the developed dashboards for refinement (Few 2012; Heer et al. 2012).

Often visualisations are shared as static exports and snapshots (Few 2012; Elias & Bezerianos 2011), which are often sent to others by email, or pasted into presentations and word processing files. Dashboards should, however, keep their interactivity when shared, even if they only extend to a few granularity levels.

Promote Learning through Demos and Explanations (G11). Since users are not familiar with the terminology and general features of IV and BI, the software should promote learning through explanations (Elias & Bezerianos 2011; Grammel et al. 2010b; Heer et al. 2008a). These explanations may be graphical demonstrations, or textual descriptions of concepts, such as queries, "*measures*" and "*dimensions*", filtering, sorting and drill-down/up. Additionally, descriptions for the particular use of a visualisation type (reasons for use, advantages or disadvantages) can be provided to help users to make better visual mappings in future (Grammel et al. 2010a). Explanations can be provided using details-on demand when a user hovers over a specific point on the visualisation or menu item. Sufficient explanations with appropriate terminology is important, however, the explanations should be informative only and not replace the user's ability to figure out how to perform tasks. Despite explanations, users should have access to low-cost experimentation to view the effects of their actions. Additional learning materials, such as short demos, tutorials, sample workbooks or courses that demonstrate how trends or patterns can be analysed and interpreted are also recommended (Grammel et al. 2010b; Few 2012; Jooste et al. 2014).

In conclusion, an interactive BI tool that supports a guided, but flexible development environment for dashboard creation is proposed. The BI tool should automate various tasks through automatic visualisation creation, smart data discovery, and setup of drill-down/up hierarchies. Moreover, histories of data analysis activities should be stored and the opportunity to share visualisations and dashboards with others are encouraged. Learnability is especially important for users and the software-support features for learning through explanations, tutorials or other interactive features that encourage exploration. Users should be able to apply features for filtering, sorting, searching and linking across multiple coordinated views. These guidelines (G1-G10) were used to design the BI Scorecard in this study. The BI Scorecard can therefore be used as a tool to rate a BI tool's conformity to the suggested guidelines.

5.3 Extant Systems Analysis

The activity of designing and developing an artefact combines methods of reusing and adapting components from extant systems, inventing new components, and combining them in an innovative manner (Johannesson & Perjons 2012). In order to find an appropriate BI tool, it is important to evaluate whether existing software tools can provide a solution to the problem and satisfy the identified requirements. By investigating existing software, positive aspects and problems can be further identified and be taken into account when considering the design or adoption of a BI tool for users.

Assessing software tools are important so as to determine which functionality, features and techniques they offer with respect to the certain application domain (Zhang et al. 2012). Various studies have conducted surveys and compared the functionality of software tools in IV and BI fields (Huron et al.a 2014a; Pantazos et al. 2013; Zhang et al. 2012; Sallam et al. 2015; Ed et al. 2014). One of the most comprehensive comparisons for BI tools is provided by Miller and Lekar (2014), who provided a three step scale to evaluate the strengths and weaknesses of BI tools. This section provides an overview of an extant system's analysis that was conducted by the researcher on current tools in the IV and BI market. The BI tools were predominantly selected based on its status in the BI market (Figure 3-6). A total of four BI tools were evaluated, namely:

- Microsoft Excel PowerPivot (referred to as PowerPivot);
- Tableau;
- SAP Lumira; and
- TIBCO Spotfire.

The tools were informally evaluated by the researcher using the BI Scorecard (Appendix J). The BI Scorecard was derived from the proposed design guidelines. Each design guideline (G1-G11) was extended into several features that could be possible implementations of the guidelines. The BI Scorecard uses a three step scale to rate BI tools according to a set of features as seen in a similar approach by Miller and Lekar (2014, p9-11). These three subscales are "bad", "acceptable" and "good", using the symbols "-", "~" and "+", respectively. At the end of each evaluation, a total score(s) was calculated for each tool. A summary of the expanded design guidelines are provided in Table 5-2.

Table 5-2: Summary of features in BI Scorecard

Number	Description	Description
G1	Easy Development process	• The components are integrated in a single environment and the majority of tasks in development process are automated.
G2	Guided Development Process	• Support guides and wizards assist users through the entire IV process to easily select data and attributes, transform data, create dashboards, and refine dashboard views.
G3	Flexible Customisation and Development Process	• Data sources and attributes can be easily de/reselected with almost no learning curve. • Important parameters may be changed instantly. • Selecting alternative visualisations can be done instantly whilst maintaining the filters that have been previously applied. • Flexibility is offered to change the formatting options of visualisations (colours, position, size, fonts and labels).
G4	Dynamic, Immediate and Interactive Visual Feedback	• Explanations are provided with tooltips based on how to utilise the features. • Explanations are complimented with visual cues based on how to select appropriate data attributes. • Comprehensive learning materials such as demos, tutorials and samples are provided within the BI tool.
G5	Search, Filter, Sort, and Navigation for Drill-Down Features	• Sorting options are derived from the selected attributes and can be applied both locally and globally. • Drill-down/up hierarchies are automatically created based on smart data discovery, but are also customisable. • Highly customisable global and local filters can be derived and set by the user using various data attributes. • Search facilities for data attributes and text situated in visualisations can be used to highlight or filter data points. • Customisable navigation (customisable layout of menu items. navigation options within visualisations can be set in a flexible manner).
G6	Multiple Coordinated Views and Dynamic Queries	• Visualisations can be linked automatically or be managed with minimal effort (only a few clicks are necessary). • Linked visualisations are interactive, flexible to change, and can be set to affect all visualisations and worksheets (a wide range of functions can be used). • Dynamic queries can be derived from a wide variety of interactive objects to filter, sort, drill-down, search and aggregate data.
G7	Automatic Visualisation Creation and Suggestions with Useful Defaults	• Visualisations are created automatically with predefined, customisable defaults. • Visualisation suggestions are provided with adequate advice for alternatives based on selected data. • Highly customisable visualisations are available to create novel designs. • Comprehensive previews are provided before a visualisation is selected. • Easy to apply and reapply changes to visualisations.

Table5-2: Summary of features in BI Scorecard (cont.)

G8	User friendly Data Input for Common Data Formats and Smart Data Discovery	• Data selection is intuitive with (almost) no learning curve. • Connection to data source is intuitive and minimal manual tasks are necessary. • Supports multiple file formats which can be freely integrated. • A diverse set of pre-defined formulas that are highly customisable are supported.
G9	History Tools, Storytelling and Annotations	• Version control options are incorporated to recover a previous state (in addition to undo and redo). • Advanced history tools to review, re-visit and retrieve previous analysis steps. • Storytelling features are interactive with story templates for playback. • Features for showing analysis steps, findings and explanations based on how to interpret results. • Annotations are supported with interactions (dynamic interaction, time horizons, visual indicators, expand/collapse, and linking of different granularity levels for drill-down).
G10	Saving, sharing and collaboration	• Supports different export variants in interactive, graphical and textual formats. • Dashboards can be shared with permissions (read/write/data access). • Saved as multiple formats and for re-use and editing on multiple devices.
G11	Promote learning through demos and explanations	• Adequate explanations with tooltips for how to utilise the feature. • Adequate explanations with cues based on how to use and select appropriate data attributes, visualisations and BI features. • Comprehensive learning materials such as demos, tutorials and samples are provided.

The detailed BI Scorecard is documented with the sub-scales for each design guideline and feature (Appendix J). The comparison and respective ratings for each BI tool that was evaluated using the BI Scorecard is presented in Table 5-3. A total of 38 features were derived from the design guidelines (G1-G11). A maximum of three points could be awarded for each feature according to the following scales:

- Bad = 1 point;
- Acceptable = 2 points; and
- Good = 3 points.

Two additional features were added for the purposes of licence availability. For this reason, a maximum score of 120 points could be awarded if the BI tool satisfied the requirements of the features. The extant systems analysis revealed that the evaluated BI tools exhibit the necessary features to create dashboards in a single environment and provide functionality that can assist users. Tableau scored the highest (S=115) in the extant systems analysis, which was followed by TIBCO Spotfire (S=109). Although these two BI tools scored the highest, SAP Lumira can be considered as an alternative BI tool as it also scored highly (S=105). These three tools satisfied most of the design guidelines on either the "acceptable" or "good" subscales. PowerPivot had the lowest score of the four BI tools and did not satisfy all of the design guidelines on the "acceptable" or "good" subscales. However, PowerPivot could still be used to satisfy the basic requirements of users and the features to create dashboards.

The final decision for selecting BI tools was influenced by licence availability. For this reason, PowerPivot and Tableau were selected for further evaluations as complete academic licences TIBCO Spitfire and SAP Lumira could not be obtained for evaluations with multiple participants. PowerPivot was already installed at the university as the software serves as an Add-in for Microsoft Excel and is part of the Microsoft PowerBI stack that may be used at no additional cost (Microsoft, 2015). Bulk academic licences were received from the Tableau Academic Program to install the software on the PCs in the computer laboratories at the NMMU.

Table 5-3: Comparison of BI tools using the BI Scorecard

Number	**Features for each guideline**	**BI tools evaluated in the extant system analysis**			
		Microsoft PowerPivot	***Tableau***	***SAP Lumira***	***TIBCO Spotfire***
G1	Integrated environment	+	+	+	+
G2	Guides	-	~	+	+
G3	Flexible data selection	~	+	+	+
	Visualisation formatting (reasonable defaults, colours, labels and size)	~	~	~	+
	Flexible visualisation selection	+	+	+	+
	Positioning of menus and visualisations in work areas (minimising, moving)	+	+	+	~
G4	Feedback	+	+	+	+
	Interaction with visualisations	+	+	+	+
G5	Sorting	+	+	~	+
	Drill-down/up hierarchy	~	+	+	+
	Filters	~	+	+	+
	Search facilities	~	+	+	+
	Navigation	~	+	+	+
G6	Coordinated views setup	~	+	~	+

	Coordinated views scope	~	+	~	+
	Dynamic queries	~	+	~	+

Table 5-3: Comparison of BI tools using the BI Scorecard (cont.)

G7	Automatic creation	+	+	+	+
	Visualisation suggestions	+	+	+	+
	Visualisation diversity	+	+	+	+
	Visualisation previews	+	~	~	+
G8	Ease of data selection	+	+	+	~
	Ease of data import (or connection to data source)	~	+	+	+
	Supported import data formats or sources	+	+	+	+
	Functions for data transformation	+	~	~	~
	Versatility of formula application	+	+	~	+
	Smart data discovery	~	+	+	+
	Merging and joining of tables	~	+	+	+
	Previews of data	~	+	+	+
G9	Undo and redo	+	+	+	+
	History tools	-	~	~	~
	Storytelling provides updated explanations on playback	-	+	+	+
	Annotations	-	+	+	+
G10	Export dashboards	~	+	+	+
	Dashboard sharing	+	+	~	+
	Saving a dashboard or workbook	+	+	+	+
G11	Explanations for tool's features	~	~	~	~
	Explanations for visualisations	+	+	-	-
	Built-in tutorials and demos	-	~	+	+
Licence	Licence availability	+	+	~	~
	Commercial vs trial licence	+	+	~	+
Score out of a maximum of 120 points (S)		**97**	**115**	**105**	**109**

5.4 Evaluation Criteria

Usability is increasingly recognised as an important quality factor for interactive software systems (Seffah et al. 2006). Usability focusses on criteria for effective, efficient and satisfactory task execution and aims to support the ordinary and uninterrupted interaction between the user and the system (Tsakonas & Papatheodorou 2008). Usability evaluations are particularly useful when aiming to improve the UI of a system, or to establish the system's quality in use within a given context. Since many problems were identified in the Field Study 1, a second field study (Field Study 2) was designed to evaluate the usability of one of the BI tools identified from the extant systems analysis, namely PowerPivot. One of the objectives of Field Study 2 was to investigate how a BI tool that provides integrated development environment to create dashboards may alleviate the problems experienced in Field Study 1.

A number of objectives and requirements are identified for a BI tool (Section 4.3.2). In order to measure whether the BI tool satisfies these objectives and requirements, they can be classified according usability goals (Rogers et al. 2011; Seffah et al. 2001). These goals depend on the characteristics of each part of the BI tool, including software, hardware and the users. Therefore, measurable usability goals need to be specified as usability criteria (Seffah et al. 2001; Rogers et al. 2011) and the users' performance should be measured against their target goals (Tullis & Albert, 2013, p. 50).

Lassaad, Abdelwaheb and Mahfoudhi (2015) motivate that usability is one of the most important quality factors that determine the success or failure in the actual use of an interactive system. Richey (2013) and Goldberg et al. (2011) maintain that usability is a measureable quality of designed objects that have some user interaction. Quality in use is defined by the degree to which a software product or system meets the users' needs to achieve specific goals with effectiveness, efficiency, freedom from risk, and satisfaction in a specific context of use (ISO/IEC 25010 2011). For this reason, measuring usability in itself has no intrinsic value, but is defined in terms of the people who use the system to achieve their own goals (Goldberg et al. 2011).

Usability is not a quality that exists in an absolute sense, but can only be defined with reference to a particular context or purpose (Brooke, 1996). This means that when usability is applied to a particular system and context of use, it assesses how easy it is to use a system's UI (UI) to achieve the goals of the user (Nielsen 1994; Bevan 1995). The context of use for any system is defined by the specified conditions in which the system is used. These conditions include the nature of the tasks, users, equipment (hardware, software and materials), and the physical and social settings in which the systems are used (Goldberg et al. 2011; Jokela et al. 2003; Gebus & Leiviskä 2009; ISO/IEC 25010 2011). These conditions typically influence the scope of the usability design and evaluation requirements (Bevan 2013).

Rogers et al. (2011) state that usability aims for interactive products that are easy to learn, effective to use, and are enjoyable from a user's perspective. The definition provided by Nielson (1994) complements the former definition and describes usability as a quality attribute that assesses the acceptability of a system and its affinity to satisfy the requirements of the users. Nielsen (1994) also proposes that usability comprises of five criteria, such as learnability, efficiency, memorability, errors and satisfaction. However, the International Organisation of Standards (ISO) and motivate that usability comprises three primary criteria: efficiency, effectiveness and satisfaction (ISO/IEC 25010 2011). ISO (2011) defines usability as "*the degree to which the software product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use*". The term usability was replaced in the ISO25010 standard by "operability". Operability refers to the degree to which a software product is easy to operate and control (ISO/IEC 25010 2011). For consistency, the term usability is used throughout this study.

Numerous classification schemes have been proposed to define usability criteria (Gebus & Leiviskä 2009; Rogers et al. 2011; Nielsen 1994; Goldberg et al. 2011; ISO/IEC 25010 2011; Seffah et al. 2006). Since usability needs to be evaluated in terms of its context of use, this study will use criteria that are relevant for the purposes of evaluating software tools in the fields of BI and IV. Criteria for evaluating BI usability are limited, particularly for users. Jooste, Van Biljon and Mentz (2014) proposed one of the most comprehensive lists of BI usability criteria that could be identified by this study and recommended five usability criteria namely: visibility, flexibility, learnability, error control and helpfulness, and operability. These five criteria will be used in conjunction with satisfaction, efficiency and effectiveness for upcoming evaluations and field studies. Additional references have also been sourced to support that these criteria are required for evaluating software that support the generation of BI dashboards or visualisations (Table 5-4).

Effectiveness: The effectiveness of a software system relies on its capability to enable users to accomplish specified tasks with accuracy and completeness (Seffah et al. 2006). In other words, effectiveness is a criterion that evaluates the quality and quantity of a task's outputs and how successful the users are in achieving their goals. The criteria used for rating completeness, accuracy and error rates are both indicative of a system's level of effectiveness (Hornbæk & Law 2007).

Efficiency: A system must be efficient in the sense that the users can successfully accomplish a task, or set of related tasks, by spending the least amount of time and effort as possible (Faulkner 2000). Efficiency describes how fast a task can be completed in a specified context of use. For this reason, a system should be efficient to use to allow users to maintain a high-level of productivity once the system is learned. Efficiency is also referred to as the resources expended in relation to accuracy and completeness of goals achieved (ISO/IEC 25010 2011). Lazar, Feng and Hochheiser (2010) state that efficiency and accuracy are not isolated, but do require a trade-off. Accuracy refers to the state in which the system or user experiences errors. Accuracy is also defined by the capability of the software to provide the correct or agreed results or effects with the needed degree of precision (ISO 2000). Criteria that are used to evaluate efficiency are *task completion times* and *error rates*. When measuring efficiency, benchmark values need to be defined in order to compare results (Bevan & Macleod 1994). Efficiency criteria express the level of effectiveness achieved in relation to the expenditure of resources. These resources can be either mental or physical efforts (Bevan 1995).

Table 5-4: Usability criteria for BI tools

Functional grouping	Usability criteria description	References
Visibility	Information, instructions, navigation options and system statuses should well-structured and clear at all times. Components can be viewed easily.	Bostock and Heer (2009) Carpendale (2008) Jooste et al. (2014)
Flexibility	The user should feel in control and be able to customise the application for individual or collaborative usage.	Carpendale (2008) Gebus and Leiviskä (2009) Heer et al. (2005) Jooste et al. (2014) Tobiasz et al. (2009)
Learnability	Learnability should be promoted using familiar terminology, features for limiting memory loads and provide cues to assist infrequent users.	Antoniadis et al. (2015) Jooste et al. (2014) Heer et al. (2005) Lam et al. (2012)
Error Control and help	Provision should be made for features such as error prevention, recovery, help on demand and user support. Additionally, training should be available (initial training and refresher courses).	Carpendale (2008) Jooste et al. (2014) Lam et al. (2012)
Operability	The application should display a hierarchical map to determine data granularity. Data attributes and dimensions should be easy to identify and access on all level of granularity. Data should be up-to date, allowed to be filtered and shared. Multiple views of different data should be accompanied by various IV techniques. The application should provide a rapid response rate and behave consistently.	Jooste et al. (2014)
Satisfaction	The application should be satisfying to use.	Lam et al. (2012)

Effectiveness	The tool should enable users to perform the activities they need to perform accurately and be able to complete their tasks.	Carpendale (2008) Lam et al. (2012)
Efficiency	The least amount of time needs to be spent when performing a task.	Carpendale (2008) Lam et al. (2012) Tullis and Albert (2013)

Satisfaction: The satisfaction of a system depends on the user's response to interacting with the system in a specified context of use, which directly influences the user's attitude towards the use of the system (ISO/IEC 25010 2011). If the system provides a pleasant experience, the user is more likely to be satisfied and would prefer to use the system in the future. Subjective satisfaction can be evaluated by using a questionnaire which requires users to rate their overall opinion about the system (Faulkner 2000). Individual results will initially be subjective criticism (Seffah et al. 2006; Faulkner 2000). However, an objective measurement can be obtained by averaging individual results and comparing these to a predefined benchmark rating. The cause of dissatisfaction is typically coupled to low ratings of effectiveness and efficiency of the system's design (Tullis & Albert 2013).

Visibility: The system status should be communicated at all times to keep users informed about what is going on. The status should be communicated timeously with terminology that is familiar to the user. Functions should be well positioned onscreen and easy to find (Carpendale 2008), which will assist users in knowing how to operate a function or to perform the next activity (Bostock & Heer 2009). Functions and feedback should also be intuitive, allowing the user to interact with the system without being frustrated (Rogers et al. 2011).

Flexibility: Flexibility refers to the extent to which a system can be used beyond the contexts of those initially intended, while still maintaining a high-level of effectiveness, efficiency, freedom from risk, and satisfaction (ISO/IEC 25010 2011). Moreover, flexibility refers to the multiple means in which a system can exchange information between the user and the interface (Dix et al. 2004). Flexibility has the potential to improve usability when considering the knowledge of the user, knowledge of interactions, tasks and the domain in which the system is used (Gebus & Leiviskä 2009). Therefore, system flexibility allows for adaptability, to suit the tasks, cultures, circumstances and individual preferences that have not been anticipated for in advance (ISO/IEC 25010 2011). The degree to which a system is *accessible* for users is often influenced by flexibility, as it enables different types of users to adapt the system's functions in a multiple contexts of use and allow for access from different platforms (Lew et al. 2010).

Learnability: Learnability refers to the extent to which a software system is easy to learn (Rogers et al. 2011) by specified users who wish to accomplish specified goals (ISO/IEC 25010 2011). Moreover, learnability expresses how well users can accomplish basic tasks the first time they interact with a system (Nielsen, 2001; Winter, Wagner, & Deissenboeck, 2008), while the system still maintain its effectiveness, efficiency, freedom from risk and satisfaction in a particular context of use (ISO/IEC 25010 2011). The perceived learnability of a BI tool are determinants for end-user acceptance are measures of a successful implementation (Antoniadis et al. 2015).

Vatrapu, Suthers and Medina (2008) explain two views of learnability. The first view refers to the capability of the software system to enable the user to it is to learn its features. Therefore, learnability can be used to evaluate the system's suitability for learning (ISO 2000). The second view refers to the capability of the system to enable the user to learn the relevant application domain. Learnability is an essential usability attribute as the first thing users do when interacting with a system is to learn its functionality and constraints (Faulkner 2000). Not only do users have the goal of learning a system's functionality quickly, but also to understand how to become productive by performing their tasks with minimum effort (Rogers et al. 2011). Learnability can be determined by assessing any performance criterion over time, such as measuring a user's *time on task*, *error rate*, *number of steps*, or *tasks per minute* (Tullis & Albert 2013). The concept of understandability is closely related to learnability.

Error control and helpfulness (Error protection): Users should not be able to make errors easily whilst using a system and sufficient assistance should be provided to recover quickly when an error is made (Nielsen 1994). Often the terms help and recoverability are associated with *error control*. Helpfulness Error and error rate are popular criteria for efficiency. The motivation is that a user will be able to work faster and more efficiently if fewer errors are made and therefore be more productive (Faulkner 2000). Moreover, when fewer errors are made less effort is required to complete the task at hand. Advisory messages and normal error prompts influence perceptions of users (Schneiderman & Plaisant 2010). It is critical that error messages are phrased appropriately for both expert and novice users. Errors occur due to a lack of knowledge, incorrect understanding, or unintentional slips that can cause frustration, confusion, anxiety or helplessness (Schneiderman & Plaisant 2010; Faulkner 2000).

Operability: Operability is defined as the extent to which a system has the capability to make it easy to control and operate (ISO/IEC 25010 2011). Operability also refers to the extent to which the system supports the user in performing the tasks specific to the domain in which it is used. Operability is an important aspect of BI tools as various features are required to conduct data analysis and to perform a number of BI functions (Jooste et al. 2014).

5.5 Evaluation Plan

The BI Framework proposed in this study should be evaluated. The BI Framework will not be evaluated directly, however, the BI tools selected when applying the BI Framework can be evaluated for usability and their conformity to the design guidelines and features can be established and. additionally, usability results can be compared the requirements and high-level objectives of users.

An evaluation plan was administered to evaluate the usability of the two selected BI tools (Figure 5-2). The outcome of the extant system analysis revealed four BI tools that could be selected for further evaluations with novice users since they satisfied most of the design guidelines and features in the BI Scorecard. However, only two tools were selected for further evaluation based on their availability.

Field Study 2 will be conducted as a usability evaluation with PowerPivot. Although PowerPivot does not satisfy all of the design guidelines, the majority of the features can still be evaluated to verify most of the design guidelines. Therefore, only a subsection of the design guidelines will be evaluated. The design guidelines to be evaluated in Field Study 2 are also considered to have less complex features. More specifically, features relating to search, drill-down and multiple coordinated views (global filtering) will not be evaluated in Field Study 2. The design guidelines that will be partially verified in Field Study 2 are:

- *Guided development process* (G2);
- *Search, filter, sort, and navigation for drill-down* (G5); and
- *Multiple coordinated views and dynamic queries* (G6).

Due to the level of complexity of features, the following two guidelines will not be evaluated in Field Study 2:

- *History Tools, Storytelling and Annotations* (G9); and
- *Saving Sharing and collaboration (G10).*

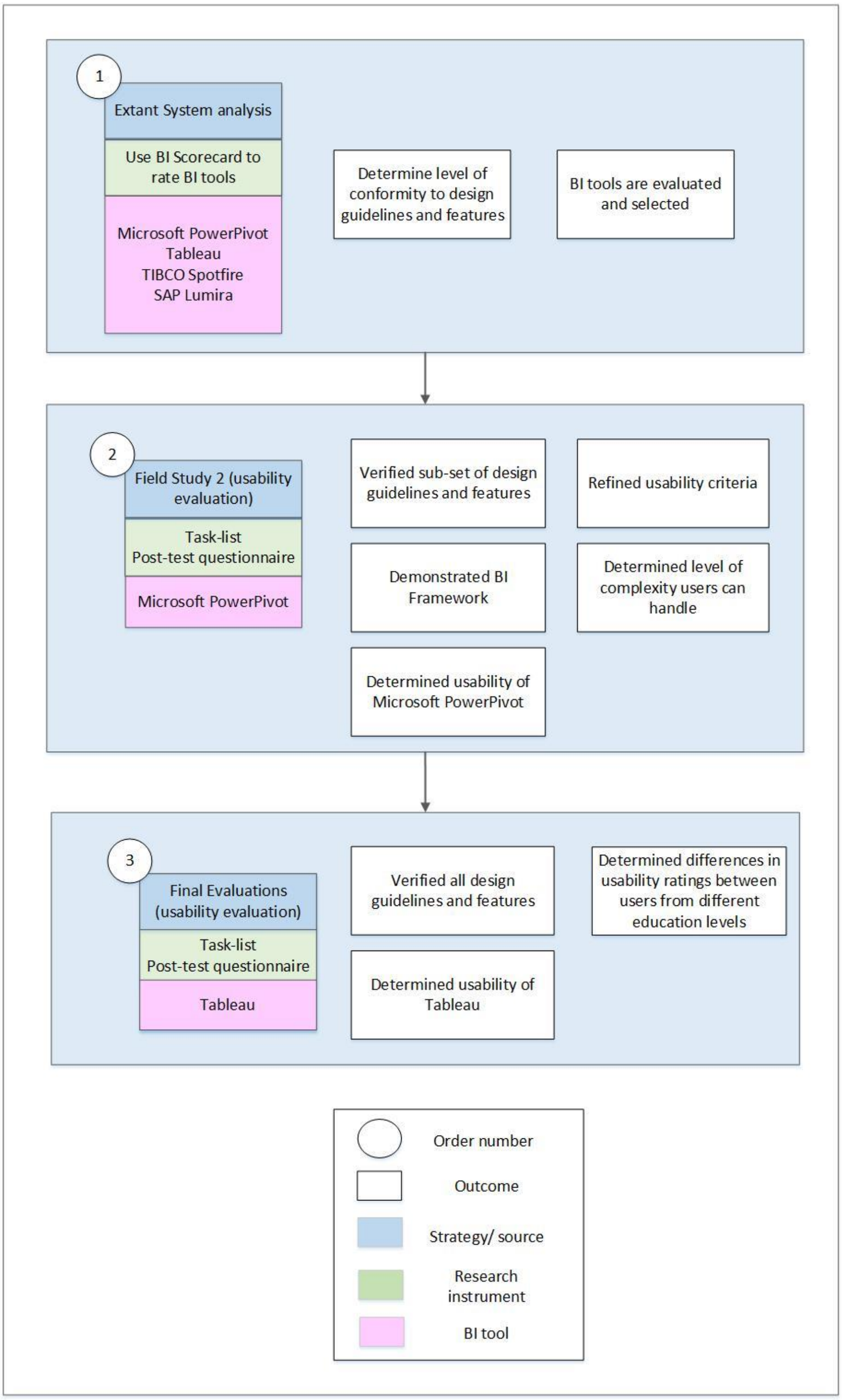


Figure 5-2: Evaluation plan for the selected BI tools

The usability criteria will also be refined in Field Study 2 as the majority of the criteria will be used for the final evaluation with second BI tool that was selected from the BI Scorecard, namely Tableau. The final evaluation will evaluate the usability of Tableau, as well as verify all of the design guidelines and features proposed in the BI Scorecard. Moreover, usability results will be analysed to identify whether novice users on different education levels perceive the usability of BI tools differently.

5.6 Field Study 2 [3]

The *Design and Development* activity of DSR methodology involves a series of cyclic evaluations, where the artefact is designed and demonstrated in iterations. Field Study 2 was conducted as a usability evaluation with PowerPivot. Before the field study could be conducted, the evaluation procedure had to be planned properly (Section 5.6.1). The participant sample used in the Field Study 2 consisted of IS students registered for the ERP module in the year 2015 and were not the same group of students that participated in Field Study 1 (Section 5.6.2). The research materials that were used mainly consisted of task-lists and questionnaires (Section 5.6.3). The internal consistency and reliability of the research materials were confirmed by means of a pilot study (Section 5.6.4) and the results were analysed (Section 5.6.5).

5.6.1 Overview of Field Study 2

Considering users need struggle to create dashboards in a distributed development environment, one objective of Field Study 2 was to test whether users could follow a development process to develop dashboards and whether a guided development process enhanced their understanding of the required steps and activities. Another objective of Field Study 2 was to conduct a usability evaluation on one of the BI tools that were selected based on the BI Scorecard and to demonstrate and validate the design guidelines and their associated features that were proposed in the BI Framework.

Prior to the evaluation, participants were given a 60 minute lecture on basic BI concepts. These concepts included the general BI architecture, capabilities, and the purpose of dashboards. The objectives of the evaluation was provided and the task-list was explained in detail. The steps to create a dashboard were mapped between the task-list and the traditional process discussed (Section 3.5). Providing an overview of the development process enables users to create a mental model of the required steps, which enables a better understanding of how the different software components work together and to infer more easily the results of the interacting

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[3] The results in this section were included in the paper “The Usability of Business Intelligence Tools for Novice Users” that was accepted and presented at SAICSIT 2015(Appendix E).

system (Schröter 2015). A mental model is an organised knowledge structure that involves the imagined possibilities and projection of data, which form part of the concept of sense making (Patterson et al. 2014). Teaching the underlying structure of the software system to users is an effective method for increasing performance with, and the understanding, of the system (Schröter 2015).

The participants had to give their consent to participate in the evaluation. The evaluation was voluntary and those participating in the study were assigned participant numbers to ensure that anonymity is maintained. When the participants had completed the consent forms, task-lists were distributed amongst all participants who then had three hours to complete them. The evaluation was conducted in a controlled environment and facilitated by the main researcher and two student assistants. The student assistants used in Field Study 2 were not the same individuals used for Field Study 1 to prevent potential bias. They were, however, trained in a similar manner to handle enquiries from students as for Field Study 1.

Participants were encouraged to attempt all tasks on their own. The assistance of facilitators could be initiated if major problems were encountered or instructions were misunderstood. The environment consisted of a typical computer laboratory with desktop computers with the software preloaded. Participants were encouraged to take notes of any problems that were encountered on the printed task-list and were required to record both the start and end times of each major task. Upon completion of all tasks, the printed task-lists were handed back to the facilitators for analyses. Additionally, participants were required to answer a post-test questionnaire to evaluate the usability of the software.

The extant systems analysis revealed that PowerPivot did not support all the design guidelines and therefore not all the accompanying features could be tested in the first evaluation. Moreover, a decision was also made to evaluate less complex features in the first evaluation. The reason was to first evaluate whether participants could handle less complex features before introducing advanced features that participants are not familiar with. The less complex features were evaluated by using tasks for organising a dashboard with multiple visualisations, applying filters and sorting, and utilising the onscreen help features to select appropriate data attributes and visualisations. According to Elias and Bezerianos (2011) more than half of their participants, who were novice users, did not understand the advanced features for the integration of coordinated views, drill-up/down activities, and storytelling. For this reason these concepts were not tested and were reserved for the second evaluation with Tableau.

5.6.2 Participant Selection

The evaluation was conducted with 32 undergraduate IS students (Table 5-5). The participant sample consisted of a group of third year ERP students at the NMMU registered for the year 2015. The participants were selected by means of convenience sampling as motivated earlier in this study (Section 4.2.3) and were not the same group of students registered for the 2014 year.

The majority (84%) of the participants had more than 10 years of experience of using a computer (n=27), while the remainder (9%) of the participants had been using computers for between 5 and 10 years (n=3). Only some of the participants (6%) had been using computers for less than five years (n=2). A small total of 6% (n=2) of the participants have never used BI or related IV software other than Microsoft Excel (or just Excel). The majority of participants (94%) had minimal experience with BI or similar IV software, however, some mentioned that they had used PowerPivot in a second year module, known as Business Systems. Since all of the participants had experience with Excel, data was also collected in terms of their experience with the tool. The third year ERP course only provided an introduction to BI dashboards and all participants were regarded as novice users of BI tools. Furthermore, the participants had no particular experience with IV and were considered novice programmers.

Table 5-5: Experience profile for Field Study 2

		Sample size (n)	***Percentage (%)***
Experience with a computer in years	Less than five (5) years	2	6
	Between five (5) and nine (9) years	3	9
	More than 10 years	27	84
	Total	**32**	**100**
Experience with BI and data analysis	No experience	2	6
	Novice	19	59
	Intermediate	11	34
	Total	**32**	**100**
Experience with Microsoft Excel	Novice	18	56
	Intermediate	14	44
	Total	**32**	**100**

5.6.3 Research Materials

The evaluation consisted of two main research materials, the task-list and the post-test questionnaire. The questionnaire consisted of three main sections (Figure 5-3). The first section asked questions regarding demographic information, such as the participants' experience with computers, BI and analysis tools. The second section of the questionnaire incorporated questions about the usability of the tool, which consisted of eight subsections. Each subsection (SS) evaluated a particular usability criterion. SS2 to SS7 consisted of several questions that the participants had to answer by rating the answers on a five-point Likert scale (1= *strongly disagree* and 5 = *strongly agree*).

Effectiveness or task completeness (SS1) required participants to specify whether they were able to complete all tasks successfully without assistance, which evaluates the BI tool's effectiveness. Participants were required to specify the task number for which assistance was required and a brief description of how the issue was solved. S*atisfaction (SS2)* was evaluated subjectively according to their overall task-times, the quality of their dashboard, and the process to create the dashboards. *Visibility (SS3)* evaluated whether the functions were displayed in an uncluttered manner, the software was easy-to-use, the system status was communicated appropriately, and whether it was easy to navigate in the software. *Flexibility (SS4)* evaluated whether the participants felt in control of the BI tool, could easily customise the application and appearance of dashboards to their needs, and select different data types and visualisations.

Learnability (SS5) included measures to evaluate how easy it is to learn the features of the BI tool, as well as to evaluate whether the terminology in the software was understandable and familiar. Additionally, *learnability* evaluated whether the process to create dashboards was difficult to learn. *Error Control and Helpfulness (SS6) evaluate*d two criteria. The first criterion evaluated the level of assistance provided by the software to recover from errors easily and efficiently. The second criterion evaluated the *helpfulness* of the software with selecting appropriate visualisations and connected to data sources.

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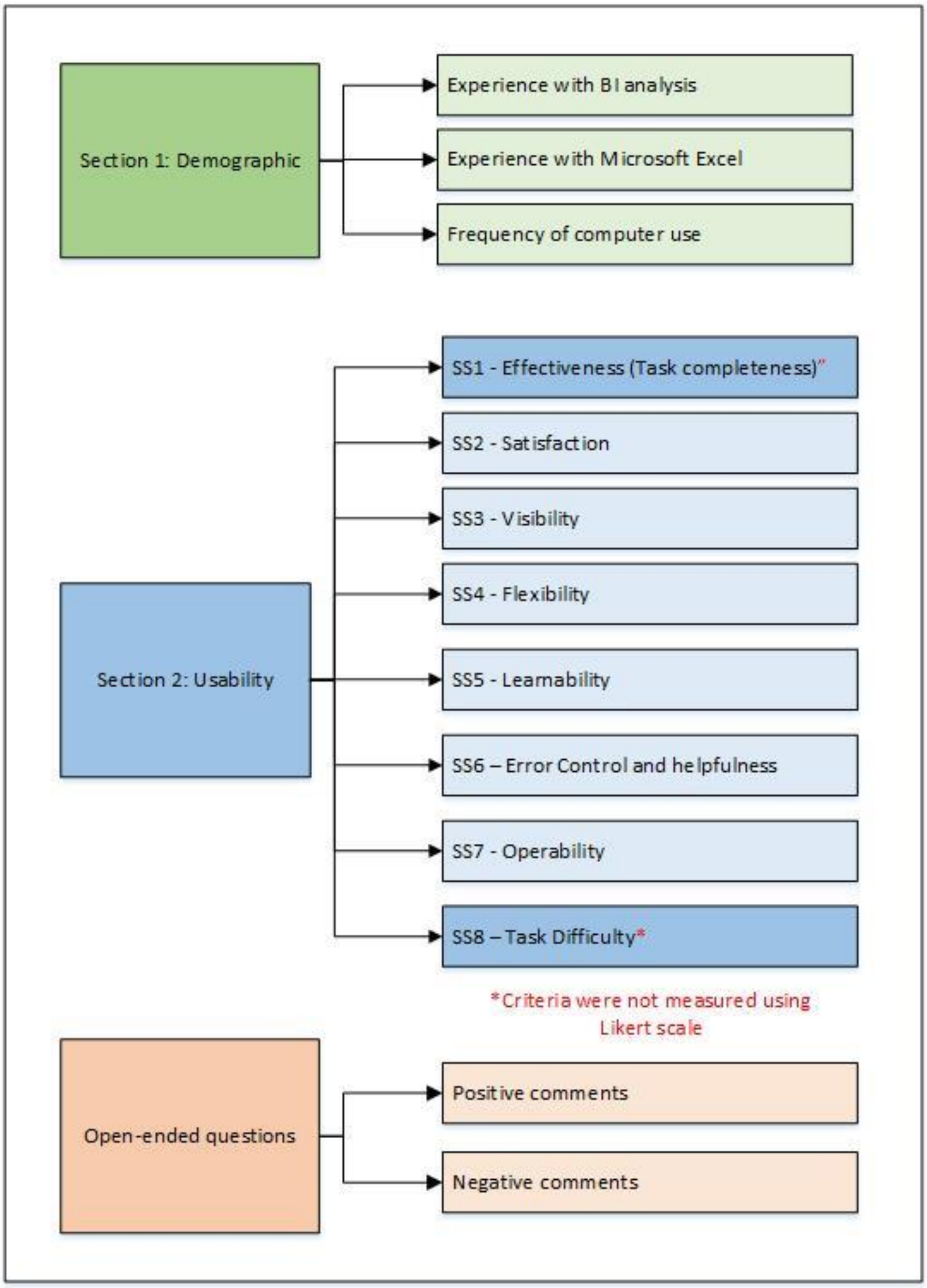


Figure 5-3: Questionnaire structure for Field Study 2

Operability (SS7) evaluated the participants perceived ability to control the software and to operate its features to easily select different data attributes, apply filters, experiment with alternative visualisations, and organise the elements of the dashboards. *Task-difficulty (SS8)* required participants to rank the four main tasks from most *challenging* to *least challenging*. *Efficiency* was not evaluated using a Likert scale, but by recording task times. The third section of the questionnaire had two open-ended-questions relating to the positive and negative features of the software.

The consent forms and questionnaires were created in an online survey tool namely, Google Forms. This allowed responses to be captured electronically in a spreadsheet. During the evaluation, participants were supplied with tasks to create a dashboard in PowerPivot. The task-list consisted of four main tasks, which each could be mapped to those of the IV process (Figure 5-4). The original IV process was depicted and discussed earlier in this study (Section 3.5). The outcome of the task-list was to derive a dashboard displaying inventory information from the SYSPRO ERP database such as cost prices, quantities, warehouses, product descriptions and sales (Appendix F).

The first task required participants to create a SQL view in Microsoft SQL server. The SQL code was supplied to participants as they were not familiar with the database. Only the necessary data tables and columns relating to inventory were selected. Heer et al. (2008) motivate that novice users are not expected to write advanced queries to export data to specific file formats, nor do they have to understand complex file formats to integrate heterogeneous data types.

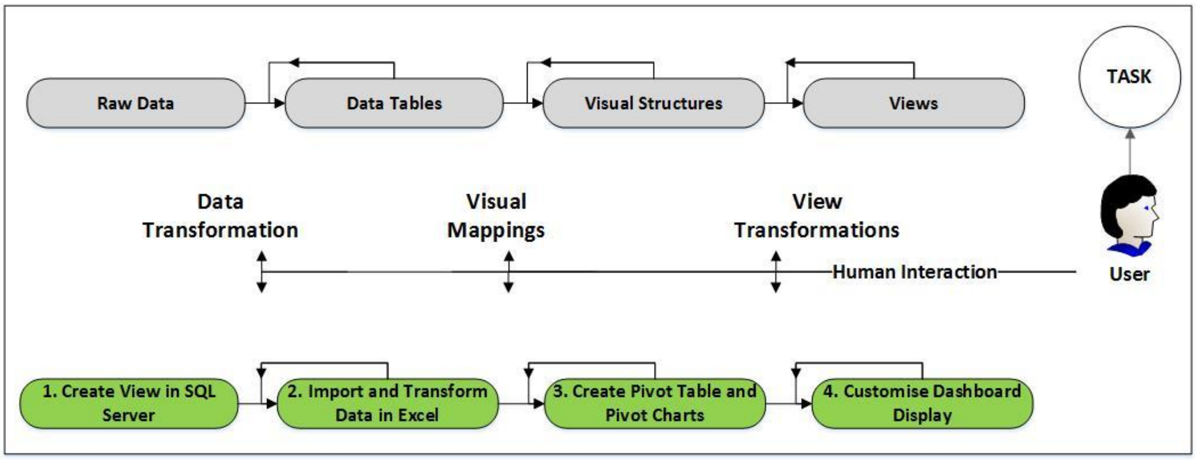


Figure 5-4: Mapping of tasks for PowerPivot and traditional IV process

The second task required the participants to connect to the SQL view from PowerPivot using a connection wizard. Once the connection was made, the data could be imported into a pivot table to add additional calculations (*Data Transformations*). These calculations related to cost value on hand and the selling value on hand. PowerPivot refer to charts instead of visualisations and therefore this section will refer to both terms where appropriate. The dashboard consisted of three pivot charts and a small pivot table to apply filters, which had to be created by using PowerPivot (*Visual Mappings*). The data attributes could either be selected from a checkbox, or dragged onto one of the pivot chart containers. This task allowed participants to experiment with predefined chart templates that were automatically based on the data attributes they have selected. The final task required the participants to customise and format the entire dashboard as they desired (*View Transformations).* Participants could arrange the chart elements, apply filters and sorting, change colours and format labels.

5.6.4 Validity and Reliability of Data

Content validity was achieved as the criteria and their associated questions were derived from literature and discussed with experts. The face validity of the questionnaire was established as the questions were derived from and agreed on by literature (Saunders et al. 2009). The questionnaire was refined and validated during pilot tests with two experts to ensure that the task-list and questionnaire were unambiguous and the questions were aligned with the objectives of the study.

The reliability and internal consistency of quantitative responses were measured using Cronbach's alpha (Saunders et al. 2009; Nunally 1978). An acceptable Cronbach's alpha coefficient is any value larger than 0.70 as it shows consistency between the items being measured (Nunally 1978; Collis & Hussey 2009; Gravetter & Wallnau 2009). However, coefficients between 0.50 and 0.69 holds evidence of reliability and is acceptable if the study is in its early stages of research (Nunally 1978; Collis & Hussey 2009; Gravetter & Wallnau 2009).

The Cronbach's alpha coefficients for the mean difference and the mean standard deviation of each criterion were calculated. The overall Cronbach's Alpha of the questionnaire rating (0.65) was slightly below the accepted standard of 0.7, but was still acceptable for explorative study and the newly developed questionnaire (Gravetter & Wallnau 2009). The individual item correlations varied from 0.76 – 0.87 and indicates that the internal consistency of the data was moderately valid and was above the acceptable range of 0.7 (Table 5-6).

Table 5-6: Results of Cronbach's alpha test for Field Study 2

Section number	Criteria	Item total correlation (α)
SS2	Satisfaction	0.83
SS3	Visibility	0.84
SS4	Flexibility	0.87
SS5	Learnability	0.86
SS6	Error control and helpfulness	0.76
SS7	Operability	0.81
Overall score		**0.65**

Item reliability was established for the Likert-scale type questions since the sections S3-S8 have Cronbach's alpha ratings between 0.76 and 0.87 (Appendix G) and are therefore considered acceptable (Gravetter & Wallnau 2009). The section on *learnability* initially scored a Cronbach's alpha of 0.43. This was due to two negatively stated questions which many of the participants did not interpret properly. The negatively worded items were rescaled for the purpose of the analysis, which improved the Cronbach's Alpha's for the *learnability* section to 0.86.

5.6.5 Results

An analysis of the data provided interesting results and is reported on according to the usability criteria identified (Section 5.4). All of the participants were able to complete the usability evaluation using the task-list, as well as the post-test questionnaire. The mean for each close-ended Likert scale item was classified according to the following ranges:

- *Strongly disagree* ($1.0 \geq \mu < 1.8$);
- *Disagree* ($1.8 \geq \mu < 2.6$);
- *Neutral* ($2.6 \geq \mu \leq 3.4$);
- *Agree* ($3.4 > \mu \leq 4.2$); and
- *Strongly agree* ($4.2 > \mu \leq 5.0$).

The results for *effectiveness* (*task completeness*) were positive, since all 32 participants completed all tasks successfully. Although all the tasks were completed successfully, nearly half (44%) of participants (n=14) required assistance at some stage of performing their tasks (Table 5-7). The reported problems were minor and related to issues, such as not reading the task-list instructions, searching for formatting options, finding specific tabs and options, and typing errors. Two participants experienced problems with the Microsoft SQL server that timed out, however, the program was restarted and the data was recovered.

Table 5-7: Problems encountered during Field Study 2

Problems	**Frequency (*f*)**	**Percentage (%)**
Finding tabs and options	6	27
Typing errors (server name)	3	14
Customisation options (dashboard layout, colours, chart types, labels)	8	36
Reading errors/ clarifying instructions	3	14
SQL server timeout	2	9
Total	**22**	**100**

The participants were instructed to submit their completed dashboard files to the ERP course's portal website, where the researchers could compare their final dashboard to the suggested solution for completeness. No specific instructions were given regarding the formatting of dashboard and participants were allowed to format their visualisations as they desired. Despite the difference in the different individual visualisations that were selected, all participants' final dashboards were regarded as sufficient when compared to the suggested solution. Since all the tasks were completed successfully and were followed as a development process, it can be deduced that a well-structured process may act a guide for users to create dashboards *effectively*.

Efficiency was evaluated subjectively as participants were asked whether they were satisfied with their task times. The participants were satisfied with their overall task times and gave a mean rating in the s*trongly agree* range (μ=4.34). The second method was to analyse the recorded task times for each participant from the printed task-lists. The mean task time to complete the task-list was 64 minutes and 45 seconds. The mean times for each of the four tasks were ranked according to those on which the most time was spent (Appendix G).

The participants spent the most time on Task 4, *Customise the Dashboard Display*, with a mean task time of 19 minutes and 22 seconds. The second longest task time was recorded for Task 3, *Create Pivot Table and Pivot Charts*, with a mean time of 17 minutes and 53 seconds. This result confirms the findings of Elias and Bezerianos (2011) and Grammel et al. (2010), since users struggle to map their selected data attributes to an appropriate visualisation and may spend some time refining the final dashboard. The second task, *Importing and Transform Data* *in Excel*, had the lowest mean time with a mean of 10 minutes and 45 seconds. The means and standard deviations are calculated for each of the usability criteria (Appendix G) and presented (Figure 5-5).

Satisfaction was subjectively evaluated according to their satisfaction with their task times, overall dashboard, and the development process. Participants were satisfied with the development process as the mean rating was *positive* in the s*trongly agree* range (μ=4.57). The high satisfaction ratings of the development process can be partially attributed to the fact that an overview was provided to participants about the development process. Participants were also satisfied with the layout and the appearance of their final dashboard since the results were in the s*trongly agree* range for the satisfaction of the final dashboard (μ=4.47). *Satisfaction* was the criterion that scored the highest mean overall rating in the questionnaire (μ=4.46). The high satisfaction levels indicate that the development process was not too complex when using PowerPivot, which is necessary for users according to the guideline *Easy Development Process* (G1). Additionally, this result indicates that they were satisfied with the overall usability of the tool.

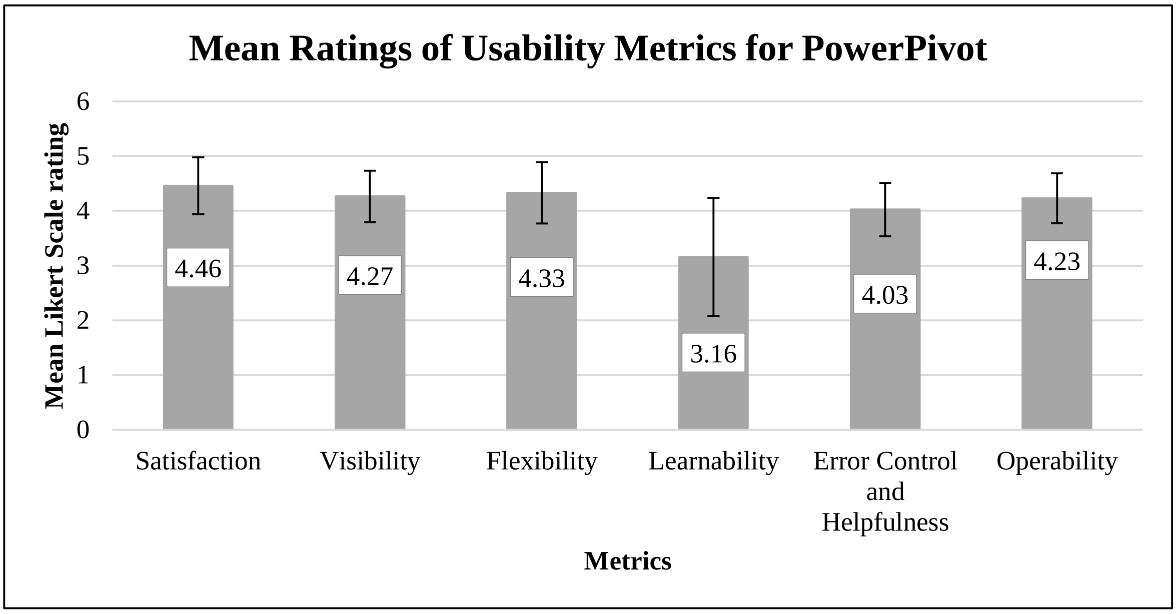


Figure 5-5: Mean ratings of usability criteria using 5 point Likert scale (n=32)

The mean rating of the *visibility* criterion was rated *positively* (μ=4.27), which falls into the s*trongly agree* range. Although *visibility* received a positive rating, some participants (27%) still required assistance due to features that were not easily found (Table 5-7). The participants perceived the features to be displayed in an uncluttered and well-structured manner (μ=4.38) and could be easily understood as they were self-explanatory (μ=4.22). The system's status was communicated fairly during the evaluation and received sufficient feedback (μ=4.22). The results also revealed that participants could navigate to the various features and screens without any problems (μ=4.25).

The high *visibility* ratings relate to three evident design guidelines. The guideline *Dynamic, Interactive, Immediate Visual feedback* (G4) enabled participants to receive feedback on the status of their dashboards every time an action was performed such as selecting/deselecting a data attribute, applying formatting changes, or choosing a different visualisation. Participants understood the features and charts easily after reading explanations and descriptions from tooltips, which verifies the guideline *Promote Learning through Demos and Explanations* (G11).

Learnability scored the lowest mean rating of all the criteria evaluated on a Likert scale (μ=3.16) and was rated the *neutral* range. As result, it can be inferred that *learnability* issues were experienced by some participants and might require to spend some time to learn additional features. The terminology used in PowerPivot was familiar to participants and they had a good understanding of the features (μ=4.22). This result is also complemented by the high mean learnability rating of PowerPivot's features (μ=4.28).

Participants stated that explanations helped them to understand which chart types can be used with certain data attributes, which again verifies the guideline *Promote Learning through Demos and Explanations*. Additionally, the guidelines relating to *Dynamic, Interactive, Immediate Visual Feedback* (G4) and *Automatic Visualisation Creation and suggestions with Useful Defaults* (G7) could have assisted participants in learning how their actions affect the appearance of visualisations, such as selecting a particular data attribute, applying filters, or changing colours and labels.

Error control and helpfulness (μ=4.03) had the second lowest mean rating, but was still rated *positively*. Participants could easily recover from their errors (μ=4.06) as sufficient assistance was provided through error messages and suggestions (μ=3.78). The explanations of functionality could be obtained through tooltips and similar descriptive features that were perceived as helpful (μ=3.78). The results indicated that participants favoured the automatic and recommended chart generation features (μ=4.06). The recommended charts were also helpful in determining its use and appropriateness, since they were supported by helpful explanations when the selected chart was not appropriate for the selected data (μ=4.16).

The high ratings for *helpfulness* of explanations and automatic visualisation generation further verify two design guidelines, namely *Automatic Visualisation Creation and Suggestions with Useful Defaults* (G7) and *Promote Learning through Demos and Explanations* (G11). Explanations do not only assist in learning, but are also helpful to convey when particular features should not be used. Other helpful features related to wizards to assist in connecting to their created SQL view (μ=4.31). This result partially verifies the need for guides or wizards to support the development of dashboards as required by the guideline *Guided Development Process* (G2).

Flexibility received a high rating with a mean overall rating (μ=4.33), which falls into the s*trongly agree* range. A great deal of *flexibility* related to the ability to experiment with different features and charts, customise the layout of overall dashboard effectively, and select different attributes from the data set. The participants *agreed* that they had a fair amount of control over the application (μ=3.97) and could easily customise the layout (or position) of the chart and PowerPivot's features (μ=4.31). The overall dashboard was easy to customise and format (μ=4.47). Furthermore, the data attributes could easily be selected or "swopped" with other available data attributes in the data set (μ=4.28).

The item that scored the highest mean rating for *flexibility* was the ability to easily change the chart type (μ=4.63). This result supports those found for the *operability* criterion and indicates that participants were able to easily experiment with different data attributes. The guidelines *Flexible Customisation Process* (G3) and *User Friendly Data Input for Common Data Formats and Smart Data Discovery* (G5) are therefore verified as participants could easily derive their own calculations or add additional data attributes.

Operability received a mean rating in the s*trongly agree* range (μ=4.23). This result indicates that the participants could effectively use PowerPivot to create dashboards and analyse a data set. Participants could analyse the data set from multiple perspectives (μ=3.97). An example of analysing a data set from multiple perspective would be when selecting more than two data attributes (product, quantity and warehouse) are selected to be displayed on a single visualisation. Moreover, features for sorting and filtering could easily be applied (μ=4.38). Participants typically sorted the charts according to quantity, and filtered the charts to show specific products or warehouses. Visualisations could be easily selected from the chart gallery (μ=4.28). The high mean ratings reveal that participants could create visualisations for their data analysis needs. Moreover, the components of the dashboard (individual charts, interactive slicers and filters) could also be easily organised and enabled participants to customise the layout of their dashboard as they desired (μ=4.25). This result reveals that participants had a high degree of control over the application. Jooste et al. (2014) classified control over the application under *flexibility* (Section 5.4). However, the International Organisation of Standardisation (ISO) defined control over the application as part of the definition of *operability* (ISO/IEC 25010 2011).

The participants perceived PowerPivot to behave in a consistent manner (μ=4.28), which is particularly important for *learnability* aspects. A number of design guidelines could be verified through the *operability* section. The *Easy Development Process* (G1) and *Dynamic*, *Interactive and Immediate Visual Feedback* (G4) guidelines could be confirmed as participants could see the effect of their actions, such as selecting various charts and data attributes, applying filters, and changing formatting of charts with a few clicks. Additionally, the *operability* ratings indicate that participants had control over the application and could make changes to their dashboards in a flexible manner, which verifies the guideline for a *Flexible Customisation Process* (G3). Participants could also easily apply features for sorting and local filtering. However, features relating specifically to search, drill-down and multiple coordinated views (global filtering) were not evaluated in Field Study 2. The guidelines for *Search, Filter, Sort, and Navigation for Drill-Down Features* (G5) and *Multiple Coordinated Views and Dynamic Queries* (G6) could only be partially verified.

None of the usability criteria received negative mean ratings in the s*trongly disagree* or d*isagree* ranges (Figure 5-5). The mean ratings for the detailed usability criteria is depicted in Figure 5-6. The criterion with highest mean rating was *satisfaction* (μ=4.46) and indicated that the participants were satisfied with the usability of PowerPivot. The item that scored the lowest overall mean was *learnability* (μ=3.16). Although the rating for *learnability* was not poor, participants will need to spend some time to learn how the features of PowerPivot work and how to apply the steps to create dashboards.

The qualitative responses were analysed and coded into themes for both the positive and negative aspects of PowerPivot. The themes identified were not classified as priori themes. The three most frequent themes that were identified for the positive aspects were for "*easy to use*" and "*easy to customise charts*" and "*helpful filtering abilities*" (Table 5-8). The participants were particularly impressed in way they could easily customise charts and select data attributes. Other positive comments related were "*it easy to change chart type*", *"it was easy to format charts*" and "*easy to select data attributes*". The participants described the filtering features to be useful and one comment was *"filters were useful as some charts became cluttered*".

Table 5-8: Positive aspects cited in the open-ended questions for PowerPivot

Positive aspects	**Frequency (*f*)**
Easy to change or customise format of charts	15
Easy to use	10
Filtering charts	9
Interactive and visually appealing	6
Guided process	6
Easy to select data attributes	5
Increased my knowledge of data analysis capabilities	4
Interface is well-structured and visible layout	4
Easy to create charts	4
Helpful for data analysis	3
Easy to connect to data source	3
Automatic features are useful	2

Positive feedback was received regarding the guided process and mention was made that the explanation helped them understand the necessary steps to create dashboards. One comment was "*discovering the capabilities through guided steps was insightful and educative*". Furthermore, a couple of participants commented on the overall UI of PowerPivot, the layout of the dashboards, and ability to easily connect to a data source.

Interesting feedback was received that the visual capabilities of PowerPivot helped participants to understand the data, and that their knowledge of data analysis was improved. Other positive comments were "*everything is automatically made for you*" and "*makes data analysis far less complex*". One participant mentioned that the drill-down features were easy to use. Nevertheless, the drill-down features were not evaluated in Field Study 2 and indicated that the users might get confused between filtering and drill-down features, which confirms the findings of Elias and Bezerianos (2011).

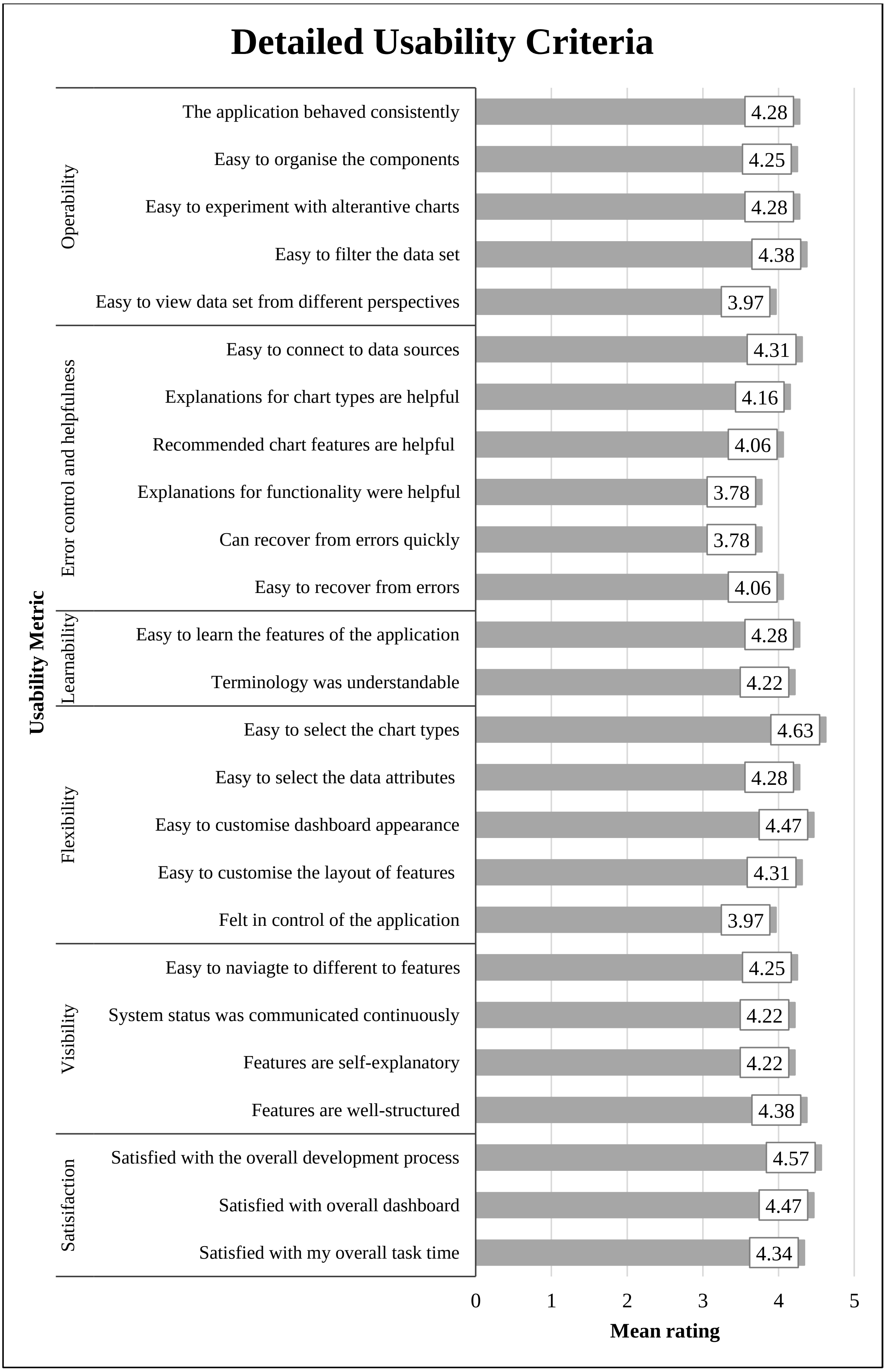


Figure 5-6: Detailed usability ratings for PowerPivot

The negative aspects mostly related to navigating between screens, charts and features. The need for adequate navigation features are therefore supported, as required by the guideline *Search, Filter, Sort, and Navigation for Drill-Down Features* (G5). Participants often became confused between the screen representing the pivot table (with the entire dataset) and a secondary screen with the dashboard (consisting of individual visualisations). Moreover, some participants were unsure where to search for particular customisation/formatting settings of visualisations. Some comments were "*changing something in the pivot table affected another chart unnecessarily*", "*was unsure whether in PowerPivot or normal Excel*" and "*some options were not visible in some cases*". Another found difficulty inserting pivot tables and customising the dashboard, while some thought that the process was difficult to follow as it was "*intense without a guide*". This result further verifies the need for a *Guided Development Process* (G2). Interestingly, a number of participants mentioned that there were a lack of search features for as required by the guideline *Search, Filter, Sort, and Navigation for Drill-Down Features* (G7). This result verifies that users would like to conduct searches on a dataset to find particular data attributes, as well as to be guided through the development process.

Table 5-9: Negative aspects cited in the open-ended questions for PowerPivot

Negative aspects	**Frequency (*f*)**
Finding menu items and screens	7
SQL programming is tedious	5
Customising the dashboard	4
No search facilities	3
Unsure how to recover from errors	3
Tutorials and explanations	3
No guide for steps	3
Re-adjust size of charts to avoid clutter	2
Transforming data set	2
Changes on one charts affects others	1
Time orientated	1

A few participants complained about the tedious process of typing the SQL statements to select data and merge tables. Some mentioned that they would not have been able to write the SQL as they were not familiar with the database or syntax of the SQL. This motivates the need *User Friendly Data Input for Common Data Formats and Smart Data Discovery (G8).* One participant mentioned that there were not enough explanations and tutorials in PowerPivot to support "*newcomers*". This result verifies BI tools need to be easy to learn, promote learning, and support users through tutorials and explanations as required by the guideline *Promote Learning through Demos and Explanations* (G10). Moreover, thorough explanations and assistance needs to be provided to support users in recovering from errors. Interestingly, one participant mentioned that it would be helpful to add a visual feature that depicts "*what time the data is from*". This result indicates that users would like to analyse data according to specific time horizons, which is also an important feature relating *History Tools, Storytelling and Annotations* (G9).

The task list allowed for multiple coordinated views to be partially evaluated with the "slicer" feature. The task list did not specially instruct participants to create global filter and setup multiple coordinated views. However, one participant did explore the features of PowerPivot in more detail and mentioned that some changes in visualisations affected other charts unnecessarily. This result indicates that multiple coordinated views and global filters are supported in PowerPivot and indicated that users want to maintain control over the visualisations that are affected by the global filters, which is important for setting up *Multiple Coordinated Views and Dynamic Queries* (G6).

The results for all the quantitative sections were overall *positive.* All of the criteria indicated that the participants were satisfied with the usability of PowerPivot. Not all of the design guidelines could be completely verified in Field Study 2. Those that were only partially verified included *Guided Development Process* (G2), *Search, Filter, Sort, and Navigation for Drill-Down* (G5), *Multiple Coordinated Views and Dynamic Queries* (G6).

5.7 BI Framework Version 2

This chapter proposed a number of design guidelines and features that could be used to design and evaluate a BI tool. These guidelines and features were incorporated into a BI Scorecard to rate potential BI tools for selection. The results of Field Study 2 confirmed that the design guidelines are required for novice users and that BI tools need to be evaluated incrementally to determine the level of complexity users can handle when performing BI tasks. These aspects can be taken into consideration when evaluating BI tools. For this reason, the BI Framework can be updated. An updated version of the framework is depicted in Figure 5-7.

The BI Framework consists of three main sections namely: Situational Analysis, Suitability Assessment and Implementation. In the former version of the BI Framework (Section 4.4), Situational Analysis was described as the activity for analysing the opportunities, requirements and objectives of a BI tool for the particular organisations' users. Users' experience play an important role in the level of complexity they can handle when using a BI tool. For this reason, Situational Analysis, also requires organisations to consider various aspects of the users' prior experience and the problems they may face with current software in the current IT infrastructure.

The second component of the BI Framework, Suitability Assessment, includes the mapping of the benefits, risks and organisational impact that BI tools may have on users. However, in order to provide a suitable BI tool for users, specific design guidelines of a BI tool have to be identified for users. A set of 11 design guidelines is proposed with a set of features that may implement these guidelines. The guidelines are important and need to be evident in BI tools to ensure that users can create and use dashboards in an effective manner. In order to evaluate whether BI tools conform the proposed design guidelines, the BI Scorecard can be used to rate the features of tools and derive at an overall score. The BI Scorecard evaluates the features of BI tools on a three-step scale. BI tools that satisfy the majority of the criteria in the BI Scorecard can be selected as potential tools for further evaluation with users.

Once the BI tools have passed the initial evaluation with the BI Scorecard in Suitability Assessment, usability evaluations need to be planned with users and specific usability criteria for BI tools need to be determined. The usability criteria should be used to evaluate a BI tool and the results should be reported on. The users' experience should be considered to determine the level of complexity users can handle when planning evaluation tasks. Users are expected to perform the easier tasks first, which test less complex features. Implementing and evaluating BI tools incrementally will also allow users to gradually learn how the BI tool operates, and possibly avoid users from feeling overwhelmed by the complexity of the features.

Implementation is an important component, since valuable feedback is provided based on whether the BI tool satisfies the requirements and objectives of the users. The Implementation should be accompanied by several evaluation iterations to deploy and evaluate the BI tool incrementally. The BI tool may not suit the needs of users in the initial evaluations. Requirements need to be reconsidered when the usability of the tool has been poorly rated and a decision needs to be made to wither conduct additional evaluations with the BI tool, or to select an alternative BI tool that can be evaluated with users. Not all of the design guidelines and requirements have to be met by the BI tools in the initial evaluations. The purpose is to produce valuable feedback in terms of matching the features of the BI tools with the needs of users.

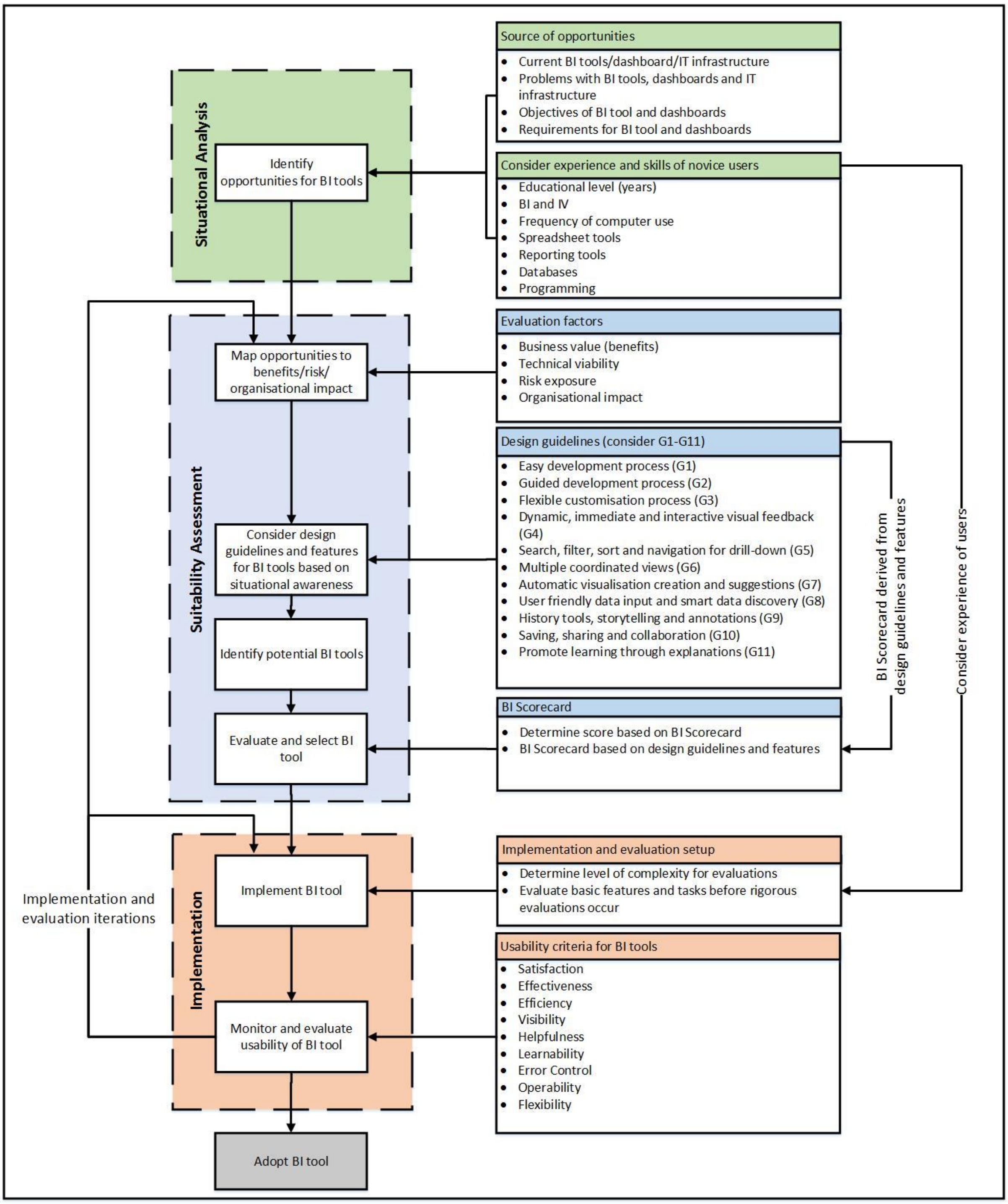


Figure 5-7: Proposed BI Framework for novice users (version 2)

5.8 Conclusions

The DSR methodology allows for a number of iterations to develop and evaluate an artefact. This chapter continued to develop and improve the components of the BI Framework. More specifically, the focus of this chapter was to improve the Suitability Assessment component of the BI Framework. This component requires that potential BI tools are identified and evaluated to determine their suitability for users' needs and requirements. In order to identify a suitable BI tool, the specific features that may satisfy the requirements and guidelines need to be known in advance. For this reason, a total of 11 design guidelines were proposed for BI tools and their importance for novice users was motivated. The design guidelines were accompanied by several features that may implement each guideline and were expanded into a BI Scorecard.

The BI Scorecard uses as a three-step scale to rate the features of BI tools so as to determine their conformity to the design guidelines. The BI Scorecard was used to informally evaluate a number of popular BI tools in an extant systems analysis. Due to licensing agreements, only two BI tools (Tableau and PowerPivot) were selected as potential tools that could be implemented at the NMMU. However, to determine whether the design guidelines and their associated features satisfy the requirements of users, Field Study 2 was conducted as a usability evaluation with a group of students at NMMU.

The objective of Field Study 2 was twofold. The first objective was to determine the usability of one of the selected BI tools (PowerPivot) and to verify the proposed design guidelines and the associated features for novice users. The second objective was to practically demonstrate the components of the BI Framework, by using the BI Scorecard to select a BI tool and to incrementally evaluate its features. Field Study 2 could not verify all of the proposed design guidelines, since PowerPivot did not support all of the features proposed. However, valuable feedback was received in terms of the necessary features as well as the level of complexity that users could handle. Moreover, the results of Field Study 2 revealed that the BI Scorecard could be used as effective tool for selecting BI tools for novice users. Before the usability evaluation commenced in Field Study 2, a number of usability criteria were identified. These criteria were specifically proposed to evaluate the usability of BI tools. The usability criteria are: *effectiveness*, *efficiency*, *satisfaction*, *learnability*, *visibility*, *flexibility*, *error control* and *helpfulness*, and *operability*.

The usability evaluation also confirmed the findings of other similar studies. Users often get confused between activities such as drill-down and filtering, which indicates the need for explanations and other learning mechanisms in BI tools. Moreover, users responded positively to a guided development process for dashboards as well as an integrated environment where the entire IV process can be executed.

A second version of the BI Framework was provided. All three components were updated and improved. The following research questions have therefore been answered in this chapter:

> ***RQ3:*** *"What are the design guidelines and features of BI tools for novice users?"*
>
> ***RQ4:*** *"What current BI tools can support novice users in creating dashboards?"*
>
> ***RQ5:*** *"What usability criteria can be used to evaluate BI tools?"*

The next chapter will discuss the final evaluation of this study. The evaluation will be conducted with the second BI tool selected based on the BI Scorecard, namely Tableau, which satisfies all of the design guidelines. The final evaluation will entail rigorous testing of all the design guidelines and suggested features, since not all of the design guidelines could be confirmed in Field Study 2. Two student groups at different education levels will be requested to participate in the final evaluation and the results will be reported on.

Chapter 6. Final Evaluation

6.1 Introduction

The BI Framework consists of a number of design guidelines accompanied by a set of features. The features were incorporated into a BI Scorecard and were used to evaluate a number of popular BI tools. As a result, two BI tools were selected for the Demonstration and Evaluation activities, namely PowerPivot and Tableau. The chapter addresses the fifth activity of the DSR methodology, namely *Evaluation*. The activity is closely related to the Design Cycle and the Rigor Cycle in the DSR methodology, which involve evaluating the developed artefact and adding the findings to the knowledge base. The building activity is iterative, allowing the final artefact to be refined until it finally satisfies the requirements and objectives it was built for. A second version of the BI Framework was explained in detail in the previous chapter (Section 5.7).

In the *Evaluation* activity, the artefact is measured to determine how well it satisfies the objective it was built for. The BI Framework was initially demonstrated and validated by means of Field Study 2 (Section 5.6). The BI tool used in Field Study 2, namely Microsoft Power Pivot, was evaluated with a set of usability criteria that were specifically formulated for BI tools. PowerPivot did not meet all of the requirements proposed in the design guidelines, but valuable results were obtained to verify the majority of the design guidelines proposed in the framework. As a result of the feedback, amendments were made to improve the BI Framework.

The final evaluation of this study is discussed in this chapter and the results are presented. The evaluation was conducted with two groups of students. The objective of the final evaluation was twofold. The first objective was to determine the success of the proposed design guidelines in the BI Framework and whether they could overcome the usability problems identified earlier in this study. The second objective was to determine the usability of Tableau and to investigate if there are any relationships between the usability ratings of users with different education levels and user experience. This chapter will therefore answer the sixth research question (RQ6)*: "Are there differences between novice users' education level and the usability ratings of BI tools?"*. The research question will be answered by formulating a hypothesis to test for both statistical and practical significance in the usability ratings between the user groups.

Although this study did not specifically develop a new BI tool, more complex features were incrementally evaluated with users to assess which levels of complexity they could handle. For this reason, the final evaluation includes additional tasks for those features that were not evaluated with PowerPivot. The evaluation was conducted with two user groups on different education levels. The objective is to determine whether users with different experience profiles and educational backgrounds perceive the usability of the same BI tool differently. The usability criteria used in this evaluation were refined and additional questions relating to the design guidelines were added to the post-questionnaire.

The formulated hypotheses were tested in the final evaluation (Section 6.2). Since two groups of users on different education levels are used, the research procedure had to be planned properly to ensure that results are sufficiently collected from each group (Section 6.3). The research materials that were used in the evaluation consisted of a task-list and a questionnaire (Section 6.4). The demographic section provided valuable information regarding participants'' experience profiles (Section 6.5). The usability results collected from the post-test questionnaires were analysed (Section 6.6) and compared to the requirements and objectives identified for a BI tool (Section 6.7). By analysing the findings of the final evaluation, a number of conclusions can be made regarding the success of the BI Framework (Section 6.8). The structure of this chapter is depicted in Figure 6-1.

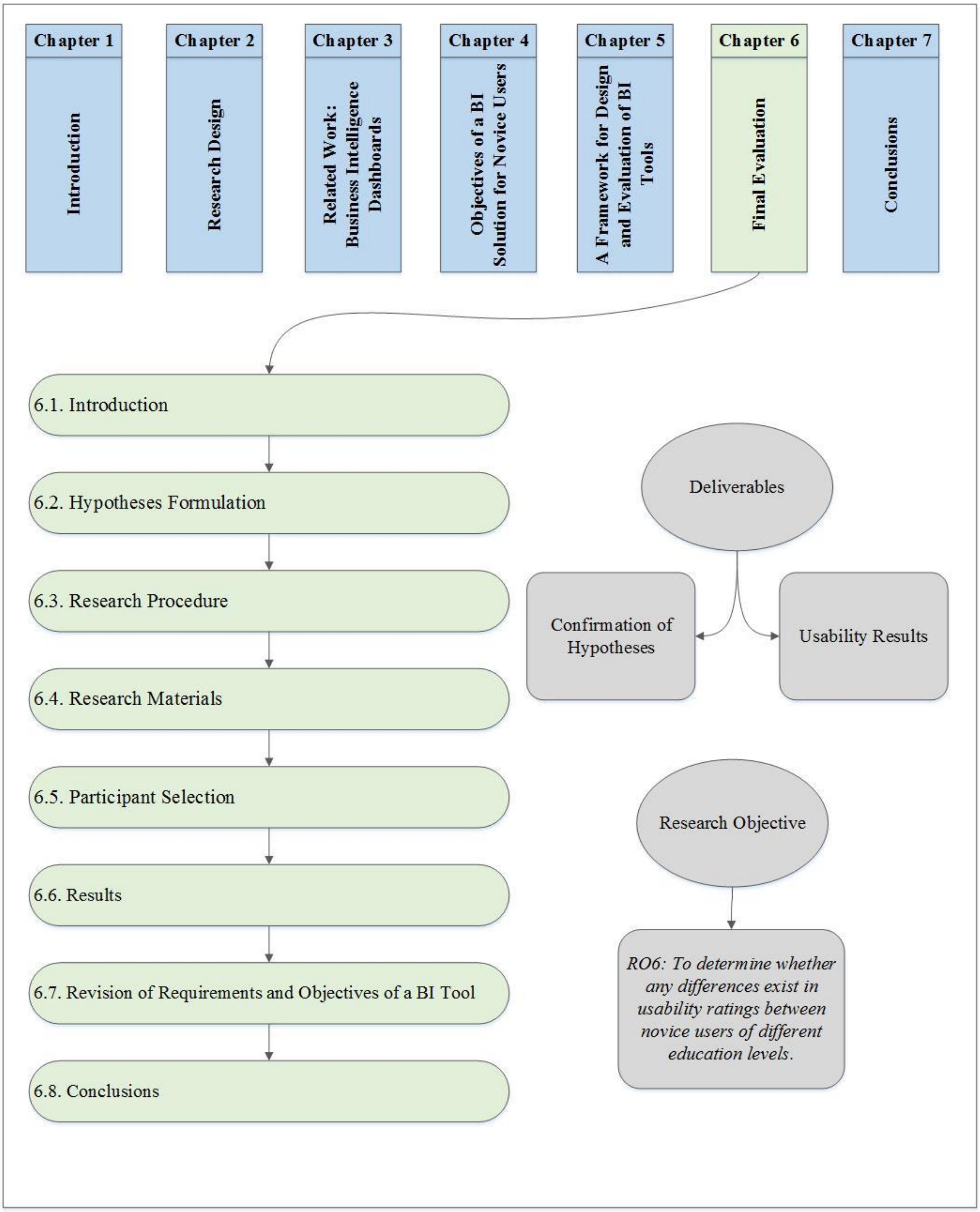


Figure 6-1: Chapter 6 layout

6.2 Hypotheses Formulation

As stated earlier, one of the main objectives of this chapter is determine the usability ratings for Tableau, however, it would also be interesting to investigate how users' experience and their different education levels impact their ratings of BI software usability. In order to answer the research question, several hypotheses were formulated by following a similar method to Veneziano, Mahmud, Khatun and Peng (2014) who investigated the usability ratings of ERP software for users with different educational backgrounds and user experiences.

The hypotheses were based on the usability ratings of the participants for Tableau, as well as, the current education level and experience level. Two hypotheses were formulated for examination and tested at the 95% significance level ($\alpha = 0.05$). A model of the hypotheses are depicted (Figure 6-2). The first hypothesis (H_1) was formulated as follows:

H_1: "*A significant difference exists between the users' education level and the usability ratings of a BI tool*".

The first hypothesis tests whether there are significant differences in the usability ratings between the education level of users (second-year and third-year student groups). A deduction can be made that the participants on different education levels should have different experience characteristics in terms of general computer use, BI tools, visualisation tools and dashboards. The second hypothesis (H_2) is therefore formulated as follows:

H_2: "*A significant relationship exists between the users' experience level and the usability ratings of a BI tool*".

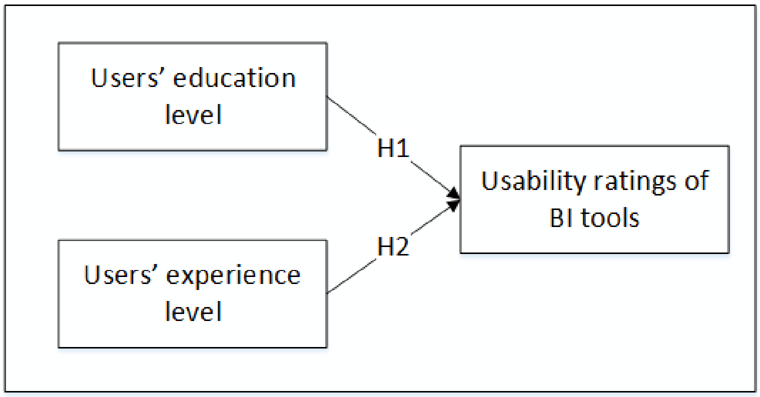


Figure 6-2: Model of hypotheses

6.3 Research Procedure

The evaluation was conducted with two student groups for two different undergraduate courses. A similar procedure, followed in the first evaluation with PowerPivot, was used for this evaluation (Section 5.6.1). Although the two participant groups conducted the evaluation separately, both groups were given the same lecture, instructions and submission requirements. Participants were provided a 60 minute lecture on BI and were given an overview of the IV process. The objectives and instructions of the evaluation were explained in detail. The participants were then provided with a brief demonstration of the Tableau software. The participants had to first provide consent to participate in the evaluation and were given printed task-lists on which they had to record their task times (Appendix H). Additionally, they had to answer 10 questions regarding their analysed data and upload their answers to the course's learning website.

The final evaluation was facilitated by the researcher and two student assistants in a controlled environment. The environment consisted of a typical computer laboratory with desktop PCs. Once again, if any problems were incurred participants could seek assistance from one of the facilitators. Major problems had to be recorded on the printed task-lists. The participants were given three hours to complete all tasks and were expected to give feedback on the usability of Tableau in the post-test questionnaire.

6.4 Research Materials

The research materials consisted of a printed task-list (Section 6.4.1) and an online post-test questionnaire (Section 6.4.2).

6.4.1 Tasks

The objective of the task-list was to analyse sales data of a fictitious retail company known as the Global Superstore. The data file was obtained through the Tableau University alliance containing 51 291 sales entries for numerous retail outlets across the globe. The data file simulates data collected from an ERP system. The task-list consisted of nine main tasks and was set up to evaluate at least one of the proposed design guidelines (Table 6-1). Additionally, participants had to record their overall task times.

6.4.2 Questionnaire

The structure of the questionnaire that was used in both Field Study 2 (PowerPivot) and the final evaluation (Tableau) were similar (Appendix I). The same criteria that were used for Field Study 2 were used in the final evaluation (Table 5-4). Minor changes were made to compensate for the additional questions relating to those features that were not evaluated in the first evaluation.

Table 6-1: Tasks for the final evaluation with Tableau

Number	Task description and purpose	Design guideline
1.	• Connecting to a data source • Selecting data tables • Merge data tables with smart queries	• Easy integrated development process (G1) • Guided development process (G2) • User friendly data input for common data formats and smart data discovery (G8)
2.	• Adding calculations • Selecting data attributes for automatic visualisation creation	• User friendly data input for common data formats and smart data discovery (G8) • Automatic visualisation creation and suggestions with useful defaults (G7) • Dynamic, interactive and immediate visual feedback
3.	• Drill-down into sales information from year to quarter, and then quarter to month	• Search, filter, sort, and navigation for drill-down features (G5)
4.	• Comparing sales data per month for 2012, 2013 and 2014 • Add an annotation when trends are identified in sales • Share findings with peers	• Multiple coordinated views and dynamic queries (G6) • History tools, storytelling and annotations (G9) • Saving, sharing and collaboration (G10)
5.	• Pivot tables to view from data different perspectives • Apply formatting (colours, labels, size, and transparency)	• Flexible customisation process (G3)
6.	• Visualisation suggestions • Search • Zoom • Highlight • Filter visualisations	• Automatic visualisation creation and suggestions with useful defaults (G7) • Search, filter, sort, and navigation for drill-down features (G5) • Promote learning through demos and explanations (G11)
7.	• Drill-down and sorting.	• Search, filter, sort, and navigation for drill-down features (G5)
8.	• Synthesising individual visualisations into a dashboard • Apply global filters	• Multiple coordinated views and dynamic queries (G6) • Search, filter and navigation (G5)
9.	• Create a data story	• History tools, storytelling and annotations (G9) • Saving, sharing and collaboration (G10)

After a consultation with an expert, a decision was made to remove the direct questions relating to the *satisfaction* section. The main reason for this removal was that a single question regarding the perceived satisfaction of the tool could appear rather subjective, and might not be a reliable indication of satisfaction when compared to the ratings of the other criteria. The overall satisfaction was considered in terms of the overall ratings of all the usability criteria and was considered together with the qualitative responses in open-ended questions. The section for *error control and helpfulness* was also split into two separate sections so that each criterion could be reported on separately.

The post-test questionnaire used in the evaluation consisted of a nine sections (Figure 6-3). The first section (S1) collected demographic information such as age, gender, the current year of study, years of experience with computers, dashboards and BI tools. Participants were also asked whether they had experience with other visualisation tools, such as spreadsheet tools, and were asked to list them. The main purpose of the demographic section was to collect data about the participants' user experience required for the hypotheses. Sections 2 to 8 evaluate the usability aspects of the tool quantitatively.

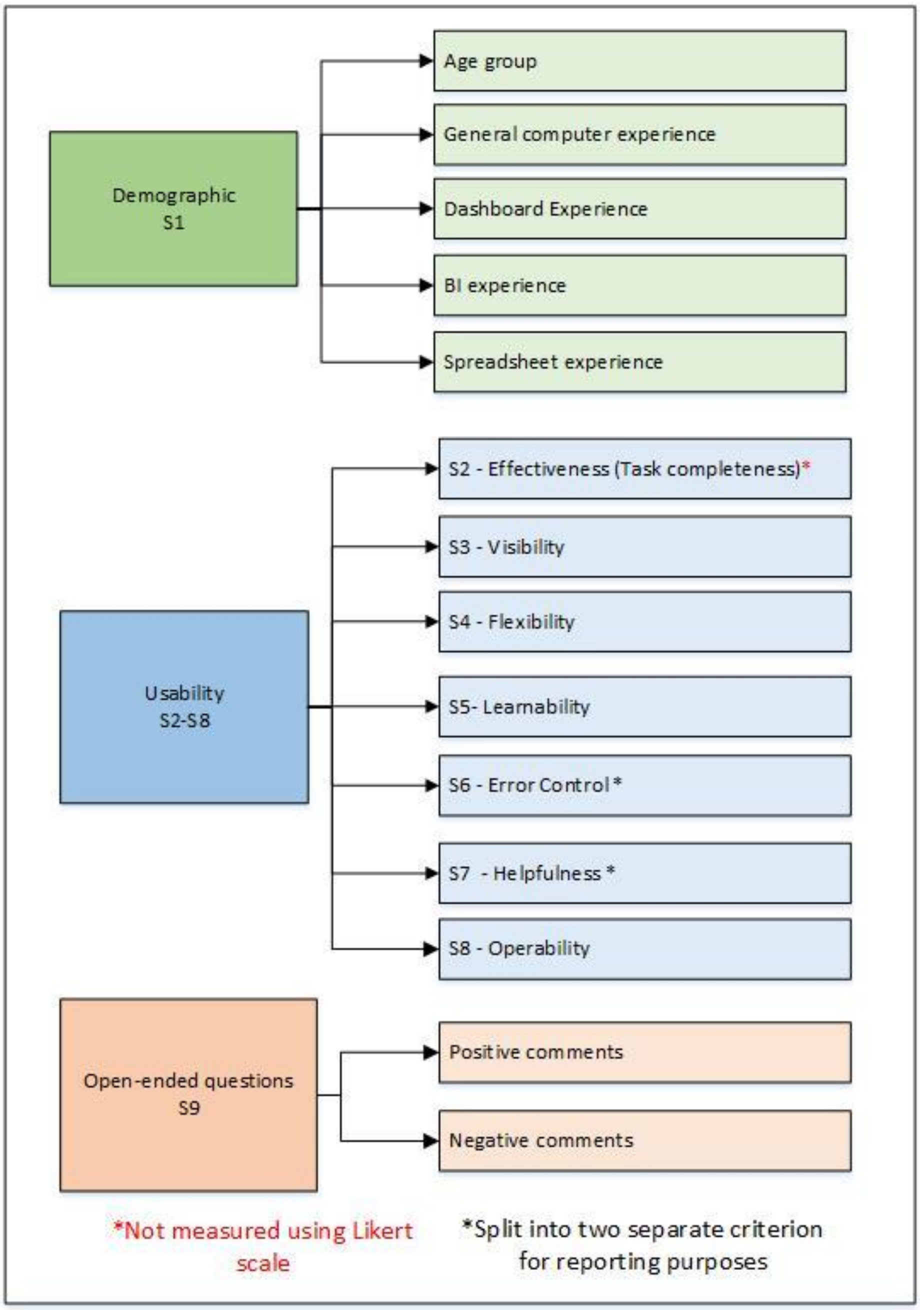


Figure 6-3: Questionnaire structure for the final evaluation with Tableau

Section 2 (S2) evaluated effectiveness and required participants to indicate whether they could complete all nine tasks based on three scales: "*successfully without assistance"*, "*successfully, but with assistance*", "*not successfully*". Participants had to evaluate Section 3 to 8 (S3-S8) using a five-point Likert scale rating with 1 representing *strongly disagree* and 5 representing *strongly agree*. Section 3 (S3) focussed on *visibility* to determine whether the UI was well-structured, information was easy to find onscreen, and system status was communicated adequately. A question regarding the interface interactivity was asked as it is forms part of the design guidelines. Section 4 (S4) addressed questions regarding *flexibility* and evaluated the perceived ability to customise the features of the system and dashboards to individual needs. Participants also had to indicate whether they could connect to various data sources, select different data attributes and visualisation types, and were able to manipulate data through calculations and merges. Section 5 (S5) focussed on *learnability* aspects, which evaluated whether it was easy to learn the software's features, and the steps required to create dashboards. Terminology could influence the ratings of *learnability*, therefore, this was included in the criteria (Jooste et al. 2014).

Section 6 (S6) related to *error control* and evaluated whether if the participants could easily recover from errors. Additionally, participants were asked whether they were encouraged to explore the system, as making errors was easy to correct and enhanced the learning experience. Section 7 (S7), *helpfulness*, evaluated and asked participants to indicate whether the system provided adequate help on demand and whether the system helped them to recover from errors. Furthermore, participants had to indicate if they perceived the automatic charts and chart suggestions to be helpful along with a guided development process. Additionally, they were asked whether the software provided adequate learning material to assist them in learning the tool's features.

Section 8 (S8) related to *operability*; which addressed general questions regarding the system's response rate, control over the system and whether the system behaved consistently. Some questions were aimed specifically at the design guidelines. These questions related to how easy it was to select data attributes, create visualisations, synthesise visualisations into a dashboard, and create a data story. Other questions related to features for drill-down, filtering, sorting, searching and sharing of dashboards. Additionally, participants were asked whether they could create a dashboard in a reasonable amount of time. Section 9 (S9) of the questionnaire included two open-ended questions regarding the positive and negative aspects of the BI tool.

The questionnaire was deemed valid as both content validity and face validity were established (Saunders et al. 2009). Face validity of the questionnaire was confirmed as the questions were derived from literature and were revised during pilot studies with experts. Content validity was established during consultations with experts to ensure that the questions were reliable and aligned with the objectives of this study. Pilot tests were conducted with two participants to test that the software and questionnaire is reliable, and to ensure that no ambiguity exists in the task-list or questionnaire.

6.5 Participant Selection

The participants were selected by means of convenience sampling as motivated earlier (Section 4.2.3). A total of 84 students registered for CS and IS courses at the NMMU were requested to participate in the usability evaluation. However, only 64 students from which the final sample was split into two groups completed the post-test questionnaire successfully. The first group consisted of 35 participants (55%) registered for a second year course namely, Business Systems II (WRBA202). The second group consisted of 29 third year students (45%) registered for the ERP course (WRER202). A total of 46 males (72%) and 18 females (28%) participated in the study (Table 6-2). In both groups the majority of participants were males, which could provide a potential bias. However, this dominance of males is representative of a typical sample of students studying CS and IS. The majority of the participants (70%) were between 20 and 24 years of age.

Table 6-2: Gender profile of participants

	Groups					
Gender	**Second year group**		**Third year group**		**Total**	
	Sample size (n)	**Percentage (%)**	**Sample size (n)**	**Percentage (%)**	**Sample size (n)**	**Percentage (%)**
Male	26	74	20	69	46	72
Female	9	26	9	31	18	28
Total (n=64)	**35**	**100**	**29**	**100**	**64**	**100**

Various factors were taken into consideration in terms of experience. The majority of the participants (64%) also had more than 10 years of experience using computers (Table 6-3). Participants had either a Low (39%) or Moderate (36%) level of experience with dashboards, but a substantial amount of participants did not have any experience with dashboards (19%). The participants’ experience with BI tools was considered fairly low (38%) and some indicated that they never had prior experience with BI tools (33%). The majority of the participants (53%)

perceived their experience with spreadsheet tools moderately high, while others thought of their experience as moderate (20%) or high (25%). These aspects were combined to derive at an overall experience level.

Table 6-3: Experience profile of participants.

Additional demographic information		**Sample size (n)**	**Percentage (%)**
General computer experience	Less than 2 years	1	2%
	2-4 years	8	13%
	5-9 years	14	22%
	10+ years	41	64%
	Total	**64**	**100**
Dashboard experience	None	12	19%
	Low	25	39%
	Moderate	23	36%
	Moderately High	3	5%
	High	1	2%
	Total	**64**	**100**
BI tool experience	None	21	33%
	Low	24	38%
	Moderate	16	25%
	Moderately High	2	3%
	High	1	2%
	Total	**64**	**100**
Spreadsheet tool experience	None	0	0%
	Low	1	2%
	Moderate	13	20%
	Moderately High	34	53%
	High	16	25%
	Total	**64**	**100%**

6.6 Results

The results of Cronbach's alpha tests will be discussed to establish the reliability and internal consistency of the questionnaire (Section 6.6.1). The quantitative results will be analysed to reveal significant differences between the usability ratings and education levels (Section 6.6.2). The participants provided valuable feedback in open-ended questions for which themes will be created from both the positive and negative comments (Section 6.6.3). When reporting on these results, they will be compared with the theoretical findings of Chapter 5, where the design guidelines and features were identified. Since many studies were identified for each design guideline and feature, the results will be compared to the individual name of each design guideline (Table 5-1) and will not refer back to the many original studies in which they were proposed.

6.6.1 Validity and Reliability of Data

The reliability and internal consistency of the data obtained from the quantitative feedback were measured using Cronbach's alpha. The Cronbach's alpha coefficients for the mean difference and the mean standard deviation for each usability criterion is shown in Table 6-4.

Table 6-4: Results of Cronbach's alpha test for the Tableau questionnaire

Criteria	**Item total correlation (α)**
Tasks completeness	0.82
Visibility	0.86
Flexibility	0.81
Learnability	0.80
Error control	0.60
Helpfulness	0.79
Operability	0.94
Overall	**0.90**

The individual values varied between 0.60 to 0.94, with an overall Cronbach's alpha value of 0.90. *Error control* was the only criterion to score below the commonly acceptable value of 0.7, however, some authors state that a Cronbach's alpha value above 0.6 is acceptable (Gravetter & Wallnau 2009; Nunally 1978). For this reason, the internal consistency of the data was considered fairly valid and reliable. Additionally, the qualitative results were used to confirm the quantitative results. The mean for each closed-ended Likert-scale item in the post-test questionnaire was classified according to the following ranges:

- *Strongly disagree* [$1.0 \geq \mu < 1.8$);
- *Disagree* [$1.8 \geq \mu < 2.6$);
- *Neutral* [$2.6 \geq \mu \leq 3.4$);
- *Agree* [$3.4 > \mu \leq 4.2$); and
- *Strongly agree* [$4.2 > \mu \leq 5.0$).

Likert-scale items could be further categorised into *negative* ($1.0 \geq \mu < 2.4$), *neutral* ($2.4 \geq \mu < 3.6$), and *positive* ($3.6 \geq \mu \leq 5$) ranges.

6.6.2 Quantitative Results

The quantitative results were analysed are reported on individually for each usability criterion. These results were also used to report on the results of the hypotheses tests.

6.6.2.1 Hypotheses Testing Results

The mean ratings for all of the usability criteria were higher for the third year group than the second year group, except for the *helpfulness* criterion (Table 6-5). Both statistical and practical significance were calculated based on the mean ratings for the two education levels (second years and third years). For the purposes of this study, a difference in the usability ratings between education levels was only considered significant if they were both statistically and practically significant. The statistical significance was calculated using an independent t-test and a p-value of <0.05 was regarded as significant. The practical significance was calculated using the Cohen's d statistic and could be classified into the following ranges (Rice & Harris 2005):

- d < 0.20: Not a significant difference;
- 0.20≤ d ≤ 0.49: Small difference;
- 0.50≤ d ≤ 0.79: Moderate difference; and
- d > 80: Large difference.

Independent t-tests were performed on the usability results to determine if significant differences existed for the usability ratings between two education levels (H_1). The results from the independent t-tests are presented and the usability criteria with significant differences are highlighted in red (Table 6-5). The results revealed significant differences in the ratings of two usability criteria for the two education levels, namely *learnability* and *operability*. The largest significant difference, both statistically and practically, was identified for *learnability* (p=.008, d=0.69). This was followed by a significant difference for *operability* (p=.011, d=0.65). Only a statistically significant difference was identified for the ratings of *error control* and the two education levels (p=.024, d=0.58) and is therefore not considered significant in this study. The Cohen's d value for all the criteria fall in the *moderate difference* range. The independent t-test results did not reveal significant differences between education level and *task completeness*, *visibility*, *helpfulness* and *flexibility*. For this reason the following statement can be made:

"H_1 is accepted only for those usability criteria relating to learnability and operability, which have shown significant differences in their ratings between the two education levels."

Table 6-5: Independent t-test results indicating the difference between education level and usability ratings

Criteria	Year of study	Mean	S.D.	Difference	t	p(d.f.=62)	Cohen's d
Tasks Completeness (Effectiveness)	2nd Year 3rd Year	2.77 2.86	0.34 0.19	-0.09	-1.23	.222	n/a
Visibility	2nd Year 3rd Years	4.05 4.32	0.75 0.50	-0.28	-1.70	.094	n/a
Flexibility	2nd Year 3rd Years	4.25 4.47	0.59 0.49	-0.28	-1.60	.115	n/a
Helpfulness	2nd Year 3rd Years	3.67 3.33	0.67 0.69	-0.24	-1.41	.162	n/a
Error control	2nd Year 3rd Year	3.75 4.18	0.82 0.64	-0.43	-2.31	.024	0.58 Medium
Learnability	2nd Year 3rd Year	3.95 4.45	0.79 0.61	-0.50	-2.76	.008	0.69 Medium
Operability	2nd Year 3rd Year	4.18 4.54	0.63 0.40	-0.35	-2.60	.011	0.65 Medium

Considering that the third year group may have a greater level of experience with BI and gave overall higher mean ratings for usability, it is expected that there is a relationship between *experience* and *usability ratings* (H_2). Therefore, the relationship was tested by means of using Pearson Product Moment Correlations. Once again, statistical significance was calculated at a p-value of <0.05 and a correlation coefficient of ≥0.246 was regarded as statistically significant (Gravetter & Wallnau 2009). Practical significance was regarded at a correlation coefficient of ≥0.300 (Gravetter & Wallnau 2009). Only those criteria for which both practical and significant relationships were identified were considered significant in this study. The results of the correlations revealed that relationships existed between experience and three of the usability criteria. Significant results are indicated in red and with an asterisk (*) in Table 6-6.

Both practically and statistically significant relationships were identified between experience and the ratings of *flexibility* ($r=0.309$) and *operability* ($r=0.352$). Only a statistically significant relationship was identified between *experience* and *error control* ($r=0.0273$) and was not regarded significant. The overall correlation coefficient was practically and statistically significant and it can therefore be deduced that an increase in experience positively influences the ratings of usability. By considering the results between of the Pearson Product Moment correlations, the following statement can be made:

"H_2 is accepted only for the criteria relating to flexibility and operability, which have shown significant relationships between experience and the usability ratings of a BI tool."

Table 6-6: Results of Pearson Product Moment correlations between experience and usability ratings

Criteria	Correlation coefficient (r)
Effectiveness (Task completeness)	0.213
Visibility	0.166
Helpfulness	0.081
Learnability	0.220
Error Control	0.273*
Flexibility	0.309*
Operability	0.352*
Overall	0.276*

6.6.2.2 Effectiveness (Task completeness)

Effectiveness was evaluated by the post-test questionnaire in which participants had to indicate whether they could complete all tasks successfully (Table 6-7). The successful tasks were compared to the unsuccessful tasks to arrive at a success rate. By analysing the task completeness results (Table 6-5), no significant differences were identified between the two education levels in terms of effectives.

From the results it was evident that some participants could not complete all the tasks successfully. These instances may not relate to unique participants, but could be that a single participant struggled with more than one task. Participants were the most unsuccessful with the final two tasks, which were Task 8, integrating the individual visualisations into a dashboard (f=3), and Task 9, creating a data story (f=5). A small number of participants struggled with Task 7, creating a hierarchy for drill-down (f=2). One participant could not complete the drill-down activities (f=1). Therefore, it can be stated that some users struggled with the features relating to the design guidelines for *navigation and drill-down* (G5), *multiple coordinated views* (G6) and *storytelling* (G10). Since these design guidelines were not evaluated during Field Study 2, this result indicates that the features that support these design guidelines are more complex than others and motivates the reasoning why they were evaluated only in the final evaluation.

Many participants required assistance to complete a task. The task that required the greatest amount of assistance related to integrating visualisations into a dashboard (f=13). The task that required the second highest number of requests for assistance was for performing drill-down activities (f=11) and applying formatting changes (f=11). An example of a formatting was to change either the size of the labels, colours of bars, or the transparency of the visualisation (Figure 6-4). None of the tasks had a success rate without assistance below 75%, which implies that the average participant could at least complete three quarters of the task-list effectively without assistance to arrive at a final dashboard (Figure 6-5).

Table 6-7: Task completeness ratings for the final evaluation with Tableau

	Not successfully		Successfully, but with assistance		Successfully without assistance	
	Frequency (*f*)	**Percentage (%)**	**Frequency (*f*)**	**Percentage (%)**	**Frequency (*f*)**	**Percentage (%)**
Task 1: Selecting a data source	0	0%	6	9%	58	91%
Task 2: Viewing market segments, adding calculations	0	0%	9	14%	55	86%
Task 3: Drill-down to sales per month	1	2%	11	17%	52	81%
Task 4: Annotating and sharing visualisations	0	0%	10	16%	54	84%
Task 5: Format colours, labels, size of visualisations	0	0%	11	17%	53	83%
Task 6: Using the visualisation suggestion, search and filtering features	1	2%	9	14%	54	84%
Task 7: Creating a hierarchy for drill-downs	2	3%	8	13%	54	84%
Task 8: Integrating visualisations into a single dashboard	3	5%	13	20%	48	75%
Task 9: Creating a data story	5	8%	8	13%	51	80%

Tableau guides the user to select data sources and merge tables automatically without requiring programming. The least assistance was therefore required from facilitators when selecting a data source and merging data tables. This result supports the motivation for two guidelines, namely *Guided Development Process* (G2) and *User Friendly Data Input for Common Data Formats and Smart Data Discovery* (G8).

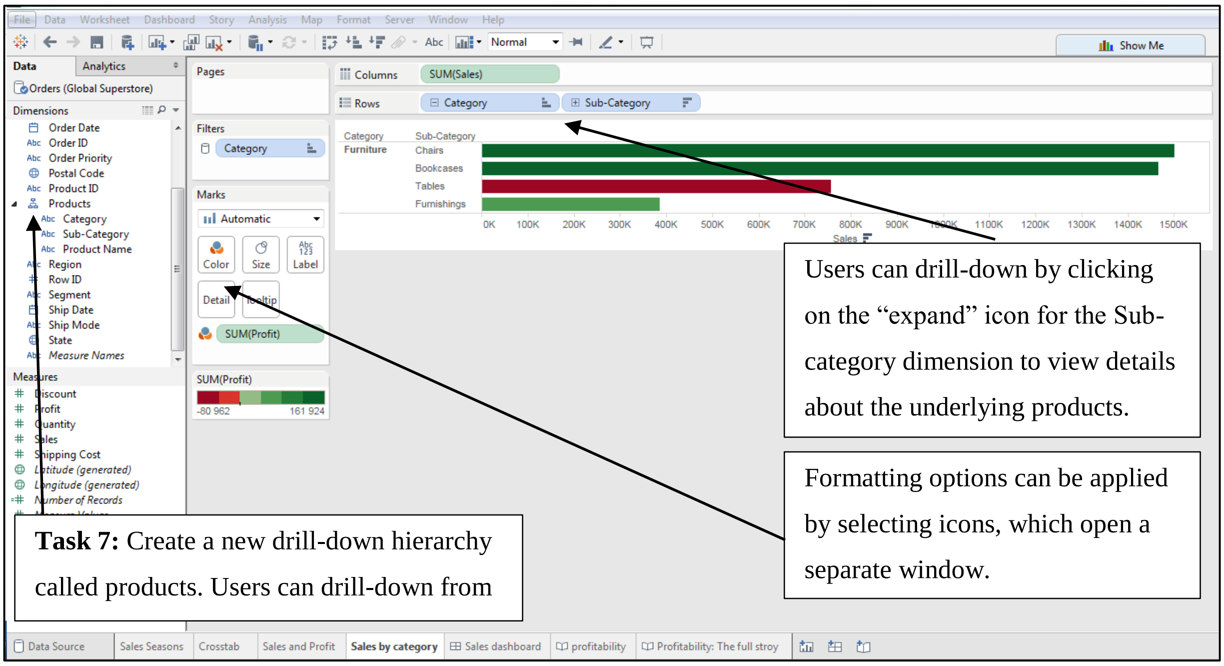


Figure 6-4: Problems experienced with tasks in Tableau

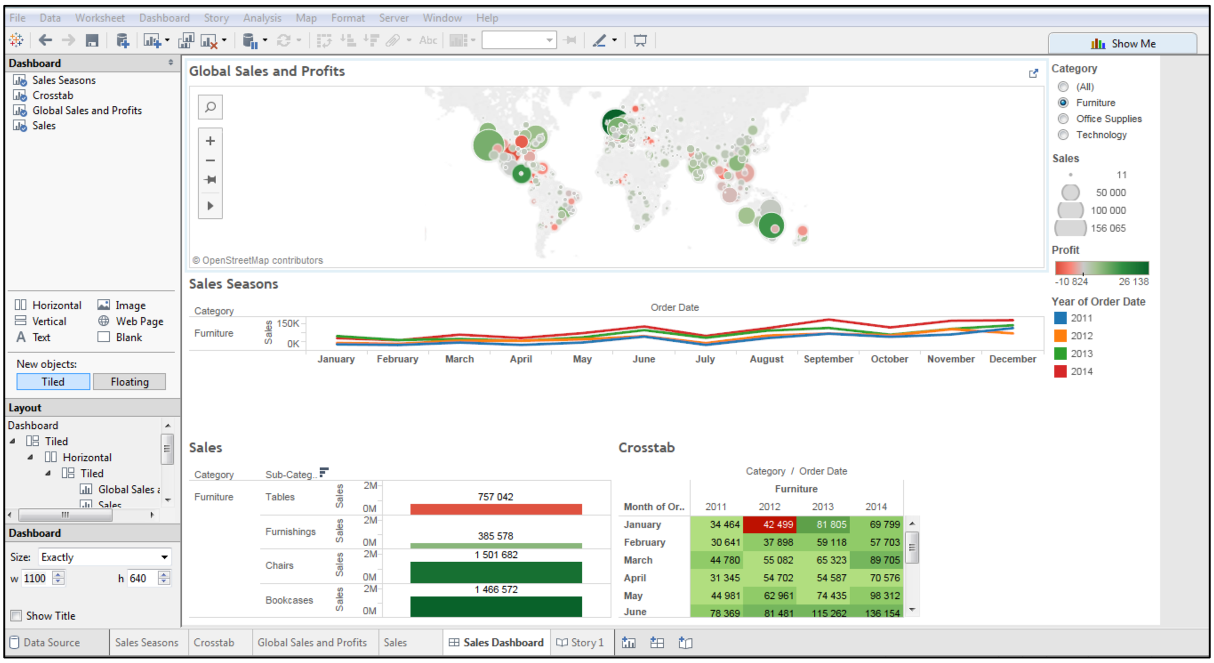


Figure 6-5: Final dashboard created in Tableau evaluation

6.6.2.3 Efficiency

The *efficiency* criterion was calculated by recording the overall task times for the duration it took to complete the entire task list and not per task. These times were compared to the pilot studies, which were carried out by two experts who were familiar with dashboards and Tableau. Additionally, participants were asked whether they were satisfied with their task-times.

The reason for this decision was to provide a more reliable value of the duration to conduct data analysis rather than to complete specific tasks, as BI dashboards are refined in a series of iterations. The mean task times to complete the evaluation were recorded as 77 minutes for all participants. The mean task times were different across the year groups, but the difference was not regarded as substantial. The second year group took longer to complete all the tasks (80 minutes) than the third year group (75 minutes). The quickest task time was 40 minutes (by a third year participant) and the slowest task time was 155 minutes (by a second year participant). The mean times and standard deviations are presented for all participants and each group (Table 6-8). Although the mean times of the novice users were not as quick as for the experts in the pilot studies, 52 minutes and 49 minutes, the mean times were acceptable and can be regarded as efficient for novice users who have never worked with Tableau or have minimal experience with dashboards.

Table 6-8: Mean and standard deviations for task times

Year	Mean	S.D.
2nd Year	79.31	24.49
3rd Year	74.83	25.51
Overall	**77.28**	**24.86**

6.6.2.4 Visibility

The mean rating for each *visibility* item was in the *positive* range (Figure 6-6). The majority of the participants *strongly agreed* that the UI was interactive (μ=4.38) and well-structured (μ=4.38). Both these criteria received the highest mean for the *visibility* criterion. The item with the lowest mean for *visibility* related to the ease of which information could be found onscreen (μ=3.91). Furthermore, participants *strongly agreed* that the system status was communicated adequately for their needs (μ=4.23) and *agreed* that the onscreen instruction were visible (μ=3.97). The high *visibility* ratings can be attributed to BI tool adhering to the guideline for *Dynamic, Interactive and Immediate Visual Feedback* (G4).

6.6.2.5 Flexibility

The mean ratings for the *flexibility* criterion were overall *positive* (Figure 6-7), falling in either the *agree* or *strongly agree* ranges ($4.14 \leq \mu \leq 4.55$). The criterion with the lowest mean (μ=4.14) was for "*the system can be adjusted for individual needs*". Despite being rated as the item with the lowest mean the item still rated *positively*. Participants perceived that a fair amount of *flexibility* was supported to alter the position and nature of the UI items such as menus, filters, visualisations, size of annotations and so on. The item with the highest mean was "*the ability to select alternative chart types*" (μ=4.55). This result can be attributed to Tableau's automatic visualisation generation and alternative visualisation suggestion features that are generated based on the nature and amount of selected data attributes.

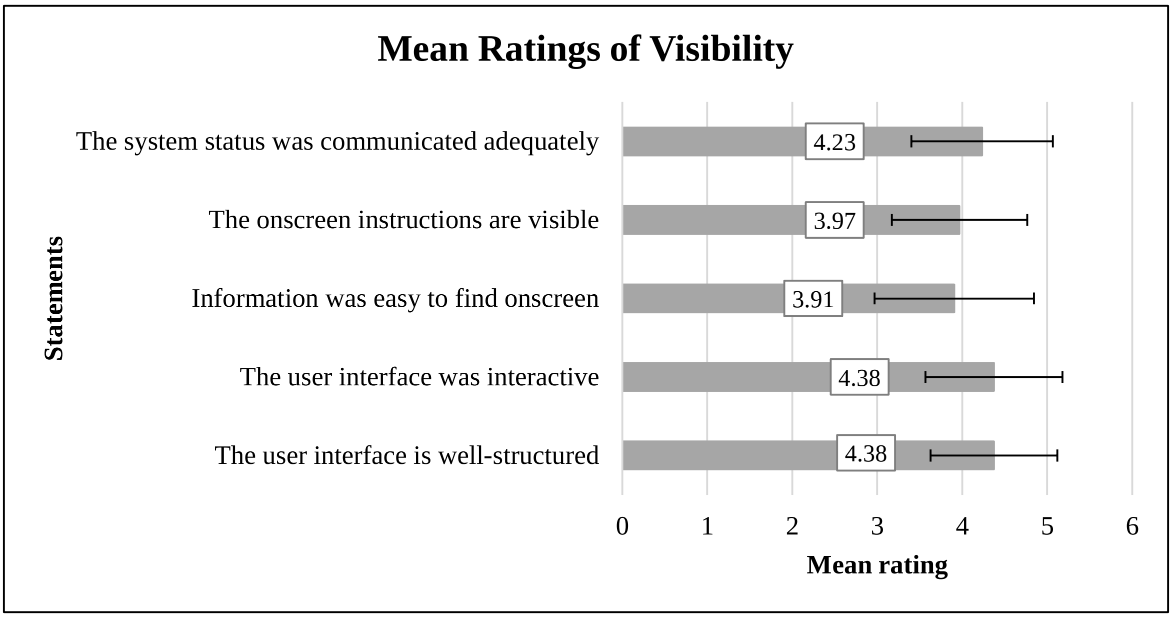


Figure 6-6: Mean ratings for visibility

The participants also rated the "*it was easy to connect to different data sources*" (μ=4.50) and "*it easy was easy to select data attributes*" favourably (μ=4.53), indicating that Tableau's interactive drag-and-drop features are highly intuitive and flexible when a different data attribute is desired. Additionally, Tableau allows for a flexible, guided process to select an alternative data source and instantly updates the data attributes for viewing. Participants gave high ratings for "*It was easy to customise dashboards*" (μ=4.16), implying that the appearance of dashboards could be easily formatted (colour, size and labels). Furthermore, "*it was easy to manipulate data to individual needs*" (μ=4.20), such as creating calculations from data (profit ratio) or applying pre-defined functions (average, sum, or standard deviation). The high ratings of *flexibility* confirm the guidelines: *Easy Development Process* (G1), *Flexible Customisation Process* (G3) and *User Friendly Data Input and Smart Data Discovery* (G8).

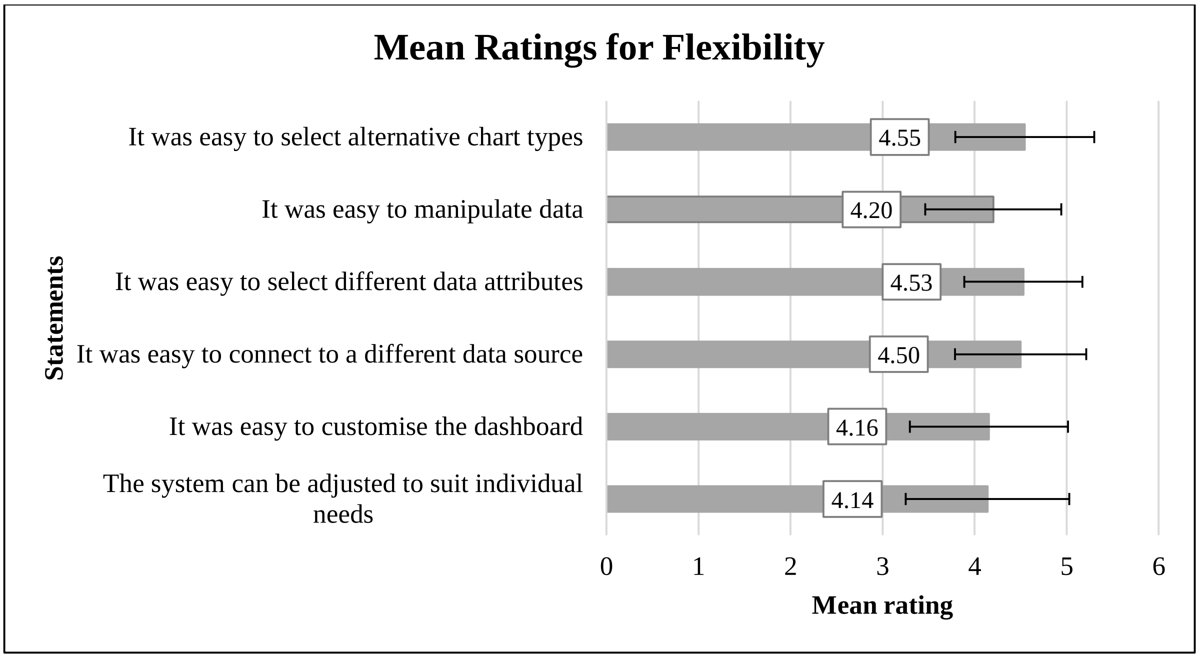


Figure 6-7: Mean ratings for flexibility

6.6.2.6 Helpfulness

A decision was made to analyse *helpfulness* separately from *error control*, since the features of the software may not only assist in recovering from, or preventing errors, but also assist the participant in learning or understanding the software's features (Jooste et al. 2014). Additionally, the software can assist in identifying patterns or trends in data, learning general analysis principles, such as selecting an appropriate chart based on the selected data, or even assist in managing data tables without programming. The mean ratings for the *helpfulness* criteria ranged across the *agree* and *strongly agree* ranges ($3.44 \leq \mu \leq 4.36$) and are depicted (Figure 6-8).

The *helpfulness* item that scored the lowest rating (μ=3.44) related to "*The system helped me to recover from errors*". Although participants *agreed* that the system provided assistance through messages and explanations, the mean rating falls into the outer boundary of the *neutral* range. This indicates that some participants might not have perceived the software to have adequate assistance to perform a specific task and needed to consult with one of the facilitators. The participants *agreed* that adequate learning materials were provided in the system through sample workbooks and built-in demos (μ=3.45). The item with the highest rating related to the automatic charts and chart suggestions (μ=4.36). The participants also *agreed* that the guided development process was helpful (μ=4.13) and that adequate help on demand was available through tooltips and explanations (μ=3.52). For this reason, the guidelines relating to G*uided*

Development Process (G2), *Automatic Visualisation Creation and Suggestions with Useful Defaults* (G7), and *Promote Learning through Demos and Explanations* (G11) could be verified as important features.

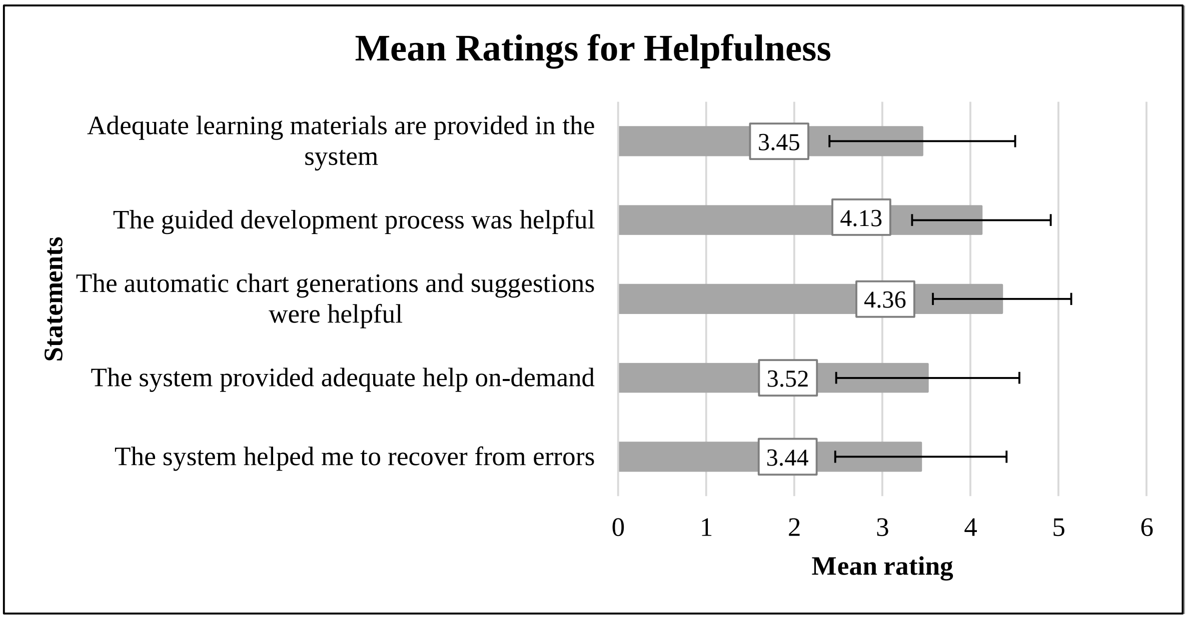


Figure 6-8: Mean ratings for helpfulness

6.6.2.7 Learnability

The results from the independent t-test revealed that the most significant difference existed between the ratings of *learnability* and the education level. Analysis of the mean ratings for *learnability* revealed that the third year group gave a higher overall mean rating for *learnability* (μ=3.76) compared to the second year group (μ=3.36).

The overall mean ratings for the *learnability* with the two groups combined (Figure 6-9) were *positive* and the criteria ranged across the *agree* and *strongly agree* categories ($4.03 \leq \mu \leq 4.33$). The participants *strongly agreed* that the steps to create a dashboard were easy to learn (μ=4.33). Moreover, participants *agreed* that terminology was easy to understand (μ=4.03) and that it was easy to learn the different features of Tableau to create dashboards and conduct data analysis (μ=4.17). The high *learnability* ratings can be attributed to the guidelines *Dynamic, Interactive and Immediate Visual Feedback* (G4) and *Promote Learning trough Demos and Explanations* (G11). The UI of Tableau is highly interactive and enables users to explore its features. The highly dynamic and interactive nature of Tableau could influence the *learnability* ratings as users could explore and view the immediate effects of their actions. Additionally, Tableau provides various explanations for features and visualisations through tooltips and descriptions.

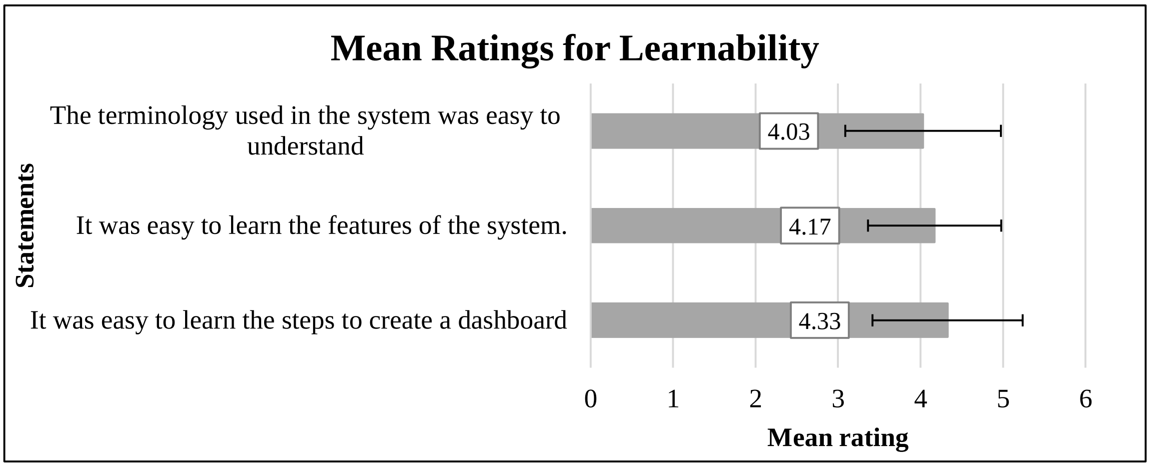


Figure 6-9: Combined mean ratings for learnability

6.6.2.8 Error Control

A significant difference was identified between the ratings of *error control* and education level. The means were analysed for the *error control* criterion. The third year group gave a higher overall mean rating (μ=3.55) than the second year group (μ=3.2). After combining the results for the *error control* criterion (Figure 6-10), a clear consensus existed amongst the participants as they *agreed* that they could easily recover from errors by applying undo or redo functions (μ=4.16). The participants also *agreed* that they had some *flexibility* to explore the software's features and make mistakes as they knew they could easily recover from errors (μ=4.16).

The participants were, however, *neutral* regarding Tableau's ability to prevent those making errors (μ=3.53), such as applying incorrect formatting options, selecting inappropriate charts or data attributes. This result is expected as this was the first time participants used Tableau and were not familiar with the UI and features. The mean ratings of the criteria ranged across the *neutral* and positive ranges ($3.53 \leq \mu \leq 4.16$). As Tableau offers various guides to connect and transform data, as well as developing visualisations, the guideline relating to a *Guided Development Process* (G2) could be confirmed. Moreover, the ability to store various histories and to easily to a previous when errors are incurred verify the guideline *History Tools, Storytelling and Annotations* (G9).

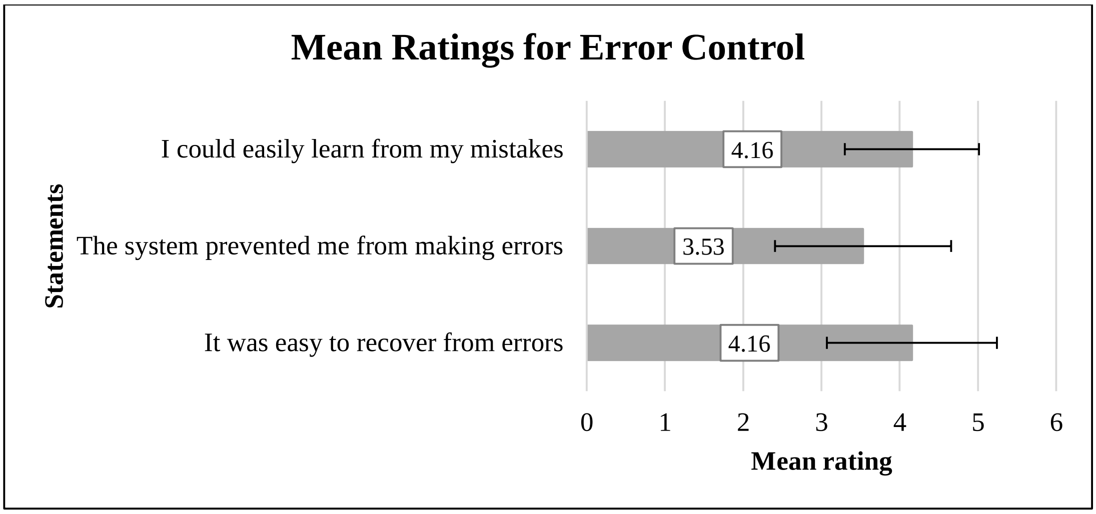


Figure 6-10: Mean ratings for error control

6.6.2.9 Operability

The *operability* criterion had the second largest significant difference in ratings between the two education levels. The positive ratings indicate that both of the groups perceived Tableau to be highly operable and could easily perform the tasks that are necessary for BI analysis. After combining the results of two groups, an analysis revealed that all *operability* criteria had *positive* mean ratings falling in the *strongly agree* range, except for the one item that fell into the *agree* (Figure 6-11). The item with the lowest mean rating was for "*I felt in control of the system*" and fell into the *agree* range (μ=4.11).

The *operability* item with the highest mean rating was for "i*t was easy to select data attributes*" (μ=4.50), which once again implies that the drag-and-drop features for selecting attributes were intuitive and easy to operate. Overall the mean ratings were *positive* and participants *agreed* that Tableau behaved consistently (μ=4.44) and provided a rapid response rate (μ=4.23). Participants could easily search for information using text search features for data attributes and data points in visualisations (μ=4.33). Sorting the data did not seem to be difficult (μ=4.44) and participant could easily apply filters to view only information of interest (μ=4.39). The participants could also effectively drill-down into different levels of data granularity (μ=4.23). The automatic chart generation allowed participants to easily create visualisations (μ=4.39), and the majority could synthesise the individual visualisations into a dashboard (μ=4.33). Many participants also favoured the ability to share visualisations (μ=4.44) and to create a data story (μ=4.38) based on the findings of the analysis. The majority of the participants were also satisfied with the task-times and stated that they created a dashboard in a reasonable amount of time (μ=4.20).

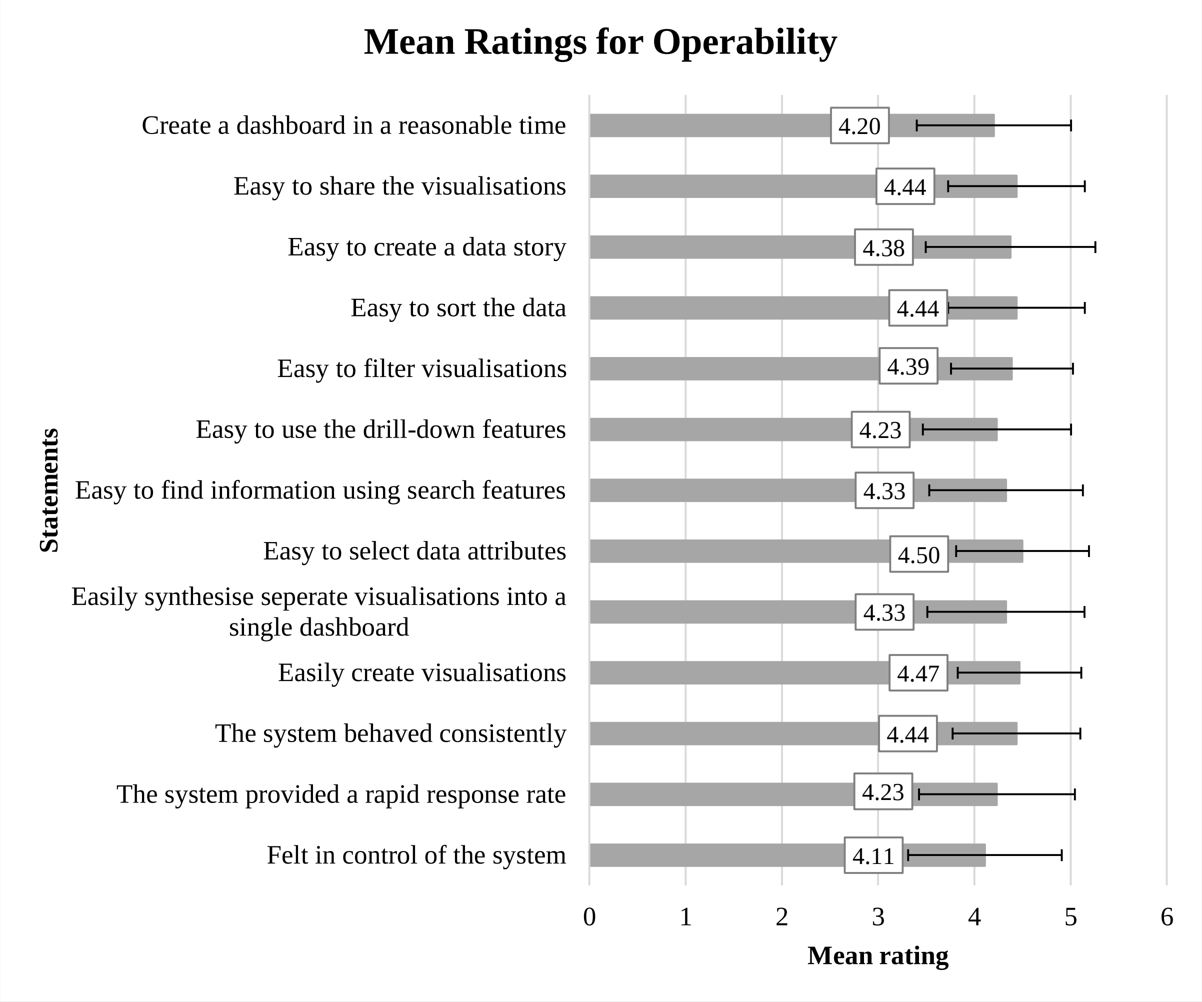


Figure 6-11: Mean rating for operability

The high *operability* ratings indicate that Tableau supports that the tool adheres to the guideline for an *Easy Development Process* (G1). The high ratings for the rapid response rate and the consistency of the Tableau can be associated with *Dynamic, Interactive and Immediate Visual Feedback* (G4). Participants could easily create visualisations, indicating that *Automatic Visualisation Creation and Suggestions with Useful Defaults* (G7) are highly favoured. The fact that participants could easily sort, filter, search and perform drill-down activities supported the need for the guideline *Search, Filter, Sort, and Navigation for Drill-Down Features* (G5). Furthermore, participants could easily link visualisations into a dashboard and gave high ratings for the features relating to *Multiple Coordinated Views and Dynamic Queries* (G6). High ratings were also observed for *Saving, Sharing and Collaboration* (G10) and participants could easily transform their analysis findings into a data story, confirming that features adhere to the guideline for *History Tools, Storytelling and Annotation*s (G9).

The mean ratings of all the usability criteria that were measured on a five-point Likert scale were combined for the two education levels (Figure 6-12). The mean ratings either fall into a*gree* and s*trongly agree* ranges, which can be stated that participants gave overall mean ratings either in the *neutral* or *positive categories*. The item with the highest mean rating was related to *flexibility* (μ=4.35), which indicates that the participants *strongly agreed* that they could easily apply a wide variety of changes to their dashboard activities. The lowest rated usability criterion related to *helpfulness* (μ=3.78), however, participants still *agreed* that Tableau supported features that were helpful for their dashboard activities. This result, therefore, implies that the participants were overall satisfied with Tableau.

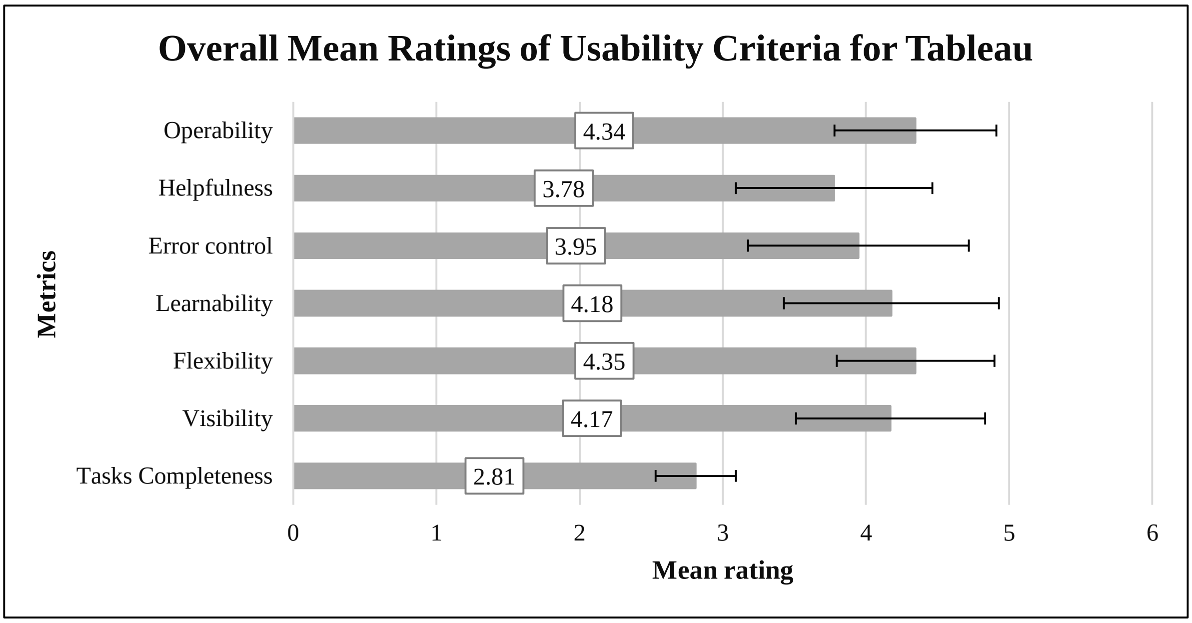


Figure 6-12: Combined mean ratings for the usability criteria

6.6.3 Qualitative Results

The participants were asked to list any positive and negative aspects about the Tableau software in open-ended questions. The open-ended questions were thematically and were not priori themes. The positive comments confirmed the high usability ratings of Tableau, while some negative comments were identified and motivated for improvements of BI tools.

6.6.3.1 Positive Qualitative Results

A total of 18 themes were identified from the positive feedback (Table 6-9). The most frequent theme identified from the positive feedback related to "*dashboard with multiple coordinated views*". Participants were particularly impressed with Tableau's ability to synthesise individual visualisations into a single dashboard, which provides an integrated view on a single screen. Moreover, two participants mentioned that the chart comparison feature was useful to view sales trends compared over three years. This result confirms that features relating to *Multiple Coordinated Views and Dynamic Queries* (G6) are useful to users when monitoring different aspects of the same data set.

The theme with the second highest frequency related to "*general UI*", where users mentioned that the UI was "*visually stimulating*", "*powerful to use*", "*well-designed*" and had "*a lot of useful functionality*". Participants were particularly impressed with the colour-coding features to compare data, as well as the interactive drag-and-drop features for when selecting "*dimensions*" and "*measures*". The drag-and-drop functionality was often cited in conjunction with the phrases "*rapid response rate*" and "*interactive*". These two themes also confirm the high ratings of the *visibility* criterion as users perceived the layout of features to be well-structured and could see the immediate effect of their actions in the dashboards.

The features for "*automatic visualisations*" and "*visualisation suggestions*" were also identified frequently. Some comments for automatic charts and suggestions were "*automation of otherwise tedious tasks (chart selection)*" and "*ability to check components needed to create a graph*". The guideline *Automatic Visualisation Creation and Suggestions with Useful Defaults* (G7), as well as *Promote Learning through Demos and Explanations* (G11) can be confirmed since participants used the explanations to view the type and amount of data attributes necessary for particular visualisation.

Positive feedback was received regarding the "*rapid response*" that Tableau provided. Additionally, many participants mentioned that the software was "*simple*" and "*easy-to-use*", confirming the high *operability* rating (μ=4.34). Some other comments were that the "*interface is very user-friendly*" and "*the simplicity of the interface made a complex program easy to use*". Feedback received on the ease of use verified the guideline for an *Easy Development Process* (G1). Positive comments were also identified for automatic queries and easy data manipulation, which indicates that participant found the visual query features helpful and verified *User Friendly Data Input for Common Data Formats and Smart Data Discovery* (G8).

Table 6-9: Themes identified for the positive aspects of Tableau

Number	**Theme**	**Frequency (*f*)**
1.	Dashboard with multiple views	20
2.	General UI and operability	19
3.	Interactive selection of *dimensions* and *measures* with (drag-and-drop)	18
4.	Automatic colour coding	18
5.	Automatic chart creation	18
6.	Filtering of charts	13
7.	Storytelling and annotations	12
8.	Formatting	12
9.	suggestions	10
10.	Drill-down	9
11.	Response time	6
12.	Easy to use	6
13.	Automatic querying and joining	6
14.	Easy to connect or integrate with a data source	3
15.	Sharing	2
16.	Easy to learn	2
17.	Easy to understand	2
18.	Easy to find information	2

The participants were impressed by the drill-down and filtering features and mentioned that "*drill-down techniques assist in data analysis*" and "*filtering options were useful*". Furthermore, information was easy to find and further verified the guideline *Search, Filter, Sort, and Navigation for Drill-Down Features* (G5). One comment was "*the labels make it easier to understand the data*". The high rating of *helpfulness* (μ=3.78) is therefore supported.

The dashboard and visualisations could be fairly easily customised and formatted, indicating that the software supported a *Flexible Customisation Process* (G3). This result supports the high *flexibility* rating (μ=4.35). The software was also perceived as easy-to-learn, which supports the overall *learnability* rating (μ=4.18). Additional comments were also identified for "*it was easy to create data story*" and "*it was useful to share visualisations with peers*", which supports the guidelines *History Tools, Storytelling and Annotations* (G9) and *Saving, Sharing and Collaboration* (G10).

6.6.3.2 Negative Qualitative Results

A total of 8 themes were identified for the negative feedback. Participants complained that they could not easily find the menu items and options. Some comments were "*icons are not always easy to interpret*", "*hidden drop-down menus*", "*if you are not working in full-screen, some buttons are hidden*" which is in contrast to the positive comments where a high frequency of responses were identified about the well-structured UI layout of Tableau. Furthermore, participants complained that the dashboards "*showed too much information*" at time and that "*the data was difficult to understand*". However, this result could be that the users were not familiar with data set and did not have strong data analysis skills. This result also typically prompted other problems relating to storytelling, filtering, and formatting options that were not easy to identify for some participants and caused confusion.

Table 6-10: Themes identified for the negative aspects of Tableau

Number	Theme	Frequency (*f*)
1.	Visibility of menu items and options	8
2.	Error control	7
1.	Visibility of charts	5
2.	Sort	4
3.	Development process	4
4.	Story	3
5.	Colour coding	2
6.	Filter	2
7.	Tutorials	2
8.	Formatting	2

Although many participants were impressed with the colour-coding feature, others complained that it was difficult to change the colours and add data labels to charts. Furthermore, participants complained that there were there was a lack of sufficient tutorials or learning features. Although Tableau provides sample workbooks, they do not demonstrate to new users how the features operate. This result is consistent with the findings of Field Study 2 where a participant also mentioned the need for additional learning features or materials within the BI tool. This result also verifies the guideline *Promote Learning through Demos and Explanations* (G11).

The lack of comprehensive error messages and support seemed to be great problem for some participants who mentioned "*error messages did not support me properly*" and "*error* *messages were unclear*". This result supports the reason why *error control* received the lowest rating of the all the usability criteria. However, the overall *error control* rating was still *positive*. Some also specifically referred to the development process and mentioned that "*it was difficult to understand the process to follow to complete certain tasks*". This result verifies that some users might require detailed explanatory cues in addition to a guided development process. Interestingly, one participant mentioned that it was not easy to find saved workbooks, which are required by the guideline *Saving, Sharing and Collaboration* (G10).

6.7 Revision of Requirements and Objectives of a BI Tool

The high-level objectives, functional and non-functional requirements for a BI tool were defined in Chapter 4 (Section 4.3). The high-level objectives were that the BI tool must provide an integrated development environment that facilitates the entire process of creating dashboards. The process typically includes connecting to a data source, importing data and transforming data, selecting data attributes to create visualisations, and creating personalised views from those visualisations. The users should also be supported through adequate guides or wizards that enable users to follow the process systematically. The environment should allow for easy visualisation creation and automate the majority of the tasks so that users have to conduct zero to minimum programming tasks. Lastly, the BI tool should encourage users to explore its features and the dataset, without having the risk of incurring major errors or loss of progress. The BI tool must provide *flexibility* to iterate through the different steps of dashboard creation. All of the high-level objectives were met as Tableau automates virtually all tasks for users and guides them to connect to a wide variety of data sources, merge tables and apply data transformations. Tableau requires no programming to create visualisations, and users can explore the software intuitively to create multiple visualisations and dashboards without the risk of losing progress. Moreover, Tableau encourages learning with explanations about its features and how to use visualisations.

The functional requirements were also met as Tableau provides immediate visual feedback reflected for any changes made to the data and visualisations (R1). Tableau can connect to various data sources as a "live" connection or data can imported as an "extract" to work on a subset of data (R2). Once the data source is connected, Tableau's smart data discovery automatically determines the data types and relationships in the dataset to assist the users in merging tables and manipulating data, such as combining columns, adding additional columns, or creating new calculations. Additionally, a wide range of pre-defined functions can be used to apply aggregations, summations, standard deviations and so on. Once the data is imported, Tableau automatically categorises the data attributes according to "*dimensions*" and "*measures*" that can be easily dragged-and-dropped onto *Columns* and *Rows* to intuitively view data from different perspectives. The selection of data attributes is highly flexible and users can easily select or deselect attributes using these drag-and-drop functions. Tableau has powerful history tools that remember the various navigation paths and changes that are applied to data attributes and visualisations. Therefore, users can easily revert to a previous state or reapply settings by using the undo (or back) features during exploration. The automatic visualisation creation features of Tableau support various pre-defined formatting settings to allow users to customise visualisations in a flexible manner. Lastly, Tableau guides users through the development process using several screens.

The non-functional requirements were met as Tableau was efficient and effective to use. The participants could create a dashboard in a reasonable amount of time with *positive* mean ratings. Participants also indicated that they could complete their tasks effectively, with only a few students that required assistance or could not complete the task-lists. It can be deduced that Tableau was easy to use as the mean *operability* ratings for all statements were *positive*. Tableau also incorporated help functions through a number of explanations and guides that assisted users in selecting and transforming appropriate data attributes for their visualisations. Participants gave high *learnability* ratings for Tableau and the overall rating was positive, indicating that the features can be easily learnt. The participants could easily customise the appearance of the individual visualisations and the final dashboard. Moreover, the participants could easily select alternative data attributes and return to a previous state if an error was made. Therefore, Tableau can be stated to be flexible. A deduction can be made from the overall ratings and positive qualitative feedback that participants were satisfied with Tableau.

The *Evaluation* activity (Activity 5) in the DSR process involves comparing the evaluation results to the objectives and requirements defined in the Activity 2 (*Define Objectives of a Solution*). During this comparison, researchers should determine whether the requirements and objectives have been met and whether it is necessary to iterate back to Activity 3 (*Design and Development*) in order to improve the proposed artefact. If all the requirements and objectives have been met, the researcher should proceed to Activity 6 (*Communication*), which is the final activity in the DSR process. Based on the results, it is evident that all the non-functional and functional requirements have been met. In conclusion, this study will continue to communicate the results and outcomes of the artefact, which is the proposed BI Framework.

6.8 Conclusions

The final evaluation of this study was conducted with one of the BI tools that were selected using the BI Scorecard, namely Tableau (Section 5.3). The objective of the final evaluation was to determine the usability of Tableau and to identify whether participants were satisfied with the features as proposed in the BI Scorecard. Since Field Study 2 (PowerPivot) only evaluated a subset of the design guidelines with less complex features, the final evaluation for Tableau was designed to verify all of the design guidelines, which included more complex features such as drill-down, multiple coordinated views, sharing and collaboration, and storytelling.

The evaluation was conducted with two student groups on different education levels. The first group included third year students enrolled for the ERP course for 2015 (n=29) and the second group was the second year students enrolled for a Business Systems Course for 2015 (n=35). The usability criteria that were used in the final evaluation were similar to those used for Field Study 2. However, additional questions were added to the questionnaire regarding those guidelines and features that were not evaluated in the Field Study 2. The tasks were set up to test the features of each design guideline (Table 6-1). All of the design guidelines were confirmed and positive feedback was provided regarding the features that implement each guideline.

Tableau can be considered to be effective as at least 80% of the participants could complete all the tasks successfully. The mean time to complete the task-list for all participants was recorded at 76 minutes. Although the average times were not less than the mean times recorded for the pilot study participants (51 minutes), one participant did manage to complete the tasks in 40 minutes proving that users can become efficient in the use of Tableau. Therefore, the overall mean times are acceptable and Tableau can be regarded as efficient. The overall usability results were *positive*. The usability criterion with the highest rating was *flexibility*. This indicated that participants could easily apply changes to their dashboards and selected data attributes. Additionally, participants could easily utilise the various features of the tool necessary for data analysis.

The sixth research question (RQ6) answered in this chapter was "*Are there differences between novice users' education level and the usability ratings of BI tools?*". The research question was answered by testing two hypotheses that were formulated. The results of an independent t-test revealed significant differences between some of the usability ratings for the two education levels. Only two usability criteria were deemed significant, namely *learnability* and *operability*. For this reason, the first hypotheses (H_1): "*A significant difference exists between the users' education level and the usability ratings of a BI tool"* was accepted. The results also revealed significant relationships between users' experience and two usability criteria, namely *operability* and *flexibility*. Therefore, the second hypothesis (H_2): *"A significant relationship exists between the users' experience level and the usability ratings of a BI tool.*" was also accepted. The hypothesis could only be accepted for those usability criteria that showed significant results.

The requirements and objectives of a BI tool that were identified in Chapter 4 were revisited in order to determine whether they had been met. The scope of the tasks were sufficient to determine whether the proposed design guidelines and features satisfy the defined requirements and objectives. The results of the evaluation have shown evidence that all the objectives and requirements have been met.

The study will be concluded in the next chapter, namely Chapter 7. The chapter will review the research objectives, questions and research contributions of this study by following the DSR methodology. Moreover, the problems experienced and recommendations for future research will be discussed.

Chapter 7. Recommendations and Conclusions

7.1 Introduction

The aim of this chapter is to reflect on the findings from this study and to determine whether the main objective has been achieved. This chapter concludes the study and the final DSR activity is applied, namely *Communication*. Additionally, the Rigor Cycle of the DSR is applied as the findings and generated knowledge are added to the theory and knowledge base. In order to assist in achieving the main objective, a number of secondary objectives were formulated. These secondary objectives need to be reviewed to determine whether the study was successful (Section 7.2). Several theoretical and practical contributions resulted from this study (Section 7.3) and some limitations were experienced throughout the study (Section 7.4). Future recommendations and possibilities for further research can be deduced from the research findings (Section 7.5) and final conclusions can be made (Section 7.6).

The focus of this study was specifically on novice users and to investigate how BI tools could be made more accessible to a broader user audience and not just expert users that are often the target by vendors. The research problem of this study was therefore: "*Novice users experience difficulties when creating dashboards as the design of current BI tools do not fully support an intuitive and easy creation process".* The issues contributing to this problem related specifically to the usability and design of BI tools, which were verified by means of field studies.

The main aim of this study was to design a BI Framework that assists organisations and future designers to design, select and evaluate BI tools. The main research question (RQ_M) of this study was: "*What framework can be proposed to guide the design, evaluation and selection of BI dashboard tools to support novice users*".

7.2 Research Objectives Revisited

The main research objective (RO_M) of this study was "*To investigate and propose a framework for that can guide the design, evaluation and selection of BI tools that support novice users in the creation of dashboards*".

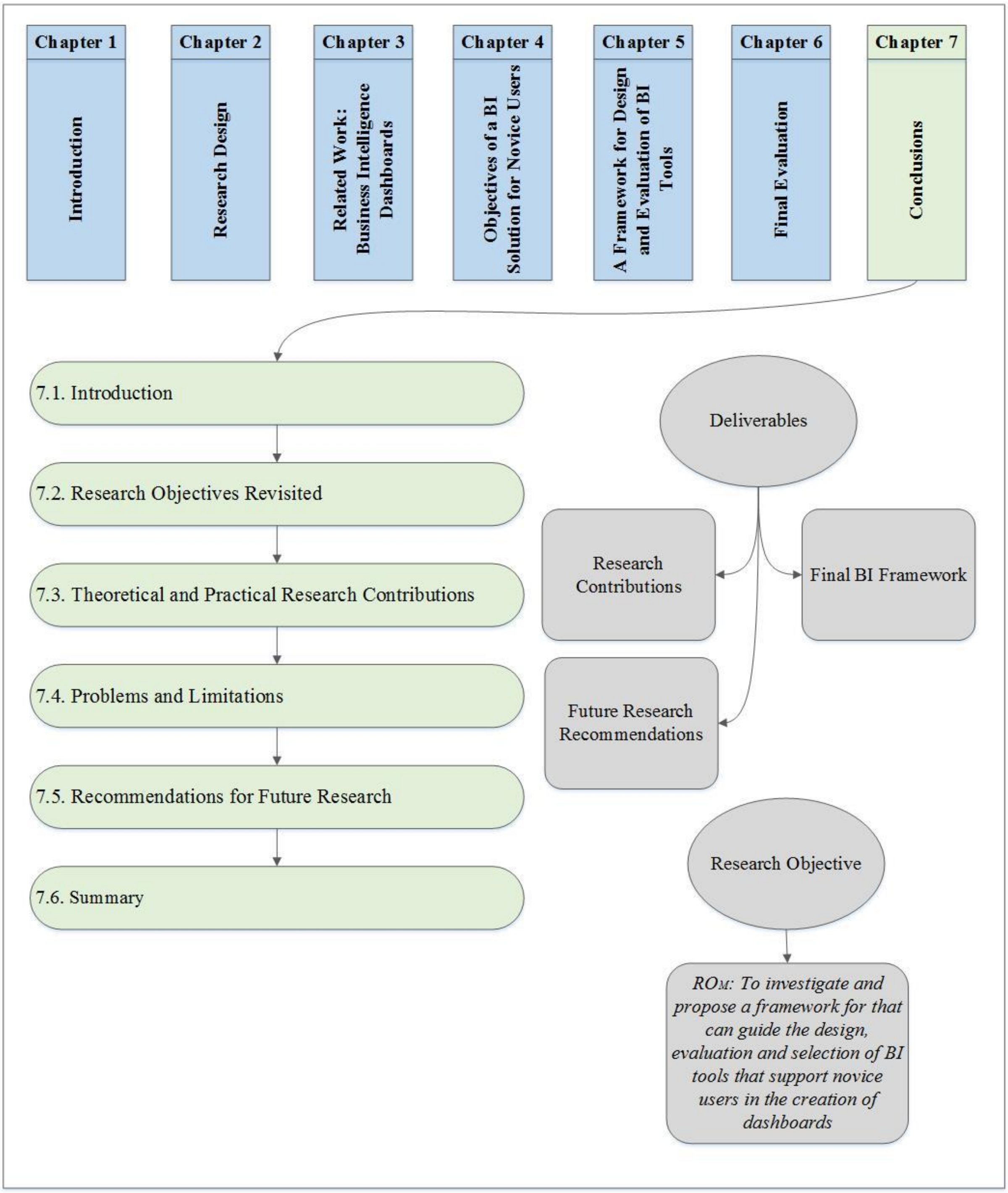


Figure 7-1: Chapter 7 layout

The main research objective has been met by designing a BI Framework that guides the design, selection and evaluation of BI dashboard tools for novice users. The BI Framework was incrementally developed and improved throughout this study as required by the DSR methodology. The BI Framework is the main contribution (artefact) of this study. Six additional research objectives were formulated in order to achieve the main research objective.

The first objective (RO_1) was to investigate the specific use of dashboards and the potential benefits and problems that users experience with BI tools when creating dashboards (Section 3.6.4). The benefits of dashboards relate to improved communication, improved decision making and improved organisational culture. Some of the problems of dashboard development identified from literature related to selecting data attributes, mapping data to appropriate visualisations, and interpreting the visual results. A number of problems relating to dashboard development were investigated in Field Study 1, which confirmed the majority of the problems identified in literature (Section 4.2.6).

The second objective (RO_2) was to define the objectives and requirements of a BI Framework that can assist in the design, evaluation and selection of BI tools for novice users. The requirements and objectives of the BI Framework were identified from literature and Field Study 1 (Section 4.3.1).

The third research objective (RO_3) was to investigate the design guidelines and features of a BI tool for novice users, which formed part of the BI Framework. A literature study was conducted on a number of design guidelines, taxonomies and features that related to design of BI tools for users. A comprehensive set of 11 design guidelines were proposed (Table 5-1). The design guidelines were expanded into a BI Scorecard documenting a set of features that can be used to implement each guideline. The BI Scorecard can be used to evaluate and select possible BI tools for implementation using a three-step rating scale (Appendix J). As a result of the BI Scorecard, the fourth research objective (RO_4) was met. Four popular BI tools were evaluated using the BI Scorecard in an extant systems analysis (Section 5.3). Two BI tools were selected for further evaluations, namely PowerPivot and Tableau.

The fifth research objective (RO_5) was to identify usability criteria specifically for BI tools (Section 5.4). The purpose was to formulate a set of criteria that could evaluate the usability of BI tool based on the proposed design guidelines and features. Usability criteria for BI tools were identified in Jooste et al. (2014) and adapted to suit the scope of this study.

A second field study (Field Study 2) was conducted after the BI tools were selected in the extant systems analysis (Section 5.6). Field Study 2 was conducted for two main purposes. The first purpose was to verify that the proposed design guidelines and its associated features. The second purpose was to evaluate the usability of one of the selected BI tools. Thus, Field Study 2 was performed as a proof of concept, which is required by the *Demonstration* activity in the

DSR methodology. Not all of the design guidelines and features were evaluated in Field Study 2. The main reason was that the first BI tool (PowerPivot), did not satisfy all the design guidelines. A decision was also made to evaluate a subset of the design guidelines, which required less complex features such as sorting, filtering and selecting appropriate data attributes and visualisations. The purpose for this decision was to determine the extent of complexity that novice users could handle. The statistical analysis of the results indicated that the majority of the participants were satisfied with PowerPivot, however, additional evaluations were necessary to verify all of the design guidelines. As a result, the final evaluation was conducted with Tableau, which satisfied all of the design guidelines and features in the BI Scorecard.

The sixth research objective (RO_6) was to evaluate the usability of a BI tool with two user groups and to determine whether there were any differences in the usability ratings of the two groups. In order to achieve the sixth research objective, two hypotheses were formulated:

> H_1: "*A significant difference exists between the users' education level and the usability ratings of a BI tool.*"
>
> H_2: *"A significant relationship exists between the users' experience level and the usability ratings of a BI tool."*

The statistical analysis of the results revealed significant differences between the usability ratings of the BI tool for participants on different education levels (second years and third years). Both practically and statically significant differences were confirmed for the ratings of *learnability* and *operability*. This result indicated that users on a higher education level give significantly higher ratings for the *learnability* and *operability* of a BI tool. As a result, the first hypothesis (H_1) was accepted only for the usability criteria relating to *operability* and *learnability*. The sixth research objective (RO6) was therefore met. The second hypothesis (H_2) is accepted only for the criteria relating to flexibility and operability, which have shown significant relationships between experience and the usability ratings of a BI tool.

A significant relationship was identified between a user's experience level and the usability ratings of a BI tool. The users' experience was determine as a combination of users' experience with computers, BI tools, spreadsheet tools, and dashboards. A significant relationship was identified between users' experience and the ratings for *flexibility* and *operability*. A conclusion can therefore be made that users perceive BI tools to more flexible and operable as they gain more experience. The results also indicated that the participants were satisfied with the features of Tableau, which verifies the proposed design guidelines and supports that the BI Framework can be used to select appropriate BI tools for novice users.

7.3 Theoretical and Practical Research Contributions

The research contributions from this research study can be broken down into two different types of theoretical artefacts (Table 2-1). The artefacts can be categorised according to the level of the knowledge contributed. These levels are referred to as maturity levels. Level 1 artefacts are typically more specific and the knowledge generated is less abstract. However, the knowledge gained on Level 1 maturity is more situation specific and serves as a practical contribution. Level 2 artefacts are more abstract in nature and the knowledge is more mature, which serves as theoretical contribution that can be applied as nascent design theory. The following section has therefore identified theoretical contributions as Level 2 artefacts (Section 7.3.1) and practical contributions as Level 1 artefacts (Section 7.3.2).

7.3.1 Theoretical Contributions

A number of theoretical contributions were produced by means of extensive literature studies and empirical evaluations. The theoretical contributions are:

- The analysis and validation of problems experienced by users when creating dashboards (Table 4-2);
- A set of 11 design guidelines that should be used for designing or evaluating a BI tool (Table 5-1);
- A BI Scorecard entailing a comprehensive list of design guidelines, features and a rating scale that can be used to evaluate BI tools (Appendix J);
- A set of usability evaluation criteria for BI tools (Appendix I);
- The finding that there is a relationship between education and usability ratings (Section 6.6.2.1); and
- The BI Framework that guides the design, evaluation and selection of BI tools for novice users (Figure 7-2).

The first theoretical contribution is a comprehensive set of problems associated with dashboard creation that were empirically validated by means of Field Study 1 with 14 participants (Section 4.2.6). The problems identified from Field Study 1 confirm the findings of related studies. The second theoretical contribution from this study is the set of 11 design guidelines for BI tools (Section 5.3). The design guidelines were empirically validated by means of Field Study 2 (Section 5.6) and the final evaluation (Section 6.6). Field Study 2 included 32 participants, whereas the final evaluation had 64 participants.

The third theoretical contribution is the BI Scorecard. The BI Scorecard documents a list of features that are needed to implement each guideline. Each design guideline is further broken down into the individual features of each design guideline (Appendix J). The scorecard uses a three step measuring approach (bad, acceptable and good). Evaluators can use the BI Scorecard to evaluate BI tools and to derive an overall rating of the tools' conformity to the design guidelines.

The fourth theoretical contribution is a set of usability criteria adapted from Jooste et al. (2014). Although the same criteria are used as proposed in Jooste et al. (2014), the criteria for each usability criterion was slightly adapted to take the features of each design guideline into consideration. The usability criteria can be used to evaluate the usability of BI tools that were selected using the BI Scorecard.

The fifth theoretical contribution is derived from the analysis and validation of the final evaluation's results with participants on different education levels (second year and third year students). The results were statistically analysed to determine whether there is a difference in the usability ratings of BI tools between participants' on different education levels. Significant differences (practically and statistically) were identified for the ratings of *learnability* and *operability* on each education level. Additionally, significant relationships (statistically and practically) were revealed between users' experience levels and the usability ratings for *flexibility* and *operability*.

The results revealed that significant differences existed between the two groups of education level and the usability ratings for two usability criteria, namely *learnability* and operability. These differences partially confirm the first hypothesis (H_1) that users on different education levels perceive the usability of a BI tool differently. The results of the evaluations performed in this study also confirmed the second hypothesis (H_2) stating that there is a relationship between users' experience and the usability ratings of a BI tool. The positive relationships were identified between users' experience and two usability criteria: *flexibility* and *operability*. For this reason, a deduction can be made that an increase in a user's experience will cause an increase in the ratings for *flexibility* and *operability*. Thus, the users will perceive the BI tool to be more flexible and operable as they are knowledgeable of what a BI tool is capable of and have more experience to interpret errors and recover from errors.

The qualitative results revealed significant practical contributions. The results revealed that participants favoured a guided creation process to create dashboards. The process is incorporated in Tableau to guide users through the tasks in the IV process, ranging from selecting and transforming data, creating visualisations, and customising the final views of the dashboards. The positive results indicated that participants were particularly impressed with the way Tableau allows creating multiple coordinated views, where users could easily and efficiently link multiple individual visualisations into a single dashboard and apply dynamic queries such as filtering, drill-down, and sorting. This enabled participants to analyse the dataset from multiple perspectives quickly by maintaining control over variables. Moreover, participants regarded the interactive drag-and-drop features for selecting data attributes very helpful, as well as the smart data discovery that automatically identified the data type and relationships in data.

The negative results revealed that some participants still struggle with error handling. These were mostly among the second year level students who have had less experience with BI and dashboards. The results showed that participants were often frustrated as they did not know how to resolve errors as some errors were unclear and was little guidance how to recover from the error. Some also mentioned that they were not sure how far back they should search for an error, as they were unsure where the error was made. This problem can be particularly attributed to the fact that BI involves exploration; however, this result is in contrast to the positive feedback received from participants where they preferred exploration, as they could easily recover from errors and learn from their mistakes. A conclusion can therefore be made to provide feedback to the user immediately when an error occurs, but gave the user the option to continue and have sufficient history tool features (G9) to revert back to a previous state.

The sixth theoretical contribution of this study is the BI Framework, which guides the design, evaluation and selection of BI tools for novice users. The BI Framework takes the other theoretical contributions of this study into consideration and consists of three main components: Situational Analysis, Suitability Assessment and Implementation (Figure 7-2).

The first component of the BI Framework, Situational Analysis, involves the activities of analysing the current situation of the organisation. Opportunities are identified where BI tools can improve the performance of users and possibly alleviate any problems. The current BI tools and IT infrastructure need to be considered along with the skills and prior experience of users. This component is concerned with identifying the requirements and objectives of users in terms of BI tools.

The second component, Suitability Assessment, is concerned with selecting an appropriate BI tool that suits the requirements and objectives of users (identified from Situational Analysis). The opportunities are mapped to the particular risks, business value and organisational impact that BI tools expose the organisation to. Additionally, the technical viability of the BI tool needs to be considered so as that the BI tool can integrate into the current IT infrastructure. Users should also be able to handle the technical complexity of the tool. Once these factors are considered, appropriate design guidelines for BI tools with features needed to identify that can assist users in creating dashboards.

Suitability Assessment should be used to select the best alternatives out of range of BI tools against a set of criteria. This calls for Multi-criterion Decision Analysis where various aspects need to be considered before selecting a BI tool. The criteria proposed in the BI Framework allows for evaluating the tools based on the design guidelines. A total is derived to identify those BI tools that are most viable to implement and satisfy the needs of users. It is important to note that during evaluation new design trends or alternative features could be identified. These can be additional design guidelines and features that are deemed important for the users and may be added to the design guidelines as additional criteria. The design guidelines are also important for future designers as these can be used to design new BI tools specifically aimed at novice users.

The third component, Implementation, is concerned with implementing the BI tool(s) that have passed the Suitability Assessment. BI tools are implemented and evaluated. The Implementation component is used to evaluate the usability of the BI tool to determine how well the requirements of users are met. The aim is also to verify the design of the BI tool's features and to establish its initial usability. The implementation may, therefore, occur in several iterations to test different features of the BI tool and the level of complexity that users can handle. The activities performed in Implementation are performed in a number of cycles until a satisfactory BI tool is adopted.

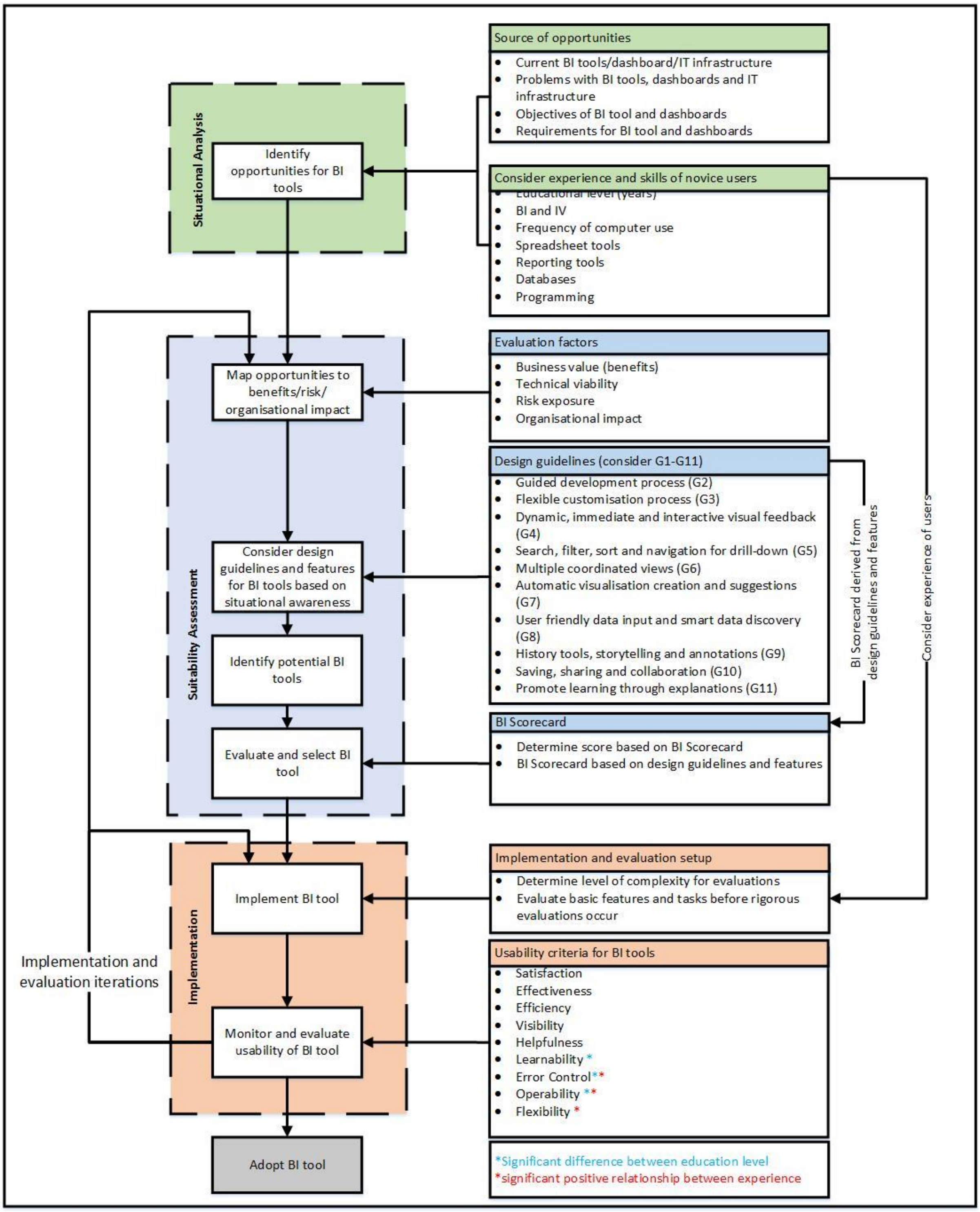


Figure 7-2: Final BI Framework for novice users

By considering that users have different experience profiles and educational backgrounds are important and will influence the usability results (confirmed in the final evaluations). Thus, users with more experience might require less assistance to learn different features of a BI tool and may have less difficulty to operate its features. For this reason, the level of complexity of the tasks should be considered to ensure that users are not overwhelmed by complex features. Users should gradually get accustomed to the more complex features to eliminate the possibility of a suitable BI tool not being adopted. For this reason, the evaluator needs to consider the users' prior experience from the Situational Analysis. Valuable feedback can be provided by users regarding the tool's features and design and whether they meet the requirements. Once the initial evaluations are complete, the evaluator should determine initial usability ratings and whether it is necessary to select a different BI tool or to continue with more rigorous evaluations. If users are satisfied with the design of the tool, rigorous evaluations can be performed where more complex tasks are performed with users.

Once all of these aspects are taken into consideration, the results of usability evaluation needs to be analysed. The results should be compared to the initial requirements to determine whether the users' need have been met. Evaluators are also allowed to update the requirements and design guidelines and select an alternative tool if rigorous evaluations do not satisfy the needs of users, and additional iterations of tool selection and evaluations can occur. The BI Framework shows that elements are iterative, and organisations can use the framework to iterate back to activities it different stages to either update requirements or select alternative BI tools.

The empirically validated problems, design guidelines and evaluation criteria form part of the aspects of the BI Framework to evaluate and adopt a BI tool, which is both a theoretical and practical contribution of this study. The positive results from the final evaluation indicated that the BI Framework was successful in evaluating and selecting BI tools.

7.3.2 Practical Contributions

The BI Framework proposed in this study can be used in organisations to practically evaluate and select BI tools in organisations. Moreover, the design guidelines and the features proposed in the BI Scorecard can be used to design new BI tools. The BI Framework was applied in a case study at NMMU in order to determine its ability to select an appropriate BI tool for novice users, such as undergraduate IS students.

The BI Scorecard was used to informally evaluate four BI tools, which is another practical contribution of this study (Section 5.3). The ratings can be used to compare the features of these tool to the needs of the organisation. Although the tools can all be used for novice users, Tableau and TIBCO Spotfire would be considered to have more features than SAP Lumira and PowerPivot. Additionally, all of the BI tools supported features for interactive drill-down, filters, sorting, and pre-defined visualisation templates. SAP Lumira was the only BI tool that fully satisfied the features for a *Guided Development Process* (G2). PowerPivot was the only tool that did not support a guided development process and did not support features for storytelling. These results support that current BI tools users aim to support novice users through the entire IV process in an interactive manner and supports the practical significance of the proposed design guidelines and features.

Two BI tools were selected and evaluated in this study from the BI Scorecard, namely PowerPivot and Tableau. PowerPivot was evaluated in Field Study 2. Although only a subset of the design guidelines and features proposed in the BI Scorecard were evaluated, insightful knowledge was generated for those features that were evaluated. After the initial evaluation of PowerPivot, a second BI tool, Tableau, was evaluated to test more advanced features required for BI dashboards. The final evaluation was conducted with two student groups at the NMMU with two goals in mind. The first goal was to evaluate the usability of Tableau, which also validated the proposed design guidelines and features in the BI Framework. The second goal was to confirm the developed hypotheses that significant differences exist between education level in terms of the two students groups (second year and third year students) and the usability ratings of a BI tool.

The usability results for Tableau were overall positive and the participants were satisfied with the features identified for the design guidelines. The positive results indicate that the BI Framework can be used by organisations as guide to evaluate and select a BI tool that aid users in creating dashboards and interactively explore data. The BI Scorecard is another practical contribution of this study, as organisations can use the design guidelines and features as a checklist to design new BI tools or rate existing BI tools (Appendix J). A recommendation can be made to incrementally develop and evaluate the BI tool as novice users need time to adapt to new features that are unique to BI. This concept was demonstrated during the study as more complex features were tested in Field Study 2 and the final evaluation.

7.4 Problems and Limitations

Several problems were encountered during the course of this study. The first problem encountered was that in the final evaluation 20 participants did not complete the post-test questionnaire as requested, but did complete the task-list. The main reason for this problem was the laboratory in which the evaluation was conducted lost internet connectivity at the end of the session and some participants could not complete the online post-test questionnaire. The final sample size was, therefore, reduced from 84 to 64 participants.

Another issue was experienced in obtaining academic licence s for BI tools. The study was therefore limited to the use of only PowerPivot and Tableau, but was still sufficient for the purposes of this study as these BI tools satisfied the basic requirements of the BI Scorecard. Significant relationships were identified between a user's experience and the usability ratings for *operability* and *flexibility*, only. The time frame in which this study was conducted was limited. This study could not confirm whether the design guidelines presented in the BI Framework would support users to advance from novices to experts.

7.5 Recommendations and Future Research

The results of the study allowed for a number of recommendations to be made. Recommendations were made to theory, which can be used by searchers in similar fields to compare findings and be used as a basis for further research (Section 7.5.1). The proposed BI Framework can also be used practically to overcome the challenges often associated with the design and evaluation of BI tool (Section 7.5.2). Recommendations were also made for possible future research opportunities that can be researched in terms of BI software for novice users (Section 7.5.3).

7.5.1 Recommendations for Theory

The proposed BI Framework can be used as an iterative approach to gather requirements from users and to evaluate BI tools. Design guidelines and requirements can, therefore, be updated and BI tools may be evaluated until a tool is identified that satisfies the requirements. However, researchers should also consider the learning effect, as iterations my influence participants' learning, which also influences the requirements of a BI tool.

The literature study identified the need to define measurable usability requirements in order to evaluate the usability of BI tools. Jooste et al. (2014) proposed a comprehensive set of usability criteria for BI tools (Section 5.4); however, these criteria were not aimed specifically at novice users. This study therefore adapted the criteria according to the proposed design guidelines and features that may increase the usability of a BI tool for novice users. These usability criteria therefore need to be considered when designing BI tools, as well as when evaluating them. The quantitative results indicated that the usability criteria that were rated the highest by participants were both *operability* and *flexibility*, and the second highest was for both *visibility* and *learnability*. The ratings for the criteria were triangulated with requirements and verified with the qualitative results.

The findings of the study indicated a significant relationship between users' experience and the ratings of two usability criteria, namely *flexibility* and *operability*. Specific attention needs to be given to these criteria when evaluating BI tools with users who have different experience profiles since different novice groups might not derive at the similar usability results.

7.5.2 Recommendations for Practice

The BI Framework can also be used practically to design, evaluate and select a BI tool. The framework can be used by HEIs to incorporate BI tools in their undergraduate curriculum. Designers of BI tools can consider the design guidelines proposed in the framework to develop an intuitive BI tool that is highly operable and easy to use for dashboard creation. Moreover, the features extend beyond the basic creation of dashboards and will enable users to utilise a wide range of analysis functions. Furthermore, an interactive and flexible environment where users can easily make changes and view the immediate effect of their changes is highly advisable, as these were reoccurring themes in the positive comments from participants.

The study confirmed that users need to be guided through the process of creating dashboards, starting at data selection to customising the final views of the dashboard. It is also important to design a tool that assists users in transforming and selecting data attributes for their needs, as well as to prevent them from making errors such as selecting an inappropriate visualisation for their data. An ideal balance should be maintained when providing support or guidance as users need to explore the features of the tool and should not be constrained. Explanations in messages should be communicated by using simple terminology that are familiar to the users. Moreover, sufficient history tools and undo/redo features should be incorporated that can be used to revert to a previous state and, by doing so, explore the features of the tool.

7.5.3 Recommendations for Future Research

The results of this study revealed that the design guidelines can be used by designers of BI tools to provide features that assist users to easily create dashboards and conduct data analysis. The participants used in this study were all students from the CS and IS Department at the NMMU. Although the sample was a reliable representation of users, the study could be repeated in a commercial environment where the users come from different HEIs and have different experience profiles in terms of the frequency of computer use, BI and business domain. Research can be conducted to implement the BI Framework to select a BI tool for industry participants and compare the possible differences and relationships between usability ratings and the experience profiles of users from industry and education. Moreover, an investigation should be conducted to determine the relationship between different usability criteria. For example, whether an increase in *flexibility* ratings might be correlated with an increase in *operability* ratings.

The study's participants were all users and were not data experts. Moreover, the participant sample used in this study only included students on two education levels, second year and third year. The participants were not familiar with the data set and assistance was often provided in the task-list to guide them in selecting data attributes and visualisations for their dashboards. A recommendation can therefore be made to evaluate how this study's results extends to expert users and how the design guidelines could support them in exploring and analysing larger or more complex datasets. Further research is also needed to determine how BI tools can assist users to transition from novices to experts as their analysis needs and tasks change in complexity as they gain more experience. Therefore, another recommendation can be made to observe users' data analysis and exploration behaviour in a long-term study and to possibly propose a BI tool that dynamically adapts to the individual user's characteristics and needs. A recommendation can be made that a comprehensive categorisation material can be designed to evaluate the stages in which users evolve and the tasks they are most likely to perform as they evolve.

The research presented in this study confirmed that users on a higher level gave a significantly higher usability rating for BI tools regarding *learnability* and *operability*. Further research is needed to prove significant differences between the education level and the other criteria used in this study. Significant differences were also identified between the users' experience and education level. However, a deduction can be made that these differences existed as a result of the third year group having more experience than the second year group, which resulted in higher ratings for some of the usability criteria. Further research is needed to determine the task-complexity users can handle and how their task requirements change in terms of data analysis as they gain more experience and knowledge.

The design guidelines proposed in the BI Framework could be used to incrementally develop a prototype to further investigate which level of task complexity users can handle. By following a similar approach to this study, features and functions can be incrementally developed, tested and feedback can be gathered regarding particular analysis tasks and the level of complexity the features should support.

The BI Framework can be used by HEIs to incorporate BI tools into their curriculum and gradually improve the data analysis skills of students. The adopted BI tool should serve as a guide to users to learn the dashboard creation process (or IV process) and other data analysis tasks, which may gradually improve the data analysis skills of students. A recommendation can therefore be made to evaluate students' data analysis skills across an extended period of time to determine whether their performance with data analysis has improved. Moreover, organisations employing these students can be surveyed to determine whether they have experienced fewer shortages of qualified BI data analysts and whether they have experienced the benefits of improved decision making, improved communication and opportunity identification.

The evaluations conducted in this study were particularly conducted with business related data. Other future research opportunities may relate to investigating the usability of IV related software in different domains, such as the usability of IV software relating to science, mathematics, geography, engineering and so on. Some of the design guidelines can, therefore, be used to improve the usability of BI tools. Additional future research opportunities include investigations regarding how users can create and analyse dashboards on mobile devices, such as smartphones and tablets. Mobile devices have become increasingly useful to view information on demand and share information relatively easily. Many factors may influence the design of software for BI tools on mobile devices as complexities exist for the connection to large data sources, interaction techniques and screen sizes.

7.6 Summary

The DSR methodology was followed throughout this study and a BI Framework was produced as an artefact to guide the design, evaluation and adoption of BI tools. The framework is the primary contribution of this study. The BI Framework should be used by organisations who wish to either develop or adopt a BI tool for users, who do not have the expertise to create their own dashboards for data analysis. The BI Framework has three main elements, namely Situational Awareness, Suitability Assessment, and Implementation.

The BI Framework can be used to identify the benefits, problems, and requirements of BI dashboards (Situational Analysis). A number of design guidelines are proposed in the framework which can be used as criteria to evaluate and select a BI tool (Suitability Assessment). Once a possible BI tool is selected it can be demonstrated to users and evaluated for usability (Implementation). Usability criteria are also proposed to evaluate the usability of tools. Evaluators also need to consider that usability ratings may differ amongst users with different educational background and experience, which could also influence the requirements of users as well as the overall decision for adopting or designing a BI tool. The framework also shows that appropriate usability criteria for BI tools should be used during evaluations.

The BI Framework was used throughout this study to select and evaluate BI tools iteratively and to eventually implement a tool that satisfied the users' requirements. The final evaluation was conducted with a popular BI tool, namely Tableau. The final evaluation was conducted with two user groups on different education levels (second year and third year). The results revealed that the users were satisfied the usability offered by the features of the tool. The results also revealed significant differences between the usability ratings for users' on different education levels, as well as significant relationships between the users' experience levels and the usability ratings of a BI tool. The study can, therefore, be concluded by stating that organisations can use the BI Framework to successfully evaluate and adopt a BI tool for novice users.

References

Abdelfattah, M., 2013. A Comparison of Several Performance Dashboards Architectures. *Intelligent Information Management*, 5(2), pp.35–41.

Aguinis, H., Joo, H. & Gottfredson, R.K., 2011. Why We Hate Performance Management — And Why We Should Love It. *Business Horizons*, 54(6), pp.503–507.

Allio, M.K., 2012. Strategic Dashboards: Designing and Deploying Them to Improve Implementation. *Strategy & Leadership*, 40(5), pp.24–31.

Antoniadis, I., Tsiakiris, T. & Tsopogloy, S., 2015. Business Intelligence During Times of Crisis: Adoption and Usage of ERP Systems by SMEs. *Procedia - Social and Behavioral Sciences*, 175, pp.299–307.

Ariyachandra, T. & Watson, H.J., 2010. Key Organizational Factors in Data Warehouse Architecture Selection. *Decision Support Systems*, 49(2), pp.200–212.

Baltzan, P. & Phillips, A., 2012. *Business Driven Information Systems* 3rd Ed., New York: McGraw-Hill.

Belmonte, N.G., 2009. JavaScript InfoVis Toolkit. Available at: http://philogb.github.io/jit/ [Accessed June 17, 2015].

Bevan, N., 1995. Measuring Usability as Quality of Use. *Software Quality Journal*, 4, pp.115–130.

Bevan, N., 2013. Using the Common Industry Format to Document the Context of Use. In M. Kurosu, ed. *Human-Computer Interaction. Human-Centred Design Approaches, Methods, Tools, and Environments*. Heidelberg: Springer, pp. 281–289.

Bevan, N. & Macleod, M., 1994. Usability Measurement in Context. *Behaviour & Information Technology*, 13, pp.132–145.

Bogdana, P.I., Felicia, A. & Delia, B., 2009. The Role of Business Intelligence in Business Performance Management. *Annals of the University of Oradea: Economic Science Series*, 18(4), pp.1025–1029.

Bostock, M. & Heer, J., 2009. Protovis: A Graphical Toolkit for Visualization. *IEEE Transactions on Visualization and Computer Graphics*, 15(6), pp.1121–1128.

Bostock, M., Ogievetsky, V. and Heer, J., 2011. D3 Data-Driven Documents. *IEEE Transactions on Visualization and Computer Graphics*, 17(12), pp.2301 – 2309.

Botan, I., Cho, Y., Derakhshan, R., Dindar, N., Haas, L., Kim, K. & Tatbul, N., 2010. Federated Stream Processing Support for Real-Time Business Intelligence Applications. In M. Castellanos, U. Dayal, & R. J. Miller, eds. *Enabling Real-Time Business Intelligence*. Berlin: Springer, pp. 14–31.

Bremser, W.G. & Wagner, W.P., 2013. Developing Dashboards for Performance Management. *CPA Journal*, 83(7), p.62.

Brooke, J., 1996. A Quick and Dirty Usability Scale. In P. W. Jordan et al., eds. *Usability Evaluation in Industry*. London: Taylor & Francis, pp. 189–191.

Bryman, A., 2012. *Social Research Methods* 4th Ed., New York: Oxford University Press.

Card, S., Mackinlay, J.D. & Shneiderman, B., 1999. *Information Visualization: Using Vision to Think*, San Fransisco: Morgan Kaufmann.

Carpendale, S., 2008. Evaluating Information Visualizations Challenges in Evaluating Information Visualizations. In A. Kerren et al., eds. *Information Visualization*. Berlin: Springer, pp. 19–45.

Chandler, N., Rayner, N. & Van Decker, J.E., 2010. Magic Quadrant for Corporate Performance Management Suites. *Gartner Research*, (March), pp.1–31.

Chaudhuri, S., Dayal, U. & Narasayya, V., 2011. An Overview of Business Intelligence Technology. *Communications of the ACM*, 54(8), p.88.

Chen, H. & Storey, V.C., 2012. Business Intelligence and Analytics: From Big Data to Big Impact. *MIS*, 36(4), pp.1165–1188.

Chi, E.H., 2000. A Taxonomy of Visualization Techniques using the Data State Reference Model. In *Information Visualization, InfoVis. IEEE Symposium*. Salt Lake City, pp. 69–75.

Chiang, R.H.L., Goes, P. & Stohr, E.A., 2012. Business Intelligence and Analytics Education, and Program Development: A Unique Opportunity for the Information Systems Discipline. *ACM Transactions on Management Information Systems*, 3(3), pp.1–13.

Clavier, P.R., Lotriet, H.H. & Van Loggerenberg, J.J., 2012. Business Intelligence Challenges in the Context of Goods- and Service-Dominant Logic. In *45th Hawaii International Conference on System Sciences*. Maui: IEEE, pp. 4138–4147.

Collis, J. & Hussey, R., 2009. *Business Research: A Practical Guide for Undergraduate & Postgraduate Students* 3rd Ed., New York: Palgrave Macmillan.

Creswell, J.W., 2013. *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* 4th Ed., Los Angeles: SAGE Publications.

Dawson, L. & Van Belle, J.-P., 2013. Critical Success Factors for Business Intelligence in the South African Financial Services Sector. *SA Journal of Information Management*, 15(1), pp.1–12.

Dix, A., Finlay, J., Abowd, G.D. & Beale, R., 2004. *Human-Computer Interaction* 3rd Ed., New York: Prentice-Hall.

Durrheim, K., 2006. *Research in Practice: Applied Methods for the Social Sciences* 2nd Ed.

M. Terre-Blanche, K. Durrheim, & D. Painter, eds., Cape Town: UCT Press.

Eckerson, W., 2011. *Performance Dashboards: Measuring, Monitoring, and Managing Your Business* 2nd Ed., New Jersey: John Wiley & Sons.

Eckerson, W., 2009. *TDWI Checklist Report: Self-Service BI*,

Eckerson, W. & Hammond, M., 2011. *Visual Reporting and Analysis. TDWI Best Practices Report*, Chatsworth.

Ed, J.A., Janvrin, D.J., Raschke, R.L. & Dilla, W.N., 2014. Making Sense of Complex Data Using Interactive Data Visualization. *Journal of Accounting Education*, 32(4), pp.31–48.

Elias, M., 2012. *Enhancing User Interaction with Business Intelligence Dashboards*. Ecole Centrale Paris.

Elias, M., Aufaure, M. & Bezerianos, A., 2013. Storytelling in Visual Analytics tools for Business Intelligence. In P. Kotze et al., eds. *Human-Computer Interaction – INTERACT 2013*. Berlin: Springer, pp. 280–297.

Elias, M. & Bezerianos, A., 2012. Annotating BI Visualization Dashboards: Needs & Challenges. In *Proceedings of the 2012 ACM Annual Conference on Human Factors in Computing Systems*. ACM, pp. 1641–1650.

Elias, M. & Bezerianos, A., 2011. Exploration Views: Understanding Dashboard Creation and Customization for Visualization Novices. In P. Campos et al., eds. *Human-Computer Interaction - INTERACT 2011*. Berlin: Springer, pp. 274–291.

Fan, W. & Bifet, A., 2013. Mining Big Data: Current Status, and Forecast to the Future. *ACM SIGKDD Explorations Newsletter*, 14(2), pp.1–5.

Faulkner, X., 2000. *Usability Engineering*, London: Macmillian Press.

Fekete, J.D., Hémery, P.L., Baudel, T. & Wood, J., 2012. A Meta-Toolkit to Encapsulate Tnformation Visualization Toolkits - One Toolkit to Bind Them All. In *Proceedings of the Visual Analytics Science and Technology Conference (VAST)*. IEEE, pp. 91–100.

Few, S., 2012. Criteria for Evaluating Visual EDA Tools. *Visual Business Intelligence Newsletter*, (June), pp.1–10.

Few, S., 2007a. Dashboard Confusion Revisited. *Visual Business Intelligence Newsletter*, pp.1–6.

Few, S., 2007b. *Dashboard Design for Real-Time Situation Awareness*,

Few, S., 2006. *Information Dashboard Design: he effective visual communication of data*, CA: O'Reilly.

Franco-Santos, M., Kennerley, M., Micheli, P., Martinez, V., Mason, S., Marr, B., Gray, D. & Neely, A., 2007. Towards a Defintion of a Business Performance Measurement System.

International Journal of Operations & Production Management, 27(8), pp.784–801.

Frolick, M.N. & Ariyachandra, T.R., 2006. Business Performance Management: One Truth. *Information Systems Management*, 23(1), p.41.

Gartner, 2015. IT Glossary. Available at: http://www.gartner.com/it-glossary/business-intelligence-bi/ [Accessed September 9, 2015].

Gebus, S. & Leiviskä, K., 2009. Knowledge Acquisition for Decision Support Systems on an Electronic Assembly Line. *Expert Systems with Applications*, 36, pp.93–101.

Ghazanfari, M., Jafari, M. & Rouhani, S., 2011. A Tool to Evaluate the Business Intelligence of Enterprise Systems. *Scientia Iranica*, 18(6), pp.1579–1590.

Goldberg, L., Lide, B., Lowry, S., Massett, H. a., O'Connell, T., Preece, J., Quesenbery, W. & Shneiderman, B., 2011. Usability and Accessibility in Consumer Health Informatics: Current Trends and Future Challenges. *American Journal of Preventive Medicine*, 40(5), pp.S187–S197.

Golfarelli, M., Rizzi, S. & Castenaso, V., 2004. Beyond Data Warehousing: What' s Next in Business Intelligence? In *Proceedings of the 7th ACM international workshop on Data warehousing and OLAP*. ACM, pp. 1–6.

Google Inc., 2015. Google Charts. Available at: https://developers.google.com/chart/interactive/docs/gallery/controls [Accessed June 16, 2015].

Grahovac, D. & Kučinar, R., 2009. Cost Management Tools as Business Intelligence Base and Continues Improvements Assumption. Big Things are Packed in Small Boxes. *International Journal for Quality Research*, 3(1), pp.53–61.

Grammel, L., Tory, M. & Storey, M., 2010. How Information Visualization Novices Construct Visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 16(6), pp.943–52.

Grammel, L., Treude, C. & Storey, M., 2010. Mashup Environments in Software Engineering. In *Proceedings of the 1st Workshop on Web 2.0 for Software Engineering - Web2SE '10*. New York: ACM, pp. 24–25.

Gravetter, F. & Wallnau, L., 2009. *Statistics for the Behavioral Sciences* 8th Ed., Belmont, CA: Wadsworth: Cengage Learning.

Greenberg, S. & Buxton, B., 2008. Usability Evaluation Considered Harmful (Some of the Time). In *Proceedings of the Twentysixth Annual CHI Conference on Human Factors in Computing Systems (CHI 08)*. New York: ACM, p. 111.

Gregor, S. & Hevner, A.R., 2013. Positioning and Presenting Design Science Research for Maximum Impact. *MIS Quarterly*, 37(2), p.337.

Gregor, S. & Jones, D., 2007. The Anatomy of a Design Theory. *Journal of the Association for*

Information Systems, 8(5), pp.313–334.

Guimarães, R.V., Soares, A.G.M., Carneiro, N.J.S., Meiguins, A.S. & Meiguins, B.S., 2011. Design Considerations for Drill-Down Charts. In *Proceedings of the 15th International Conference on Information Visualisation*. London: IEEE, pp. 73–79.

Hart, S.G., 2006. NASA-Task Load Index (NASA-TLX): 20 Years Later. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. SAGE Publications, pp. 904–908.

Hart, S.G. & Staveland, L.E., 1988. Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. *Advances in psychology*, 52, pp.139–183.

Hawking, P., 2013. *Factors Critical to the Success of Business Intelligence Systems*. Victoria University.

Heer, J. & Bostock, M., 2010. Declarative language design for interactive visualization. *IEEE Transactions on Visualization and Computer Graphics*, 16(March), pp.1149–1156.

Heer, J., Card, S. & Landay, J., 2005. Prefuse: A Toolkit for Interactive Information Visualization. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, pp. 421–430.

Heer, J., Ham, F., Carpendale, S., Weaver, C. & Isenberg, P., 2008. Creation and Collaboration: Engaging New Audiences for Information Visualization. In A. Kerren et al., eds. *Information Visualization*. Berlin: Springer, pp. 92–133.

Heer, J., Mackinlay, J.D., Stolte, C. & Agrawala, M., 2008. Graphical Histories for Visualization: Supporting Analysis, Communication, and Evaluation. *IEEE Transactions on Visualization and Computer Graphics*, 14(6), pp.1189–1196.

Heer, J., Shneiderman, B. & Park, C., 2012. A Taxonomy of Tools that Support the Fluent and Flexible Use of Visualizations. *Interactive Dynamics for Visual Analysis*, 10(2), pp.1–26.

Heinrich, C.J. & Marschke, G., 2010. Incentives and Their Dynamics in Public Sector Performance Management Systems. *Journal of Policy Analysis and Management*, 29(1), pp.183–208.

Hennink, M., Hutter, I. & Bailey, A., 2010. *Qualitative Research Methods*, London: SAGE Publications.

Hevner, A.R., 2007. A Three Cycle View of Design Science Research. *Scandinavian Journal of Information Systems*, 19(2), pp.87–92.

Hevner, A.R. & Chatterjee, S., 2010. *Design Research in Information Systems*, London: Springer.

Hevner, A.R., March, S.T., Park, J. & Ram, S., 2004. Design Science in Information Systems Research. *MIS quarterly*, 28(1), pp.75–105.

Hočevar, B. & Jaklič, J., 2010. Assessing Benefits of Business Intelligence Systems – A Case Study. *Management: Journal of Contemporary Management Issues*, 15(1), pp.87–119.

Hornbæk, K. & Law, E.L.-C., 2007. Meta-Analysis of Correlations Among Usability Measures. In *Proceedings of the SIGCHI conference on Human factors in computing systems (CHI '07)*. New York: ACM, p. 617.

Huron, S., Carpendale, S., Thudt, A. & Tang, A., 2014. Constructive Visualization. In *The 2014 Conference on Designing Interactive Systems*. ACM, pp. 433–442.

Huron, S., Jansen, Y. & Carpendale, S., 2014. Constructing Visual Representations: Investigating the Use of Tangible Tokens. *Visualization and Computer Graphics*, 20(12), pp.2102–2111.

IBM, 2015. What is MapReduce? Available at: https://www-01.ibm.com/software/data/infosphere/hadoop/mapreduce/ [Accessed November 20, 2015].

Işik, Ö., Jones, M.C. & Sidorova, A., 2013. Business Intelligence Success: The Roles of BI Capabilities and Decision Environments. *Information and Management*, 50(1), pp.13–23.

ISO, 2000. Information Technology - Software Product Quality. *ISO/IEC FDIS 9126-1*, pp.1–26. Available at: http://www.cse.unsw.edu.au/~cs3710/PMmaterials/Resources/9126-1 Standard.pdf [Accessed May 14, 2015].

ISO/IEC 25010, 2011. Systems and Software Quality Requirements and Evaluation (SQuaRe). Available at: http://www.iso.org/iso/catalogue_detail.htm?csnumber=35733 [Accessed May 14, 2015].

Jansen, Y. & Dragicevic, P., 2013. An Interaction Model for Visualizations Beyond the Desktop. *IEEE Transactions on Visualization and Computer Graphics*, 19(12), pp.2396–2405.

Johannesson, P. & Perjons, E., 2012. *A Design Science Primer*, Lexington: CreateSpace.

Jokela, T., Iivari, N., Matero, J. & Karukka, M., 2003. The Standard of User-Centered Design and the Standard Definition of Usability: Analyzing ISO 13407 Against ISO. *Design*, 46(1), pp.53–60.

Jooste, C., Van Biljon, J. & Mentz, J., 2014. Usability Evaluation for Business Intelligence Applications: A User Support Perspective. *South African Computer Journal*, 53(1), pp.32–44.

Keim, D.A., Mansmann, F., Schneidewind, J. & Ziegler, H., 2006. Challenges in Visual Data Analysis. In *Proceedings of the Tenth International Conference on Information Visualization*. London: IEEE, pp. 9–16.

Kelliher, F., 2005. Interpretivism and the Pursuit of Research Legitimisation: An Integrated Approach to Single Case Design. *Electronic Journal of Business Research Methods*, 3(2), pp.123–132.

Kemper, H.G., Rausch, P. & Baars, H., 2013. Business Intelligence and Performance Management. In P. Rausch, A. Sheta, & A. Ayesh, eds. *Business Intelligence and Performance Management*. London: Springer, pp. 3–10.

Kerrigan, M. & Mocan, A., 2008. The Web Service Modeling Toolkit. In S. Bechhofer et al., eds. *The Semantic Web: Research and Applications*. Berlin: Springer, pp. 812–816.

Kienle, H.M. & Muller, H.A., 2007. Requirements of Software Visualization Tools: A Literature Survey. In *Proceedings of the 4th IEEE International Workshop on Visualizing Software for Understanding and Analysis*. pp. 2–9.

Kuechler, W. & Vaishnavi, V., 2012. A framework for theory development in design science research: Multiple perspectives. *Journal of the Association for Information Systems*, 13(6), pp.395–423.

Kuechler, W. & Vaishnavi, V., 2008. On Theory Development in Design Science Research: Anatomy of a Research Project. *European Journal of Information Systems*, 17(5), pp.489–504.

Kuhail, M.A., Pandazo, K. & Lauesen, S., 2012. Customizable Time-Oriented Visualizations. In G. Bebis et al., eds. *Advances in Visual Computing*. Berlin: Springer, pp. 668–677.

Lam, H., Bertini, E., Isenberg, P., Plaisant, C. & Empirical, S.C., 2012. Empirical Studies in Information Visualization: Seven Scenarios. *Visualization and Computer Graphics, IEEE Transactions*, 18(9), pp.1520–1536.

Lassaad, A.B., Abdelwaheb, T. & Mahfoudhi, A., 2015. A Model-Driven Approach for Usability Engineering of Interactive Systems. *Software Quality Journal*.

Lauesen, S., Kuhail, M.A., Pantazos, K., Xu, S. & Mads, A.B., 2013. Uvis : Visualization and Interaction with a Drag-Drop-Formula Tool. , pp.1–16.

Lazar, J., Feng, J.H. & Hochheiser, H., 2010. *Research Methods in Human-Computer Interaction*, Chichester: John Wiley & Sons.

Lee, B., Isenberg, P., Riche, N.H. & Carpendale, S., 2012. Beyond Mouse and Keyboard: Expanding Design Considerations for Information Visualization Interactions. *IEEE Transactions onVisualization and Computer Graphics*, 18(12), pp.2689–2698.

Lempinen, H., 2012. Constructing a Design Framework for Performance Dashboards. In *Nordic Contributions in IS Research*. Berlin: Springer, pp. 109–130.

Letouzé, E., 2012. Big Data for Development: Challenges & Opportunities. *Global Pulse is a United Nations initiative*, pp.2–47.

Lew, P., Zhang, L. & Olsina, L., 2010. Usability and User Experience as Key Drivers for Evaluating GIS Application Quality. In *Proceedings of the18th International Conference on Geoinformatics*. Beijing: IEEE.

Lewis, J.R., 1995. IBM Computer Usability Satisfaction Questionnaires: Psychometric

Evaluation and Instructions for Use. *International Journal of Human-Computer Interaction*, 7(1), pp.57–78.

Lim, E., Chen, H. & Chen, G., 2013. Business Intelligence and Analytics: Research Directions. *ACM Transactions on Management Information Systems*, 3(4), pp.1–10.

Liu, S., Cui, W., Wu, Y. & Liu, M., 2014. A Survey on Information Visualization: Recent Advances and Challenges. *The Visual Computer*, 30(12), pp.1373–1393.

Lofvinga, V., 2013. *The Purposes of Performance Dashboard Use: A Case of a Procurement Performance Management SaaS*. Aalto University.

Lönnqvist, A. & Pirttimäki, V., 2006. The Measurement of Business Intelligence. *Information Systems Management*, 23(1), pp.32–40.

Macneil, S. & Elmqvist, N., 2013. Visualization Mosaics for Multivariate Visual Exploration. *Computer Graphics Forum*, 32(6), pp.38–50.

Marjanovic, O., 2010. The Importance of Process Thinking in Business Intelligence. *International Journal of Business Intelligence Research*, 1(4), pp.29–46.

McAfee, A. & Brynjolfsson, E., 2012. Big Data: The Management Revolution. *Harvard Business Review*, 90(10), pp.60– 68, 128.

Mcbride, N., 2014. Business Intelligence in Magazine Distribution. *International Journal of Information Management*, 34(1), pp.58–62.

Microsoft, 2015. Microsoft PowerPivot. Available at: https://support.office.com/en-nz/article/Power-Pivot-Add-in-a9c2c6e2-cc49-4976-a7d7-40896795d045 [Accessed June 16, 2015].

Miller, A. & Lekar, D., 2014. *Evaluation of Analysis and Visualization Tools for Performance Data*. Institute of Stuttgart Technology.

Monk, E. & Wagner, B., 2009. *Concepts in Enterprise Resource Planning* 3rd Ed., Boston: Course Technology.

Mungree, D. & Morien, D., 2013. A Framework for Understanding the Critical Success Factors of Enterprise Business Intelligence Implementation. In *Proceedings of the Nineteenth Americas Conference on Information Systems*. Chicago, pp. 1–9.

Muntean, M., Sabau, G., Bologa, A.R., Traian, S. & Alexandra, F., 2010. Performance Dashboards for Universities. In *The 2nd International Conference on Manufacturing Engineering, Quality and Production Systems*. pp. 206–211.

Muriithi, G.M. & Kotzé, J.E., 2013. A conceptual framework for delivering cost effective business intelligence solutions as a service. In *Proceedings of the 2013 Annual Research Conference of the South African Institute of Computer Scientists and Information Technologists (SAICSIT '10)*. New York: ACM, pp. 96–100.

Negash, S. & Gray, P., 2008. *Business Intelligence*, Berlin Heidelberg: Springer.

Nelson, G.S., Edia, M. & Ntertainment, E., 2010. *SAS Global Forum 2010 Business Intelligence/Analytics Business Intelligence 2 .0: Are we there yet ?*, New York.

Nielsen, J., 1994. *Usability Engineering*, Boston: Academic Press.

Nielsen, J., 2001. Usability Metrics. Available at: http://www.nngroup.com/articles/usability-metrics/ [Accessed March 1, 2015].

Nofal, M.I. & Yusof, Z.M., 2013. Integration of Business Intelligence and Enterprise Resource Planning within Organizations. *Procedia Technology*, 11, pp.658–665.

Nudurupati, S.S., Bititci, U.S., Kumar, V. & Chan, F.T.S., 2011. State of the Art Literature Review on Performance Measurement. *Computers & Industrial Engineering*, 60(2), pp.279–290.

Nunally, J., 1978. *Psychometric Theory* 2nd Ed., New York: McGraw-Hill.

Olbrich, S., Poppelbuß, J. & Niehaves, B., 2012. Critical Contextual Success Factors for Business Intelligence: A Delphi Study on Their Relevance, Variability, and Controllability. In *The 45th Hawaii International Conference on System Sciences*. Wailea: IEEE, pp. 4148–4157.

Ong, I., Siew, P. & Wong, S., 2011. A Five-Layered Business Intelligence Architecture. *Communications of the IBIMA*, 2011, pp.1–11.

Oxford Dictionary, 2013. Oxford University Press. *Oxford Advanced Learner's Dictionary*. Available at: http://www.oxfordlearnersdictionaries.com/definition/english/framework [Accessed March 14, 2014].

Palpanas, T., Chowdhary, P., Mihaila, G. & Pinel, F., 2007. Integrated Model-Driven Dashboard Development. *Information Systems Frontiers*, 9(2-3), pp.195–208.

Pantazos, K., Kuhail, M.A., Lauesen, S. & Xu, S., 2013. uVis Studio: An Integrated Development Environment for Visualization. In *Proceedings of the IS&T/SPIE Electronic Imaging Conference*. Burlingham: International Society for Optics and Photonics, pp. 1–6.

Pantazos, K. & Lauesen, S., 2012. Constructing Visualisations with InfoVis tools : An Evaluation from User Perspective. In *Proceedings of the International Conference on Information Visualization Theory and Applications*. Rome, pp. 731–736.

Patterson, R.E., Blaha, L.M., Grinstein, G.G., Liggett, K.K., Kaveney, D.E., Sheldon, K.C., Havig, P.R. & Moore, J. a., 2014. A Human Cognition Framework for Information Visualization. *Computers & Graphics*, 42(1), pp.42–58.

Pauwels, K., Ambler, T., Clark, B.H., LaPointe, P., Reibstein, D., Skiera, B., Wiesel, T. & Wierenga, B., 2009. Dashboards as a Service Why, What, How, and What Research Is Needed? *Journal of Service Research*, 12(2), pp.175–189.

Peffers, K., Tuunanen, T., Gengler, C.E., Rossi, M., Hui, W., Virtanen, V. & Bragge, J., 2006. The Design Science Research Process: A Model for Producing and Presenting Information Systems Research. In *Proceedings of the First iIternational Conference on Design Science Research in Information Systems and Technology (DESRIST)*. pp. 83–106.

Peffers, K., Tuunanen, T., Rothenberger, M.A. & Chatterjee, S., 2007. A Design Science Research Methodology for Information Systems Research. *Journal of management information systems*, 24(3), pp.45–77.

Plattner, H., 2009. A Common Database Approach for OLTP and OLAP Using an In-Memory Column Database. In *Proceedings of the ACM SIGMOD International Conference on Management of data (SIGMOD)*. Rhode Island: ACM, pp. 1–8.

Ramakrishnan, T., Jones, M.C. & Sidorova, A., 2012. Factors influencing Business Intelligence (BI) Data Collection Strategies: An Empirical Investigation. *Decision Support Systems*, 52(2), pp.486–496.

Ranjan, J., 2009. Business Intelligence: Concepts, Components , Techniques and Benefits. *Journal of Theoretical and Applied Information Technology*, 9(1), pp.60–70.

Rice, M.E. & Harris, G.T., 2005. Comparing Effect Sizes in Follow-Up Studies: ROC Area, Cohen’s D, and R. *Law and Human Behavior*, 29(5), pp.615–620.

Richey, R.C., 2013. *Encyclopedia of Terminology for Educational Communications and Technology*, Detroit: Springer Science & Business Media.

Ritsos, P.D. & Roberts, J.C., 2014. Towards more Visual Analytics in Learning Analytics. In *Proceedings of the EuroVis Workshop on Visual Analytics*. Swansea: IEEE, pp. 9–13.

Rogers, Y., Sharp, H. & Preece, J., 2011. *Interaction Design: Beyond Human-Computer Interaction*, West Sussex: John Wiley & Sons.

Rouhani, S. & Asgari, S., 2012. Review Study: Business Intelligence Concepts and Approaches. *American Journal of Scientific Research*, 1(50), pp.62–75.

Sabherwal, R., 2007. Succeeding with Business Intelligence: Some Insights and Recommendations. *Cutter Benchmark Review*, 7(9), pp.5–15.

Sabherwal, R. & Becerra-Fernandez, I., 2011. *Business Intelligence Practices, Technologies and Management*, Hoboken: John Wiley & Sons.

Sallam, R.L., Hostmann, B., Schlegel, K., Tapadinhas, J., Parenteau, J. & Oestreich, T.W., 2015. *Magic Quadrant for Business Intelligence and Analytics Platforms*,

SAP AG, 2011. Meeting the Challenges of Reporting and Dashboards In a Microsoft Software. , pp.1–10.

Satyanarayan, A. & Heer, J., 2014. Lyra: An Interactive Visualization Design Environment. *Computer Graphics Forum*, 33(3), pp.351–360.

Saunders, M., Lewis, P. & Thornhill, A., 2009. *Research Methods for Business Students* 5th Ed., Sussex: Pearson Education.

Schneider, D.A., 2007. Practical Considerations for Real-Time Business Intelligence. In C. Bussler et al., eds. *Proceedings of the First International Workshop for Business Intelligence for the Real Time Enterprise (BIRTE)*. Seoul, pp. 1–3.

Schneiderman, B. & Plaisant, C., 2010. *Designing the User Interface* 5th Ed., Boston: Addison-Wesley.

Schröter, B.H., 2015. *Helping Novices Explore Data: Facilitating Mental Model Creation of an Information Visualization System by Displaying Information Flows*. Technische Universiteit Eindhoven.

Seffah, A., Donyaee, M., Kline, R.B. & Padda, H.K., 2006. Usability Measurement and Metrics: A Consolidated Model. *Software Quality Journal*, 14(2), pp.159–178.

Seffah, A., Kececi, N. & Donyaee, M., 2001. QUIM: a Framework for Quantifying Usability Metrics in Software Quality Models. In *Proceedings of the Second Asia-Pacific Conference on Quality Software*. Hong-Kong: IEEE, pp. 1–7.

Seibold, M., Jacobs, D. & Kemper, A., 2013. Operational Business Intelligence: Processing Mixed Workloads. *IT Professional*, 15(5), pp.16–21.

Shi, Z., 2013. Research and Application of Business Intelligence in the Nuclear Power Maintenance. In K. Jia et al., eds. *Proceedings of the Ninth International Conference on Intelligent Information Hiding and Multimedia Signal Processing*. Beijing: IEEE, pp. 619–622.

Shiravi, H., Shiravi, A., & Ghorbani, A., 2012. A Survey of Visualization Systems for Network Security. *Visualization and Computer Graphics*, 18(8), pp.1313–1329.

Siau, K. & Rossi, M., 2007. Evaluation Techniques for Systems Analysis and Design Modelling Methods - A Review and Comparative Analysis. *Information Systems Journal*, 21(3), pp.249–268.

Søilen, K.S. & Hasslinger, A., 2012. Factors Shaping Vendor Differentiation in the Business Intelligence Software Industry. *Journal of Intelligence Studies in Business*, 2(3), pp.48–54.

Sridhar, P. & Dharmaji, N., 2013. A Comparative Study on How Big Data is Scaling Business Intelligence and Analytics. *International Journal of Enhanced Research in Science Technology & Engineering*, 2(8), pp.87–96.

SYSPRO, 2010. Enterprise Performance Management. , pp.1–6. Available at: http://www.syspro.com/resources/whitepapers/2010_EPM_Whitepaper.pdf.

SYSPRO, 2014. SYSPRO Reporting and Analysis Management. Available at: http://www.syspro.com/product/reporting-analysis [Accessed March 15, 2015].

Tableau, 2015. Tableau Desktop. Available at: http://www.tableausoftware.com/products/desktop [Accessed June 16, 2015].

Taticchi, P., Balachandran, K. & Tonelli, F., 2012. Performance Measurement and Management Systems: State of the Art, Guidelines for Design and Challenges. *Measuring Business Excellence*, 16(2), pp.41–54.

Taticchi, P., Tonelli, F. & Cagnazzo, L., 2010. Performance Measurement and Management: A Literature Review and a Research Agenda. *Measuring Business Excellence*, 14(1), pp.4–18.

Thomas, J.J. & Cook, K. a., 2006. Visualization Viewpoints: A Visual Analytics Agenda. *IEEE Computer Graphics and Applications*, 26(February), pp.10–13.

Thomas, W.S., Spillan, J.E. & Carolina, N., 2012. The Impact of a Focus on Change in Technology in Successful Implementation of SAP Enterprise Resource Planning Systems in North and South America. *Journal of Management Policy & Practice*, 13(5), pp.19–34.

Tobiasz, M., Isenberg, P. & Carpendale, S., 2009. Lark: Coordinating Co-located Collaboration with Information Visualization. *IEEE Transactions on Visualization and Computer Graphics*, 15(6), pp.1065–1072.

Toker, D., Conati, C., Steichen, B. & Carenini, G., 2013. Individual User Characteristics and Information Visualization: Connecting the Dots through Eye Tracking. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. Paris, France: ACM, pp. 295–304.

Tsakonas, G. & Papatheodorou, C., 2008. Exploring Usefulness and Usability in the Evaluation of Open Access Digital Libraries. *Information Processing & Management*, 44(3), pp.1234–1250.

Tullis, T. & Albert, B., 2013. *Measuring the User Experiecne* 2nd Ed., Burlington: Morgan Kaufmann.

Turban, E., Aronson, J.E., Liang, T.P. & Sharda, R., 2007. *Decision Support and Business Intelligence Systems*, NJ: Pearson Prentice Hall.

Ullman, J.D., 2012. Designing Good MapReduce Algorithms. *XRDS*, 19(1), p.30.

Vaishnavi, V. & Kuechler Jr, W., 2007. *Design Science Research Methods and Patterns: Innovating Information and Communication Technology*, Boca Raton: Auerbach.

Vaishnavi, V. & Kuechler, W., 2015. *Design Science Research Methods and Patterns: Innovating Information and Communication Technology* 2nd Ed., Taylor and Francis Group.

Vatrapu, R., Suthers, D. & Medina, R., 2008. Usability, Sociability, and Learnability: A CSCL Design Evaluation Framework. In *Proceedings of the Sixteenth International Conference on Computers in Education (ICCE)*. Taipei: APSCE, pp. 369–373.

Velcu-Laitinen, O. & Yigitbasioglu, O.M., 2012. The Use of Dashboards in Performance Management: Evidence from Sales Managers. *International Journal of Digital Accounting Research*, 12(November 2011), pp.39–58.

Veneziano, V., Mahmud, I., Khatun, A. & Peng, W.W., 2014. Usability Analysis of ERP Software: Education and Experience of Users' as Moderators. In *Proceedings of the 8th International Conference on Software, Knowledge, Information Management and Applications (SKIMA)*. Dhaka: IEEE, pp. 1–7.

Victor, B., 2013. Drawing Dynamic Visualizations. Available at: http://worrydream.com/DrawingDynamicVisualizationsTalkAddendum/ [Accessed June 16, 2015].

Waghmare, M.P. & Mehta, M.B., 2014. Information Technology and Supply Chain Management Practices in Global Business Organizations - A Study. *IBMRD's Journal of Management and Research*, 3(2), pp.107–112.

Ward, M.O., Grinstein, G. & Keim, D., 2010. *Interactive Data Visualization: Foundations, Techniques, and Applications* 2nd Ed. A. K. Peters, ed., London: CRC Press.

Watson, H.J., 2009. Tutorial: Business Intelligence - Past, Present, and Future. *Communications of the Association for Information Systems*, 25(39), pp.487–510.

Watson, H.J. & Wixom, B.., 2007. The Current State of Business Intelligence in Academia: The Arrival of Big Data. *IEEE Computer Society*, 40(9), pp.96–99.

White, C., 2004. Now is the Time for Real-Time BI. *Information Management*.

Winter, R., 2008. Design Science Research in Europe. *European Journal of Information Systems*, 17(5), pp.470–475.

Winter, S., Wagner, S. & Deissenboeck, F., 2008. A Comprehensive Model of Usability. In J. Gulliksen et al., eds. *Engineering Interactive Systems*. Berlin: Springer, pp. 106–122.

Wixom, B. & Goul, M., 2014. The Current State of Business Intelligence in Academia: The Arrival of Big Data The Current State of Business Intelligence in Academia : The Arrival of Big Data. *Communications of the Association for Information Systems*, 34(1), pp.1–10.

Yi, J.S., Kang, Y.A., Stasko, J. & Jacko, J., 2007. Toward a Deeper Understanding of the Role of Interaction in Information Visualization. *IEEE transactions on visualization and computer graphics*, 13(6), pp.1224–1331.

Yigitbasioglu, O.M. & Velcu, O., 2012. A Review of Dashboards in Performance Management: Implications for Design and Research. *International Journal of Accounting Information Systems*, 13(1), pp.41–59.

Yin, R.K., 2013. *Case Study Research: Design and Methods* 5th Ed., London: SAGE Publications.

Yu, E., Lapouchnian, A. & Deng, S., 2013. Adapting to Uncertain and Evolving Enterprise

Requirements: The Case of Business-Driven Business Intelligence. In *Proceedings of the International Conference on Research Challenges in Information Science*. New York: ACM.

Zhang, L., Stoffel, A., Behrisch, M., Mittelstadt, S., Schreck, T., Pompl, R., Keim, D., Weber, S. & Last, H., 2012. Visual Analytics for the Big Data Era - A Comparative Review of State-of-the-Art Commercial Systems. In *Proceedings of the Visual Analytics Science and Technology (VAST) Conference*. Seattle: IEEE, pp. 173–182.

Appendices

Appendix A: Ethics Clearance

Nelson Mandela Metropolitan University

for tomorrow

• PO Box 77000 • Nelson Mandela Metropolitan University
• Port Elizabeth • 6031 • South Africa • www.nmmu.ac.za

Vice-Chairperson: Research Ethics Committee (Human)
Tel: +27 (0)41 504-2235 **Ref: [H14-SCI-CSS-007/Approval]**
Contact person: Mrs U Spies

18 August 2014

Dr B Scholtz
Faculty of Science
Department: Computing Science
09-01-01c
South Campus

Dear Dr Scholtz

A REFERENCE MODEL FOR THE DESIGN OF INTEGRATED DEVELOPMENT ENVIRONMENT FOR DASHBOARD DEVELOPMENT

PRP: Dr B Scholtz
PI: Mr M Smuts

Your above-entitled application for ethics approval served at Research Ethics Committee (Human). We take pleasure in informing you that the application was approved by the Committee.

The ethics clearance reference number is **H14-SCI-CSS-007** and is valid for three years. Please inform the REC-H, via your faculty representative, if any changes (particularly in the methodology) occur during this time. An annual affirmation to the effect that the protocols in use are still those for which approval was granted, will be required from you. You will be reminded timeously of this responsibility, and will receive the necessary documentation well in advance of any deadline. We wish you well with the project. Please inform your co-investigators of the outcome, and convey our best wishes.

Yours sincerely

CB Cilliers

Prof CB Cilliers
Chairperson: Research Ethics Committee (Human)

cc: Department of Research Capacity Development
Faculty Officer: Science

Appendix B: Task List for SYSPRO Evaluation

Participant number: ________________

PC number: ________________

SYSPRO Executive Dashboard Development Workshop

Outcome:

The objective of the workshop is to create a Customized SYSPRO Executive Dashboard that will display the stock valuation at cost price vs. stock valuation at selling price indicating if the variance of gross profit percentage is within the allowed range of target gross profits.

Pre-Requisites:

- SYSPRO 7 with Demo Data (SQL Database – the Outdoors Company)
- SQL Server 2008 R2
- SAP Business Objects Xcelsius 2008 or Crystal Dashboard Design
- Microsoft Excel 2010 or 2013

Tools Used:

1. **SQL Server Management Studio** – create a SQL View that will extract Inventory Information
2. **SYSPRO Data Dictionary** – Mapping the view so that it can be used inside of SYSPRO
3. **SYSPRO REPPAC Report Writer** – a method of converting the data to xml
4. **Crystal Dashboard Design** – Create a dashboard and map it to the underlying data
5. **SYSPRO Customized panes** – Execute the SYSPRO Report writer and pass the data to a the SYSPRO Executive Dashboard

Setup username and password

Select **Setup**> **Operators**. Select the Admin operator and click on the edit icon . In the **Activities** and **Fields** group make sure that the Selection is set to **All** as shown in figure 1.

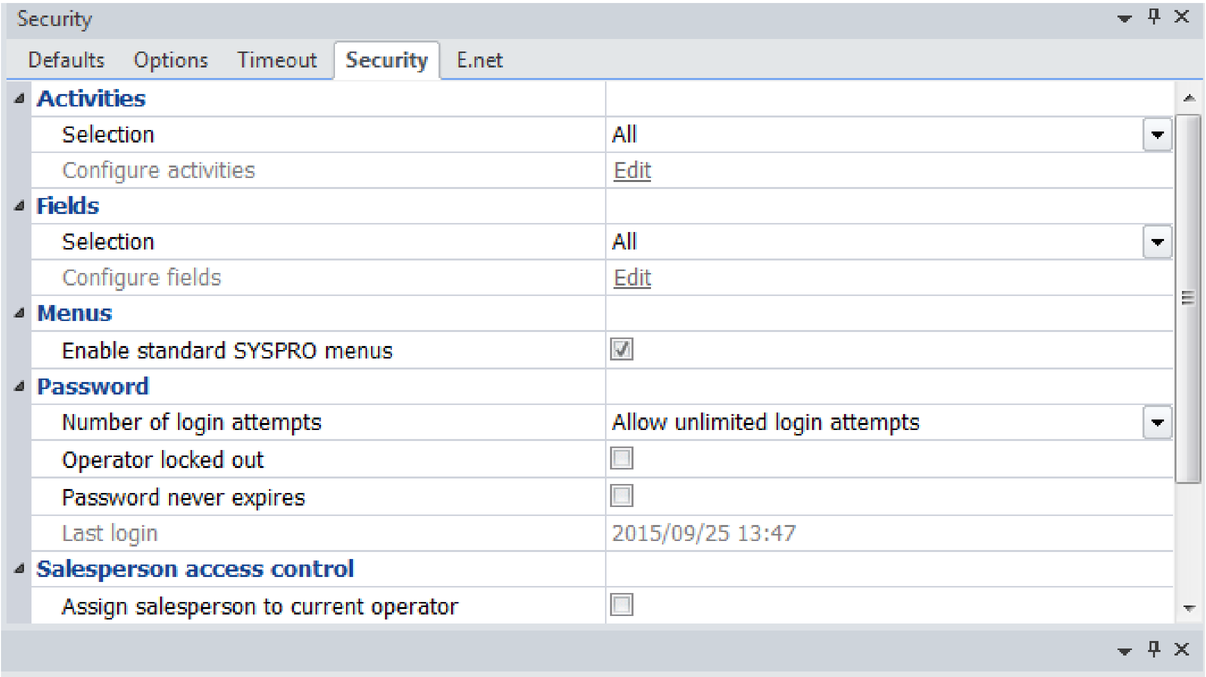


Figure 1, Operator Screenshot.

1. Click on the **Add** icon and add a new operator. Enter your participant number as the Operator and then press **Enter** or Tab. Enter your name again as the participant number. Select ADMIN as the Group. No subgroup must be allocated. In the Activities and Fields group make sure that Selection is set to **All** as shown in the screenshot below.

2. **Optional:** Select the **Password** tab and then the **Set Password** link to setup a password if required. Write down the Operator for the newly added operator. (Remember your password). This is vitally important as your log files will be accessed to determine the success of your tasks in this practical session.

Evaluation Task-list:

1. SQL Server Management Studio

Create a SQL View that will link the SYSPROCompanyEdu1 database that will link InvWarehouse, InvWarehouseCtl and the InvPrice tables to extract the Stock Valuation at cost and selling prices according to Warehouse using the following SQL statement as a query:

```
Create View vw_invVal as
Select
       InvWarehouse.Warehouse,
       InvWhControl.Description as WarehouseName,
       CAST(Round(Sum(InvWarehouse.QtyOnHand),2) as decimal(14,2)) QtyOnHand,
       CAST(Round(Sum(InvWarehouse.QtyOnHand*InvWarehouse.UnitCost),2)        as
decimal(14,2)) as CostValueOnHand,
       CAST(Round(Sum(InvWarehouse.QtyOnHand    *    InvPrice.SellingPrice),2)     as
decimal(14,2)) as SellingValueOnHand

From InvWarehouse
             Inner     Join      InvWhControl      on      InvWarehouse.Warehouse      =
InvWhControl.Warehouse
             Left Outer Join InvPrice on InvWarehouse.StockCode = InvPrice.StockCode
and InvPrice.PriceCode = 'A'
Group By InvWarehouse.Warehouse, InvWhControl.Description
```

2. *SYSPRO Data Dictionary*

Map the SQL view that you have just created to SYSPRO and create the SYSPRO data dictionary's tables and columns as a report:

a. Log into SYSPRO using Admin, Company 0.
b. Make sure that the Browses Category is included (right click on a blank space in the **Program List** menu and select include category **Browses**).
c. Navigate to SYSPRO Program List> Report Writer > Browses > Data Dictionary Tables > and select new table (white page with star icon).
d. Add the table as in figure 2.

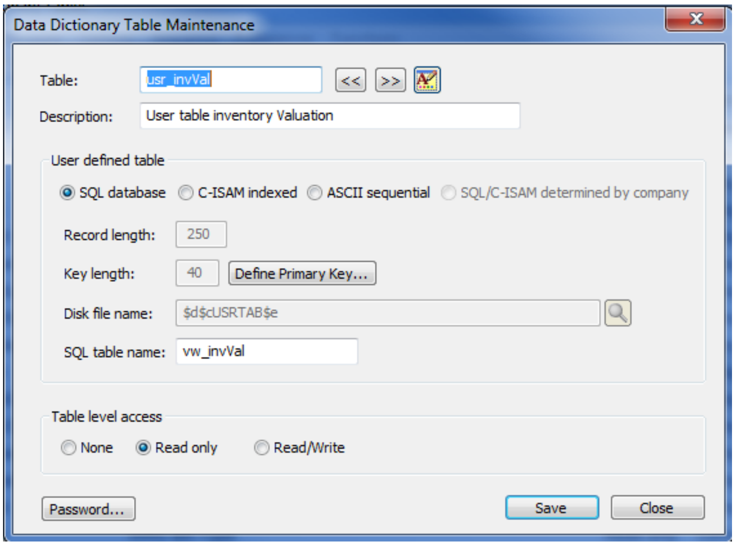
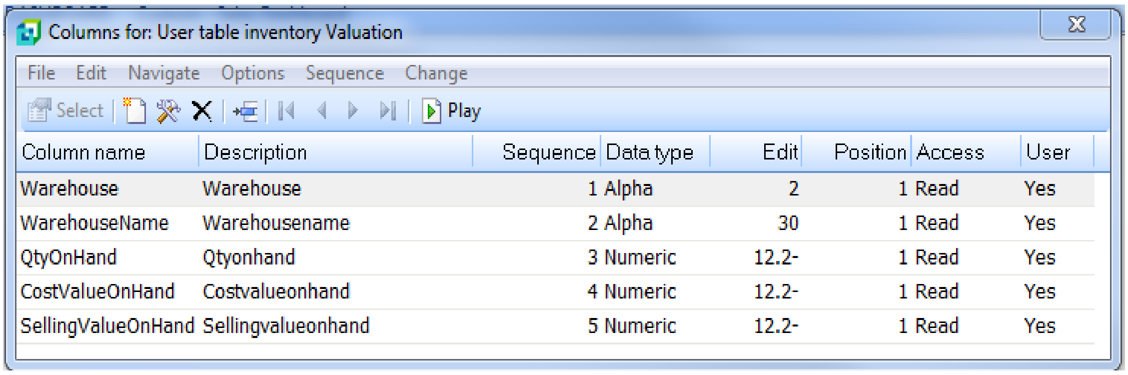


Figure 2, Data Dictionary Table Maintenance

e. Select the table and Functions> Column Maintenance> Add
   Enter the column information as follows ensuring that the column names are exactly the same as the columns of the SQL view and in the same order as in the SQL statement



Columns for: User table inventory Valuation

File Edit Navigate Options Sequence Change

Select Play

Column name	Description	Sequence	Data type	Edit	Position	Access	User
Warehouse	Warehouse	1	Alpha	2	1	Read	Yes
WarehouseName	Warehousename	2	Alpha	30	1	Read	Yes
QtyOnHand	Qtyonhand	3	Numeric	12.2-	1	Read	Yes
CostValueOnHand	Costvalueonhand	4	Numeric	12.2-	1	Read	Yes
SellingValueOnHand	Sellingvalueonhand	5	Numeric	12.2-	1	Read	Yes

Figure 3, Columns for: User table inventory valuation

3. *SYSPRO Report Writer*

a. Open Report Writer> Browses> Browse on Reports> Edit > Add
b. Change the settings accordingly and select Add Report and Edit it:

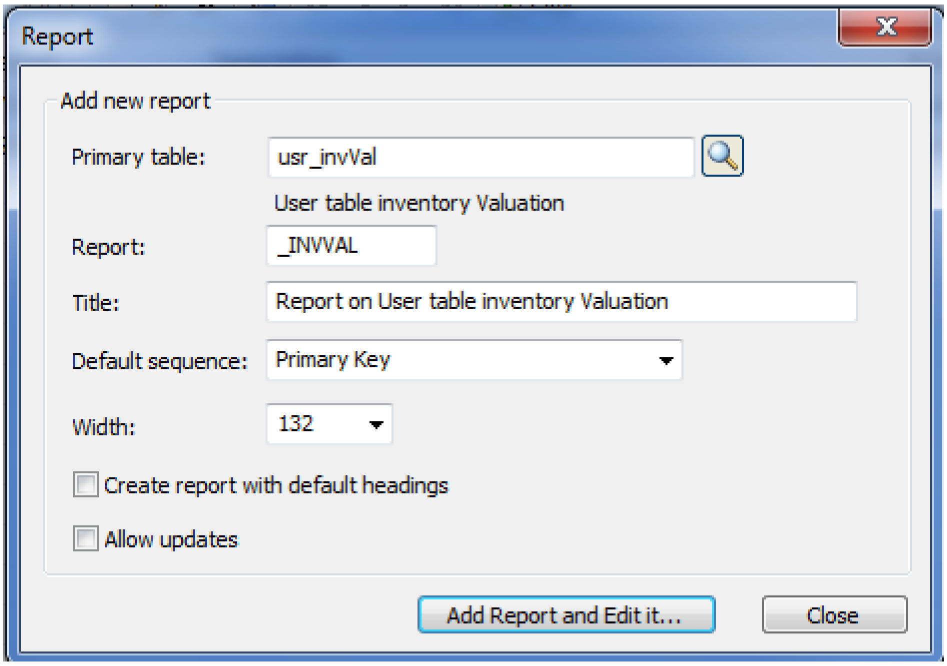


Figure 4, Report settings

c. Convert the report to an XML file in the Options setup (figure 5):

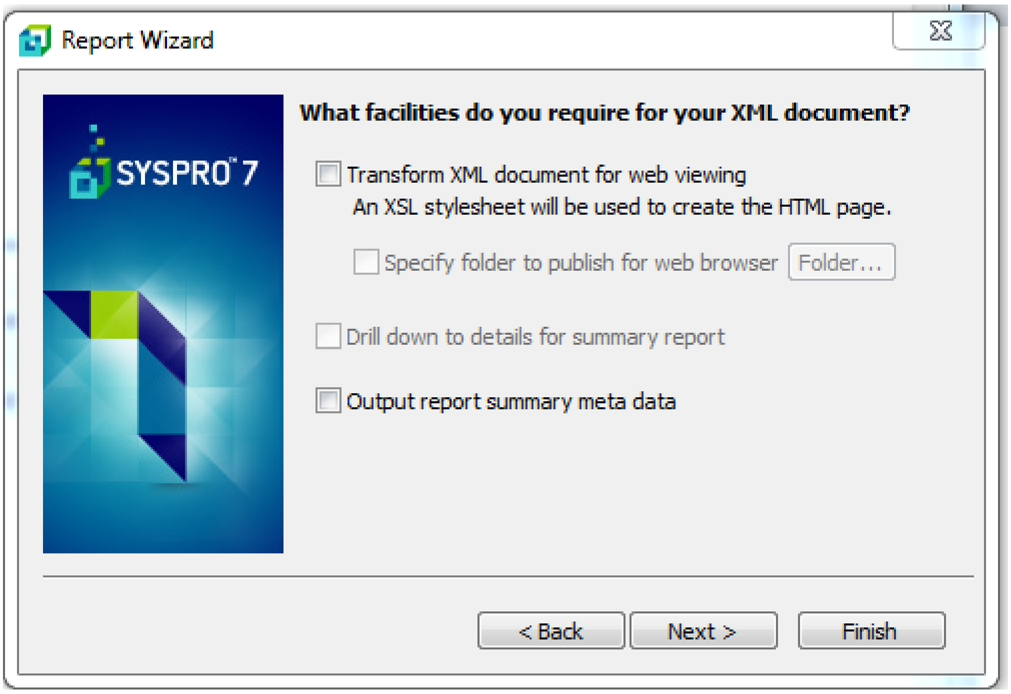


Figure 5, Convert to XML file

d. And follow the XML wizard and then save in your H:\ drive

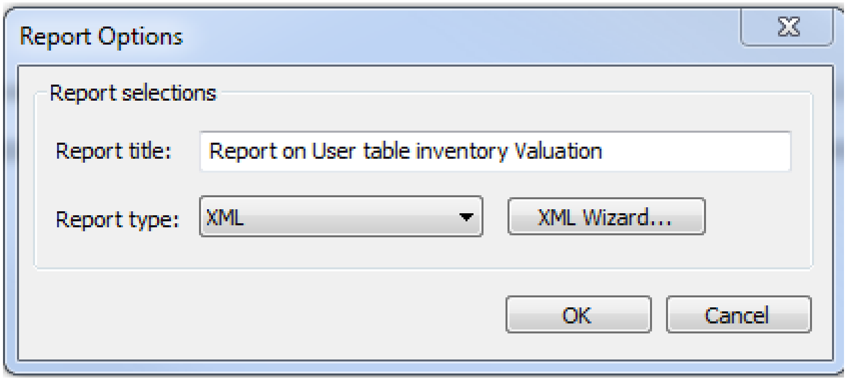


Figure 6, Report options

e. Add all of the columns whilst in the Detail Layout.
f. Save the report and print.

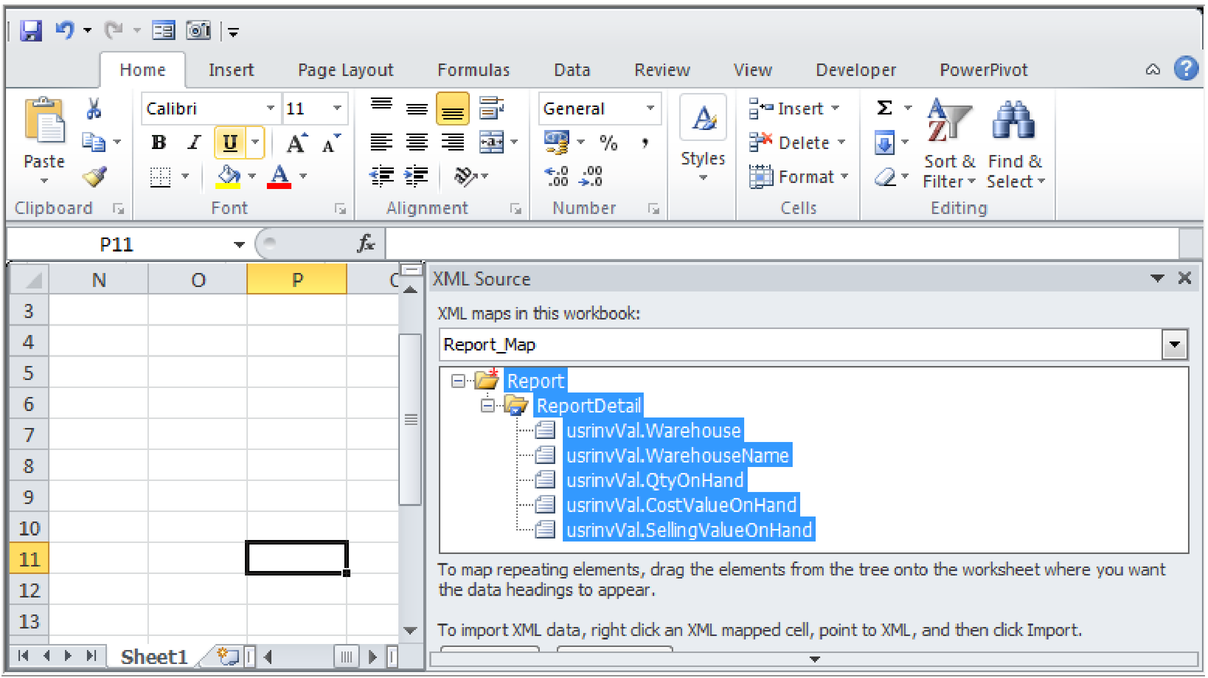
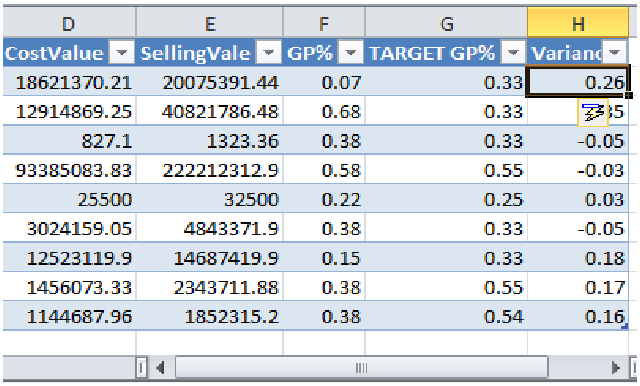


Figure 7, SAP Xcelsius XML mapping

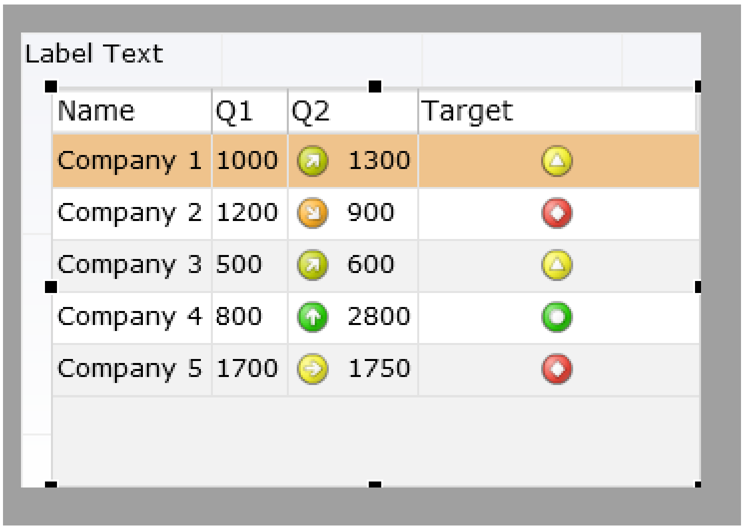
4. Xcelsius 2008 Dashboard Design

a. Open up a new Xcelsius dashboard design window and map the XML from your H\: to the spreadsheet pane within the Xcelsius application; to do this you have to ensure that the Developer Tab within the spreadsheet pane has been enabled.
b. Drag the report to cell A1 and click the refresh button.
c. Add 3 new columns:
    i. Column F – GP% (gross profit percentage) =ROUND(((E2-D2)/E2), 2)
    ii. Column G – target GP% (the target for the gross profit percentage) – Enter manually from the screenshot below.

iii. Column H – Variance (difference between the two preceding columns) =F2-G2



D	E	F	G	H
CostValue	SellingVale	GP%	TARGET GP%	Varianc
18621370.21	20075391.44	0.07	0.33	0.26
12914869.25	40821786.48	0.68	0.33	[illegible]35
827.1	1323.36	0.38	0.33	-0.05
93385083.83	222212312.9	0.58	0.55	-0.03
25500	32500	0.22	0.25	0.03
3024159.05	4843371.9	0.38	0.33	-0.05
12523119.9	14687419.9	0.15	0.33	0.18
1456073.33	2343711.88	0.38	0.55	0.17
1144687.96	1852315.2	0.38	0.54	0.16



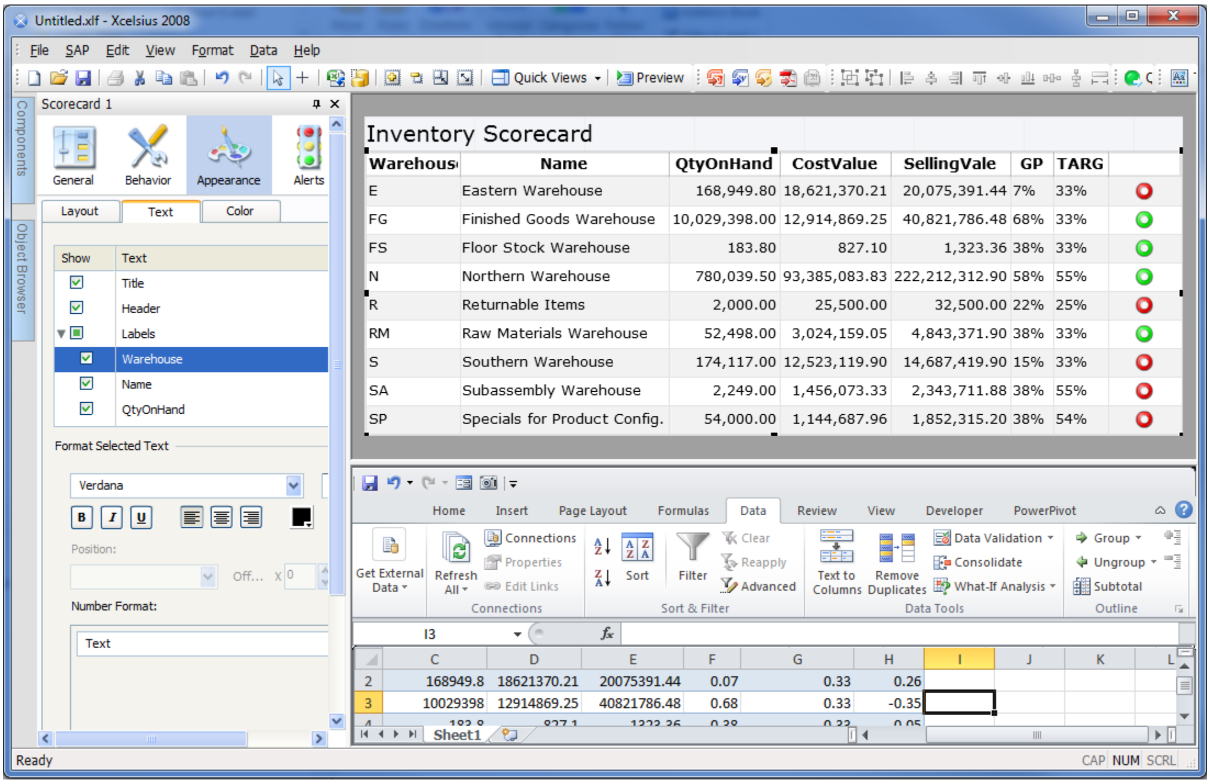
Label Text

Name	Q1	Q2	Target
Company 1	1000	1300	
Company 2	1200	900	
Company 3	500	600	
Company 4	800	2800	
Company 5	1700	1750	

d. Rename the Label Text to Inventory Scorecard

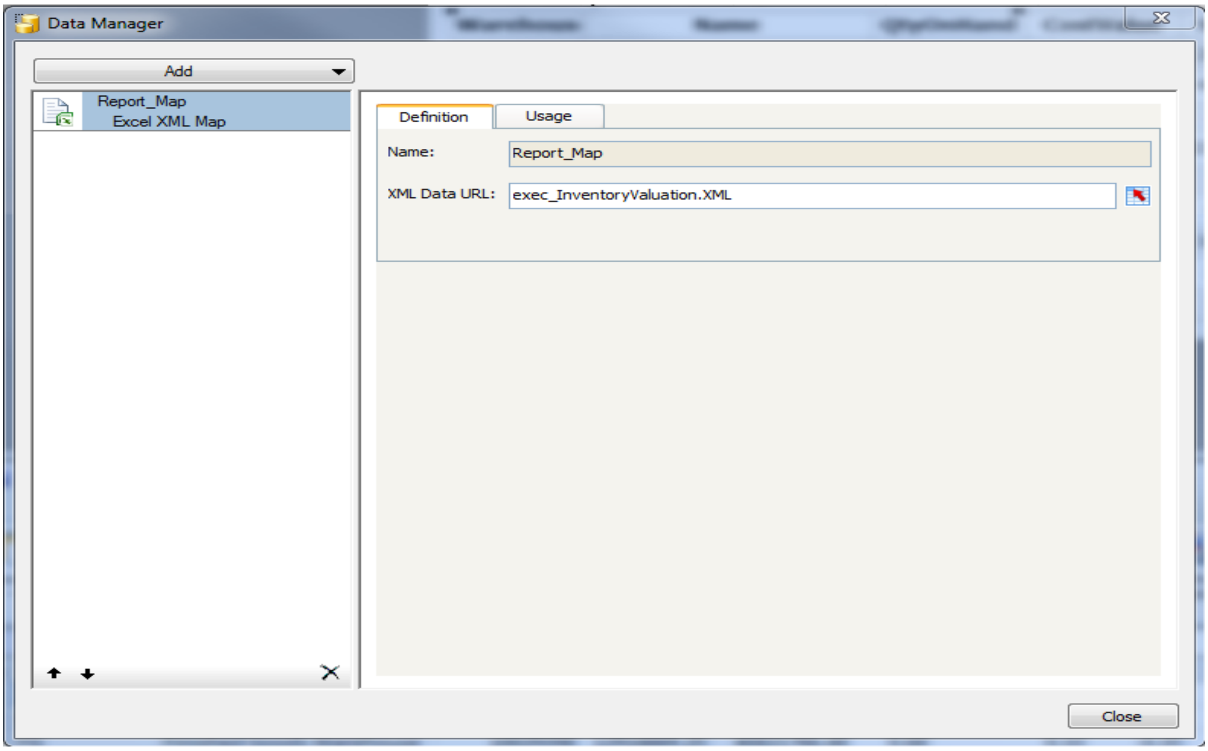
e. Map the Score Card to the Spreadsheet

f. Configure the Score Card component



g. Add a XML Map Connection to the Dashboard so that it is dependent on a XML document that will be generated by the business object

h. Set the Usage to Refresh Every 5 Seconds



i. Export to SWF File as Exec_InventoryValuation.swf

j. Save the Crystal Dashboard as exec_InventoryValuation.xlf

5. SYSPRO Customized panes

a. Create a text file with the following VB Script.

exec_InventoryValuation.txt - Notepad

File Edit Format View Help

```
\viewkind4\uc1\pard\qc\cf1\ul\b\f0\fs18 Inventory Valuation\cf2\ulnone\b0\par
\par
\pard This Dashboard demostrates The Inventory Valuation and the GP% Variance\par
\par Values shown include:\par
\par Qty On Hand x Unit Cost by Warehouse, Qty On Hand x Selling Price by Warehouse
\par
\pard\par
}
[rtf:end]

' This Script extracts the data from SYSPRO using the SYSPRO Report Writer REPPAC
' ------------------------------------------------------------------

Option Explicit

Function CustomizedPane_OnRefresh()
        dim XMLOut
        dim XMLIn
        dim SYSPROXmlOut
        dim SYSPROXmlIn

' Call REPQRY to retrieve XML
        SYSPROXmlIn = " <Query>" & _
                "<Key>" & _
                "<Report>_INVVAL</Report>" & _
                "</Key>" & _
                "</Query>"

        on error resume next
        SYSPROXmlOut = CallBO("REPQRY",SYSPROXmlIn ,"auto")
        if err then
                msgbox err.Description, vBCritical, "Calling Business Object WIPQ67"
                exit function
        end if

'Output XML to file
        dim Dom
        Set Dom  = createobject("MSXML.DOMDocument")
        Dom.LoadXml(SYSPROXmlOut)

        dim dashfile
        dashfile = SystemVariables.CodeObject.baseSettingsFolder & "Dashboards\exec_InventoryValuation.xml"
        Dom.save(dashfile)

End Function

Function CustomizedPane_OnLoad()

        dim SwfXmlOut
        dim SwfXmlIn
        dim dashname
        dim swffile

        dashname = "InventoryValuation"
        swffile = SystemVariables.CodeObject.baseSettingsFolder & "Dashboards\exec_" &
SystemVariables.CodeObject.SYSPROUserNumber & "_" & dashname & ".swf"

' Call COMGET to retrieve swf file
        SwfXmlIn = " <Query>" & _
                "<Key>" & _
                "<Filetype>EX</Filetype>" &_
                "<Filename>exec_"&dashname&".swf</Filename>" &_
                "</Key>" & _
                "</Query>"

        on error resume next
        SwfXmlOut = CallBOFile("COMGET",SwfXmlIn ,"auto",swffile)
        if err then
                msgbox err.Description, vBCritical, "Calling Business Object COMGET"
                exit function
        end if

'Do Refresh to get xml output
        CustomizedPane_OnRefresh()
```

exec_InventoryValuation.txt - Notepad

File Edit Format View Help

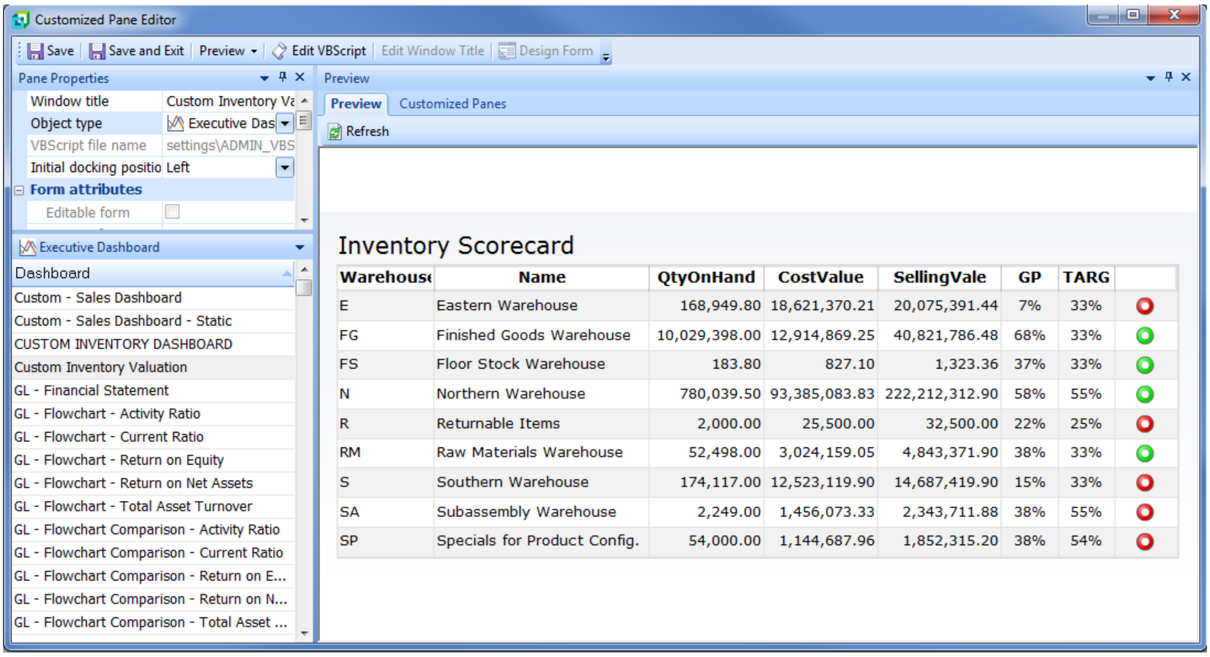
```
'Point browser to swf file
        CustomizedPane.CodeObject.BrowserAddress =  SystemVariables.CodeObject.baseSettingsFolder & "Dashboards\exec_" &
SystemVariables.CodeObject.SYSPROUserNumber & "_" & dashname & ".swf"

End Function
```

b. Save the Text File as exec_InventoryValuation.txt

c. Copy the exec_InventoryValution.swf, exec_InventoryValuation.txt and exec_InventoryValuation.xlf to the SYSPRO61>Base>Execdashboards folder

d. Log into SYSPRO and add the Inventory Valuation Customized pane



e. Click Save and Exit and you should see a the dashboard that was created.

Appendix C: Field study of Development Environments for Dashboards in SYSPRO

Section A: Demographical Questionnaire

Participant number (please use the number provided on the task list e.g. P80). *

PC number *

Gender

- ○ Male
- ◉ Female

Age

- ○ 18-20
- ○ 21-29
- ○ 30-39
- ○ 40-49
- ○ 50+

Dashboard development experience
Read the descriptions below and select the most appropriate user profile that represents you.

- ○ No experience - I have never created a dashboard.
- ○ Novice - I have created dashboards using predefined dashboard templates that support functions for position, size, shape and colour manipulation.
- ○ Intermediate - I have applied basic programming knowledge to create dashboards in conjunction with predefined dashboard templates.
- ○ Expert - I have created advanced dashboards by applying strong programming knowledge to manipulate the position, size, shape and colour of data without assistance from predefined templates.

Do you have any ERP experience besides the ERP course offered at NMMU? *
e.g. Additional ERP courses, certifications, practical experience

- ○ Yes
- ○ No

If you answered YES, please specify.

Section B: Post-Task Questionnaire

Please answer this section after you have completed the workshop.

Cognitive load

	Strongly disagree	Partially disagree	Neither agree nor disagree	Partially agree	Strongly agree
Mental Demand: The tasks were mentally demanding	○	○	○	○	○
Physical Demand: The tasks were physically demanding	○	○	○	○	○
Temporal Demand: The pace of the tasks were hurried or rushed	○	○	○	○	○
Performance: I was unsuccessful in accomplishing what I was asked to do	○	○	○	○	○
Effort: I had to work hard to	○	○	○	○	○

	Strongly disagree	Partially disagree	Neither agree nor disagree	Partially agree	Strongly agree
accomplish my level of performance					
Frustration: I felt insecure, discouraged, irritated, stressed, and annoyed	○	○	○	○	○

B. Overall satisfaction *

Answer the questions by considering the various software components and steps involved in the development environment.

	Strongly disagree	Partially disagree	Neither agree nor disagree	Partially agree	Strongly agree
Overall, I am satisfied with how easy it is to use the system to develop dashboards.	○	○	○	○	○
It was easy to learn to use this system e.g. different	○	○	○	○	○

	Strongly disagree	Partially disagree	Neither agree nor disagree	Partially agree	Strongly agree
software component.					
It was easy to learn the various development steps.					
It was simple to use the different software components involved in the system.					
Whenever I made a mistake using the system, I could recover easily and quickly without assistance.					
Overall, I am satisfied with the system and the dashboard development process and					

	Strongly disagree	Partially disagree	Neither agree nor disagree	Partially agree	Strongly agree
software components.					
Overall, I am satisfied with the amount of time it took to complete the tasks .	○	○	○	○	○

Describe at least 3 negative aspects identified from the current development environment.

Describe at least 3 positive aspects identified from the current development environment.

Appendix D: IDIA Paper

Usability Guidelines for Designing Information Visualisation Tools for Novice Users

Martin Smuts
Nelson Mandela Metropolitan University
South Africa

Brenda Scholtz
Nelson Mandela Metropolitan University
South Africa

Andre P. Calitz
Nelson Mandela Metropolitan University
South Africa

Abstract

Despite the benefits of effective Enterprise Resource Planning (ERP) and Business Intelligence and Analytics (BI&A) systems, the adoption of such systems remains fairly low in developing countries due to a number of factors. Research has indicated that severe skills shortages are predicted in the field of BI&A, as university graduates are not properly prepared to conduct data analysis. Several studies have proposed curricula to increase the skills of Information Systems (IS) graduates studying towards BI&A fields. Additionally, BI vendors are realising that a wider audience of users are participating in the process of data analysis and are not limited to the stereotypical statisticians or technical experts. The field of Information Visualisation (IV) is addressing the need to produce software products that eliminate the technical skills required to operate such software tools. This study aims to investigate some of the usability factors hindering BI&A knowledge transfer and skills in developing countries by conducting a field study at a South African university. A number of problem categories was identified during the field study and a set of guidelines for designing IV tools for novice users is proposed to eliminate these problems.

Keywords

Visualisation guidelines, Business Intelligence (BI), information visualisation tools.

Introduction

Business Intelligence and Business Analytics (BI&A) have become increasingly important fields in both academic and business communities over the past two decades (Chen & Storey 2012). Developing countries are generating very large amounts of data through the use of mobile technologies, which can be mined to improve human well-being, track emerging markets, or identify the needs of customers. Many organisations have implemented Enterprise Resource Planning (ERP) systems to integrate their various processes and departments, which gives employees a holistic view of all information that has a financial impact on the organisation. BI, together with ERP systems, is seen as a priority in an increasing number of organisations, with benefits to different levels of the organisation ranging from front-end workers to executives in strategic management. According to Gartner, the BI market grew by 9% and is projected to grow at a compound annual growth rate of 8.7% until 2018 (Sallam et al. 2015). Sallam et al. (2015) further motivate that capabilities such as smart data-discovery and self-service BI are extending data discovery to a wider range of non-traditional users of BI to enhance insights and data interpretation. These capabilities allow users to identify hidden patterns in large, complex and increasingly multi-structured datasets, without having the foundational skills to build models or write algorithms and queries (Sallam et al. 2015). Moreover, the increase in interactive information visualisation (IV) tools is enabling non-traditional users of BI to explore, understand and analyse data through progressive and iterative visual exploration (Schröter 2015). These tools are often desktop software that have the capabilities to connect to underlying data architectures that are set up for BI and are often marketed as “Visualisation”, “Data Discovery”, “Business Analytics” or “Data Exploration” tools.

A number of studies has shown that the adoption of BI remains low, particularly amongst smaller institutions and organisations with resource constraints (Muriithi & Kotzé 2013; Pitula & Radhakrishnan 2011). Many of these constraints relate to high failure rates, problems with data irregularities and lack of compatibility with existing systems (Nofal & Yusof 2013). Additionally, current research has predicted severe shortages in the number of graduates prepared to work in the field of BI and ERP (Calitz, Cullen & Greyling, 2015; Chiang, Goes, & Stohr, 2012; Gupta et al., 2015; Wang & Harbert, 2015; Wixom & Goul, 2014). Research produced by the McKinsey Global Institute (MGI) reported that by 2018, the United States alone may experience a shortage of 140,000 to 190,000 data analysts professionals as well as 1.5 million data-savvy managers (Manyika et al. 2011). A need exists to increase the knowledge and skills of students intending to work in the field of data analysis and BI. Skills in data analysis are especially necessary to improve the socio-economic status in developing countries and to provide real-time feedback on socio-economic programs and policies that might require rapid alternations (Letouzé 2012). A number of projects have addressed curriculum design for BI&A in order to lessen the shortage of BI skills and knowledge (Wixom & Goul 2014; Gupta et al. 2015; Chiang et al. 2012; Wang & Harbert 2015). The Developing and Strengthening Industry-driven Knowledge-transfer between developing Countries (DASIK) project (DASIK, 2014) and Global Pulse (Global Pulse, 2015) are initiatives that aim to increase the data analysis skills of people in developing countries.

The low usability of BI tools makes it difficult for novices to gain the required skills (Jooste et al. 2014). BI platforms are developed using a range of software tools from different vendors that require users to have strong technical skills and domain knowledge. Novice users do not have such skills as they are in the process of learning and struggle to develop and interpret moderately complex visualisations of data. The low usability of tools worsen the situation (Bostock & Heer 2009; Elias 2012; Yigitbasioglu & Velcu 2012). Fan and Bifet (2013) motivate that the main task of data analysis is how to visualise data, but is often difficult to find user-friendly visualisations that are interpretable by less experienced users. The poor usability of BI systems makes it difficult for users to interact with these systems, which often creates an environment where users are expected to either apply strong programming skills or domain knowledge (or both) to develop visualisations, synchronise these into different views and connect to different data sources and applications (Elias 2012; Pantazos et al. 2013). These problems often affect the learnability of the system as students need time to master the complex interface. Moreover, users follow a common development process to create visualisations of their data, which provides users with logical mental models (Liu et al. 2014). If the development process is moderately complex, users often struggle to map their data to visualisation techniques (Grammel et al. 2010; Huron et al. 2014). As a result, users with less technical knowledge must seek the assistance from experts to extract the required data from various applications, apply statistical techniques and present the reviewed data accordingly (Elias 2012). These problems are worsened in developing countries where individuals lack ICT skills.

The research problem investigated in this study is prompted by the realisation that Information Systems' (IS) graduates may not be fully prepared (knowledgeable and skilled) to satisfy the BI and data analysis requirements of industry. Moreover, novices often struggle with the usability of BI tools and mapping data to visual presentations. The primary aim of this paper is to investigate how novice users experience the usability of IV tools and the difficulties they experience when learning these tools with a particular focus on dashboards. The secondary aim proposes a set of guidelines for designing or evaluating IV tools that can aid novices in learning data analysis.

The structure of this paper is as follows. A literature review analyses the problems encountered in the field of ERP and BI. This is followed by a discussion of the research methodology adopted and the participants involved in this study. The results of a field study are then presented and guidelines are proposed based on the findings from literature and the field study results. The final section deals with conclusions and future recommendations.

Information Visualisation

Organisations have realised that the implementation of ERP and BI systems is a key strategic tool. The most current information is collected from ERP systems and then loaded into data warehouses, which can then be linked to BI tools for analysis. The term BI can be understood as a set of tools, techniques and processes that aids organisations in retrieving, analysing and distributing information retained, in large data sets, to make effective decisions (Sabherwal & Becerra-Fernandez 2013). The overall objective of BI is to increase organisational performance through decision support. A BI system should provide both a technical and organisational platform that presents its users with historical, current and predicative information for analyses to enable effective decision making and predictive management support. Some of the benefits that can be derived from BI are faster and easier access to information, improved profitability, reduced costs and improved efficiency and customer service.

Despite the benefits of BI, many organisations and development countries have low adoption rates for these types of enterprise systems (Pitula & Radhakrishnan 2011). A recent study (Calitz, Cullen & Greyling, 2015) was conducted in South Africa and reported that BI, Business Process Management (BPM) and Knowledge Management are skills that are highly in demand, while Infrastructure Management and Information Security were skills that would be in high demand in future. These demands are aggravated in developing countries since they lack the technological infrastructures and experience high volumes of economic and human resource scarcity (Hilbert

2013). Pitula and Radhakrishnan (2011) further argue that some of the issues related to large ICT4D projects are the existence of inadequate requirements gathering from end-users. In many ICT4D projects existing technologies are introduced without sufficiently adapting or reinventing the requirements with regard to the users' needs, infrastructure or socio-cultural context (Pitula & Radhakrishnan 2011).

Chiang et al. (2012) explains that the analytics software industry produces products that are difficult and cumbersome to use when individuals do not having a deep understanding of the underlying systems and technologies. Considering that a wider audience are starting to utilise analytics tools, there is a need to develop tools that assist users throughout the whole process of learning (Ritsos & Roberts 2014). BI tools need to support users from the beginning, when they are novices, and help them advance to expert levels where they progress from shallow thinkers to deep thinkers in order to identify and solve more complex problems (Ritsos & Roberts 2014). In this study, the definition of "novice" users, or just novices, is adapted from Heer et al. (2008) and Grammel et al. (2010). Novice users refer to those who are not familiar with IV and data analysis beyond the charts and graphics encountered in everyday life, but may be domain experts in their area of expertise (Grammel et al. 2010). Additionally, novice users may be constrained by their lack of programming skills in general, let alone programming for IV (Heer et al. 2008).

IV has been widely used in a variety of data analysis applications (Liu et al. 2014). IV refers to the interdisciplinary field concerned with the visual displays of complex information to assist humans in understanding information, resolving logical problems and to think with reason (Patterson et al. 2014). The diverse nature of data requires the formulation of a various IV techniques that can communicate important patterns and trends from abstract data sources. A popular visualisation technique that is often used in the BI domain are dashboards (Elias & Bezerianos 2011; Yigitbasioglu & Velcu 2012). Dashboards are visual displays of the most important information that is consolidated and organised on a single screen to achieve one or more objectives (Yigitbasioglu & Velcu 2012). The most popular visualisation process was presented by Card, Mackinlay and Shneiderman (1999) and was also refined by others (Chi 2000; Tobiasz et al. 2009; Jansen & Dragicevic 2013). The process describes three activities of how visualisations are essentially developed, interpreted and interacted with. The first activity relates to the transformation of raw data into data tables (Data Transformations). These data tables can be further refined by applying filters, calculations and merging with other tables (Grammel et al. 2010). The data tables are then mapped to visual constructs (Visual Mappings), typically taking the form of generic visualisations such as bar, pie, or line graphs with their corresponding properties. Visual mappings have been identified as the most difficult activity for novices to perform, since they lack understanding of which visualisation types are best suited for the selected data. Views are created from visual structures (View Transformations) that display data at varying levels of abstraction, allowing users to view data from various perspectives by using operators such as zoom, filter, aggregate, drill-down and brushing (Heer et al. 2012). View transformations do not change the overall layout of the visual structure, but only allow for a data set to be viewed from a different perspective. Finally, users interpret the views with predefined objectives in mind, for example when examining the top 10 products sold.

Research Design

The main research question of this study is: *What design guidelines can be proposed to alleviate the usability problems of IV tools for novice users?* In order to answer the main research question, two secondary questions were formulated, namely:

> *RQ1: What specific problems do novice users experience when conducting IV and data analysis?*
>
> *RQ2: What guidelines can be proposed to guide the design of visualisation tools for novice users?*

The research strategies used to answer the research questions include a literature review and a field study to investigate the research problems of data analysis in more detail. The results of these were used to identify and propose guidelines for designing and developing BI tools that may aid novices. The field study was conducted by administering a dashboard workshop with third year IS students at a South African HEI, and was therefore facilitated in a controlled environment in a traditional computer laboratory with desktop PCs. Prior to the field study the students were given a small theoretical introduction to performance dashboards. The learning outcome for the workshop was to develop a dashboard of inventory data with information about quantities on hand, selling values on hand, and estimated gross profits for a number of warehouses on the SYSPRO ERP database. Students are expected to follow a number of steps to use four different software tools that constitute the dashboard system (Figure 1). These software tools are Microsoft SQL Server, SYSPRO ERP, Crystal Xcelsius and Microsoft Excel. The dashboard workshop has been often criticised by students for being complex and requiring too many steps. Students were given three hours to complete the tasks, were allowed to seek the assistance of the facilitators if a problem was encountered and were encouraged to record the problem and how the problem was solved on the task-list.

The first section of the questionnaire handled biographical information, whilst the second section of the questionnaire, Cognitive Load, was adapted from the National Aeronautics and Space Administration Task Load Index (NASA-TLX). The NASA-TLX measures the cognitive workload with three sub-scales: task-related, behaviour related, and subject related scales (Hart 2006). Measuring cognitive load during a usability study is important, since difficult tasks are likely to increase cognitive load and may cause users to forget some of the steps required to create visualisations (Toker et al. 2013). The task-related subscale measures were factors surrounding the participant's mental demand), physical demand and temporal demand. Behaviour related aspects refer to subscales measuring perceived level of effort (EF) and personal performance (PP). The subject-related subscale measures the perceived level of frustration (FR) during the evaluation (Hart 2006). The participants were required to rate each of these factors based on a 5-point Likert scale (1= Strongly Disagree and 5 = Strongly Agree). The overall workload score is calculated based on a weighted average of each subscale and presented as an overall score out of 100.
The third section of the questionnaire related to user satisfaction. Satisfaction is an important measurement of usability, as users will not utilise a tool if they are not satisfied with the way it operates. The questions relating to the overall satisfaction were adapted from the Computer System Usability Scale questionnaire (CSUQ), which was firstly introduced by Lewis (1995). The questions used in the CSUQ are

developed to evaluate the psychometric properties for use in scenario-based computer system usability evaluations. Although the CSUQ offers 19 different questions in total, only five questions were used and reported on due to time constraints and for the purposes of this evaluation. The questions that were used from the CSUQ are worded positively and measured four broad factors namely: ease-of-use, learnability, overall satisfaction and information quality. The participants were required to rate each of these factors based on a 5-point Likert scale (1 = Strongly Disagree and 5 = Strongly Agree). The third section of the questionnaire included an open-ended question, which enabled students to give feedback on the perceived negative features of the system. The participant profile consisted of 14 students who formed part of a third year ERP course. None of the participants had any industry experience and were all fulltime students enrolled for IS degrees. None of the participants had received training on ERP or BI systems before the DASIK course. The sample size was split equally between males (n=7) and females (n=7). The participants were all in the age group of 18-29.

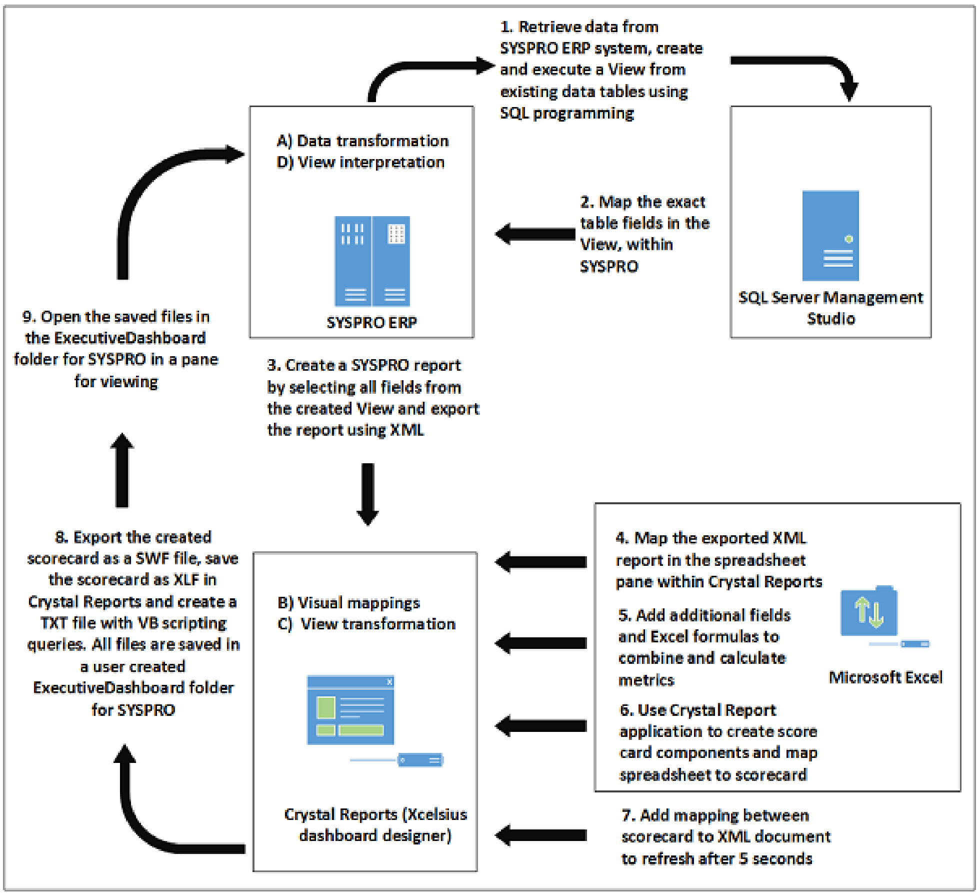


Figure 1, Software tools used to create a dashboard for SYSPRO.

Field Study Results

All participants successfully completed the task-list. The mean time to complete the task-list was 121 minutes, with the quickest time being 82 minutes and the slowest time being 143 minutes which was acceptable when compared to the expert's task time. However, the analysis of the NASA-TLX questions (Figure 2) revealed that the development process required a high cognitive load. The mean for each closed-ended Likert scale item in the NAXA-TLX was classified according to the following ranges:

- Strongly disagree [1.0 ≥ μ < 1.8)

- Disagree [1.8 ≥ μ < 2.6)
- Neutral [2.6 ≥ μ ≤ 3.4)
- Agree [3.4 > μ ≤ 4.2)
- Strongly agree [4.2 > μ ≤ 5.0)

Participants agreed that the development process was mentally challenging (μ=4.07) and required a great deal of effort (μ=4.00) to complete the complete the tasks. Participants were, however, neutral regarding the physical (μ=2.79) and temporal (μ=2.86) demand required to complete the tasks. Although all participants completed the tasks successfully, they perceived their performance with the system to be low (μ=2.43) and agreed that they experienced high-levels of frustration (μ=3.50).

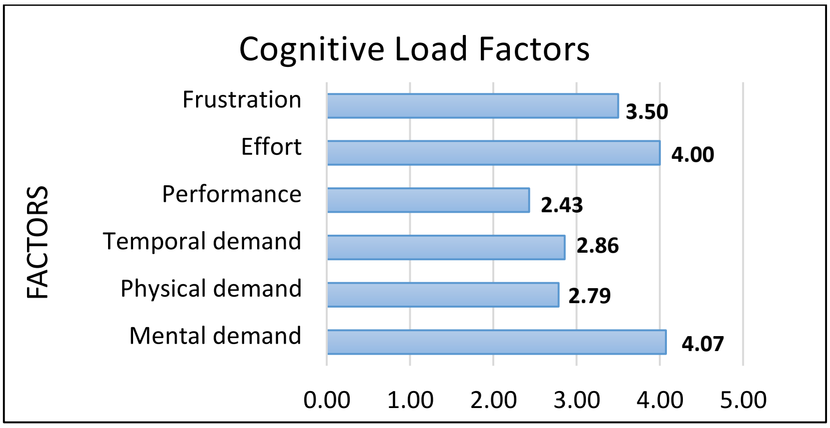


Figure 2, Cognitive load factors using a five-point Likert Scale (n=14).

The ranges for the Likert-scale items could be further categorised into negative (1.0 ≥ μ < 2.4), neutral (2.4 ≥ μ < 3.6), and positive (3.6 ≥ μ ≤ 5) ranges. The analysis of the CSUQ questions (Figure 3) revealed that the highest mean related to the overall satisfaction and was rated *neutral* (μ=2.86). Some of the metrics had mean ratings in the *negative* range. It can therefore be deduced that usability problems were encountered and this is supported by the high ratings of frustration, effort and mental demands required from the tasks. The metric with the lowest mean was information quality (μ=1.43). It can be deduced that participants did not receive sufficient assistance from the system when they encountered a problem. Participants disagreed that the system is easy to use (μ=2.43) and thought that it was difficult to learn the various development steps (μ=2.50) and software components (μ=2.57) respectively. This result indicates that students struggled to understand how software components communicate to one another. Moreover, the result may be because the students are not knowledgeable about software tools that support IV and have never worked with such tools before. Participants also disagreed that the amount of time to complete the task-list was insufficient (μ=2.36) and stated that the process takes too long to develop a single visualisation.

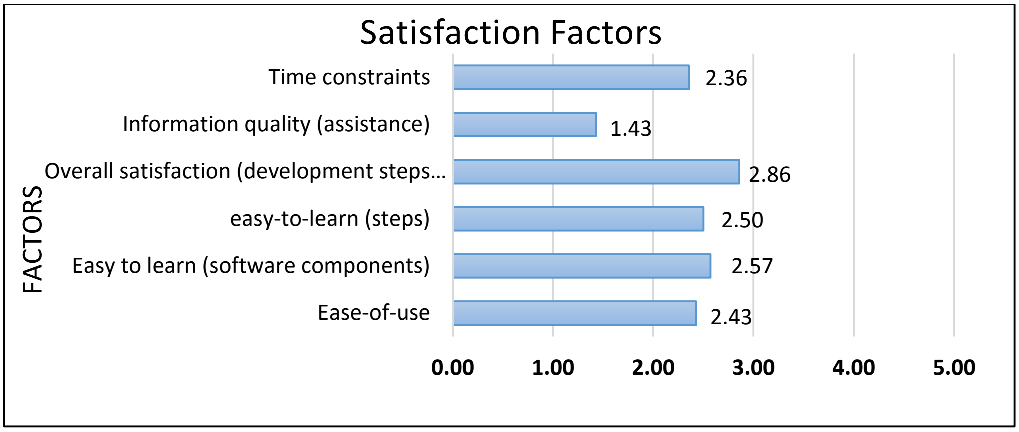


Figure 3, Satisfaction measures adapted from CSUQ.

Participants were asked to describe the features of the system that they disliked (open-ended question) as well as to make notes of any problems that were experienced during the tasks (Table 1). The responses were analysed qualitatively by using content analysis whereby the text is categorised or coded into themes. Although there were some problems relating to the UI of the SYSPRO ERP system and Xcelsius SAP Xcelsius tool, the focus was to identify problems relating to the overall development environment and process.

The highest frequency (f) of responses for the open-ended question related to the *information quality* theme. Participants struggled to identify menu items in SYSPRO and Xcelsius, and criticised the minimal feedback that the software provided to guide users in the development steps or any issues that were incurred. Moreover, participants indicated that the tasks were complex and difficult to learn. While others stated that the *system* was not designed with the user in mind, many complained that the development environment was inflexible and resulted in many participants re-doing tasks. The main reason for this was that students were not sure where exactly they made a mistake. Some of the negative comments cited by participants were: “too many steps are involved here”, “the development environment is too complex”, and “menus aren’t easy to find”. The two themes with the highest frequency of responses from the task-list related to *data selection* and *dashboard customisation and visual output.* Since the data attributes needed to be selected using a query in SQL server and then needed to be mapped manually in SYSPRO, many mistakes were made regarding the syntax and spelling of attribute names. Another issue was that only one dashboard was created and did not allow students to explore the data set.

Discussion of Design Guidelines for Visualisation Tools

The results revealed that students experienced the development of dashboard as a challenging activity. While some experienced usability issues relating to the design of the software tools’ User Interface (UI), others found it hard to remember all the steps to develop a dashboard using the various software tools. A number of guidelines are therefore proposed to guide the design of IV tools for novices (Table 2). The qualitative negative responses revealed that many of the problems related to the lack of *information quality* and *assistance* provided by the tools. These findings are consistent with a similar study on BI tools in South Africa by Jooste et al. (2014), who proposed that BI tools need to be designed with a high degree of *visibility* and *error control and* *help* functions. Students struggled to understand instructions, find menu and navigation options, and often asked assistance from human mediators. Sufficient navigation mechanisms (menu items, navigation, system status, hide/show etc.) and interactions are necessary to ensure easy navigation. Features such as tree structures, bread crumb trails, minimise and maximise icons, double click actions, and back buttons are highly important for novices when exploring the interface and moving through different levels of data granularity using drill-down/up features (Elias 2012; Heer et al. 2012).

			Open-ended questions	**Task-list notes**
Problem number	**Problem Theme**	**Description**	**Frequency (*f*)**	**Frequency (*f*)**
P1	Complexity of software	• Too many software tools. • Difficult to understand and learn. • Lack of knowledge of software tools.	6	3
P2	Development steps	• Too many steps required for each tool • Steps are difficult to learn and to remember. • Steps are time-consuming.	6	2
P3	Flexibility	• Lack of undo functions • Cannot change the data attributes easily • Cannot change visualisations	5	4
P4	Information quality	• Minimum feedback on successes or errors • Navigation and menus are not well structured • No guide for to assist in the development steps	8	7
P5	Assistance/ help	• Required assistance from a human mediator • Insufficient help functions	5	2
P6	Data selection	• Querying and mapping of the data is a difficult task since it requires a series of steps involving various tools.	4	9
P7	Dashboard customisation and visual output	• Mapping data to a visualisation is difficult • Needs immediate display of data in selected visualisation • Exporting dashboards into other software is difficult and tedious	3	9
P8	Lack of pre-knowledge	• Lack of pre-knowledge of software tools. • Also a lack of SQL and VB languages. • Lack of visualisation types and measures	4	2

Table 1, Problems identified for IV tools.

Learning the development steps and features of the software tools was also described as a problem by the students. IV tools need to support and promote learning through explanations (Elias & Bezerianos 2011; Grammel, Tory, et al. 2010; Jooste et al. 2014). These explanations should be provided with terminology that is familiar to the users and can relate to additional information about the tool's features and operations, or the visualisation types supported by the tool (reason for use, when to use, or advantages/disadvantages of each chart type). Often these explanations are provided by means of tooltips (Heer, Ham, et al. 2008; Pantazos et al. 2013). Students stated that there was no guide and the process was difficult to follow. This result emphasises the need for an easy, guided development process (Grammel, Tory, et al. 2010; Heer et al. 2012; Huron, Jansen, et al. 2014).

Guideline number	Description	Related Problem
G1	Easy navigation, onscreen help, hide/show	P4 & P5
G2	Promote learning through explanations	P5 & P8
G3	Guided development process	P2
G4	Flexible customisation process	P3
G5	History tools, storytelling, undo/ redo	P2 & P3
G6	Single, integrated environment with immediate and interactive visual feedback	P1 & P7
G7	Easily connect to a variety of data sources and select/ deselect attributes interactively	P6
G8	Search, filter and drill-down/up	P6 & P7
G9	Multiple coordinated views	P6 & P7
G10	Automatic visualisation creation and suggestion with useful defaults.	P2, 3 & P8

Table 2, Design guidelines for IV tools.

Guided development may be useful by providing a systematic set of common steps that are followed in a workflow type manner, that also allows users to keep track of where they are in the process and can alleviate the mental demand of users (Heer et al. 2012). Users do however need a rich, systematic approach to data analysis that allows them to experiment with different data types, IV techniques, and other features in a flexible manner (Heer et al. 2012). Using a systematic approach to data analyses supports users to keep track of their analyses findings (Heer et al. 2012) and is also motivated as an approach to supporting a user's mental model (Schröter 2015; Patterson et al. 2014). The use of history tools, storytelling and textual annotations are popular techniques that have been identified as affective approaches to keep track of analysis findings (Elias et al. 2013; Heer et al. 2008; Huron et al. 2014). Since users refine their visualisations in a series of iterations, novices may often want to revise their notes on the data analysis activities performed and may wish to collaborate with others to share their analyses findings (Elias et al. 2013; Huron et al. 2014).

The lack of undo functions and flexibility was another negative feature that was commonly cited. However, this poses a greater issue when users are working with different tools as they are often not aware in which tool the mistake was made and need re-do an entire step. Sufficient undo and navigation principles are important to revert to a previous state easily and quickly (Elias 2012). Flexibility is especially important for novices as they need to explore different datasets and features of the UI, as well as refine their visualisations (labels, colours, size etc.) through a series of iterations (Huron et al. 2014; Elias & Bezerianos 2011). There is a need to design a single, interactive IV tool that facilitates the entire IV process, from connecting to data sources (querying or importing data), support data manipulations (merging data or adding calculations), selecting alternative data attributes, and viewing those attributes in a variety of visualisation techniques (Pantazos et al. 2013; Elias & Bezerianos 2011). Moreover, the IV tool needs to be able to easily connect to a number of data sources and allow for selecting/ deselecting attributes. Further, users need to merge data from ERP, BI or any data source that is of interest to the user for analysis. The easy connectivity should also be complemented by strong search, filter and drill-down facilities when exploring a data set (Pantazos et al. 2013; Elias 2012; Kienle & Muller

2007; Heer et al. 2008). The search facilities are important for novices since they often know what data attribute they want to view, for example “Sales”, but it can be difficult to find that particular data attribute when sieving through hundreds of fields in the data set. Additionally, search facilities may render any text that may be of interest, whether the user is searching for specific data sources, tables, attributes or any descriptive text in the visualisation dashboard (Elias 2012; Grammel et al. 2010). Search features are typically supported by dynamic queries to efficiently and by interactive explore and change the parameters in the visualisations (Elias 2012).

The use of dynamic queries are especially relevant to multiple coordinated views, where more than one chart is displayed on a single screen, each representing the same data set from a different perspective (Few 2012). Coordinated views can also be linked together, allowing a change in the one chart to affect the other. Dynamic queries are also implemented through the use of filters and aggregation that can be applied by using radio buttons, check boxes, dropdown menu’s and sliders (Heer et al. 2012). Filtering allows removing unwanted data items from the entire display (Heer et al. 2012). Moreover, sufficient hide/show tabs should be supported when multiple views are used to avoid visualisations from being cluttered.

One of the negative statements made by a participant was that “it only started making sense when I saw the visualisation”. This result indicates that students struggled to map the data to a visual construct and this is consistent with the findings of Elias (2012) and Grammel et al. (2010). Automatic visualisation creation and useful suggestions are strongly emphasised for this reason as this may prevent the partial or incomplete selection of data attributes (Elias & Bezerianos 2011; Heer et al. 2008; Kienle & Muller 2007). This is an important requirement for novices as they need to see the immediate effect of their actions (Bostock & Heer 2009; Pantazos et al. 2013). Viewing the immediate outcome on the selected data also reduces the need for integrating visualisations in external tools, which also reduces the time to develop visualisations. By providing automatic charts or reasonable defaults, users are only presented with the most appropriate visualisations based their selected data (Heer et al. 2008). Moreover, interaction types need to be considered when selecting data attributes and visualisations, applying filters, or moving from different aggregations and granularity levels. Some tools incorporate the use of auto-completion, hovering, buttons, drag-and-drop, sliders, and checkboxes and scrolling techniques to query, select or arrange the data for visualisations (Heer et al. 2012; Pantazos et al. 2013).

Conclusion

The results revealed that the participants could effectively create a dashboard. However, a number of problems were identified. Several problems related to the usability of the UI and the results confirmed other studies reporting that novices struggle to map data to visual constructs. The main findings of this paper revealed that novices need a guided approach to developing visualisations without help from a human mediator and several design guidelines for IV tools are proposed. The most important guideline is to provide guidance for novices through an interactive environment where they can keep track of where they are in the IV process. The guidelines proposed in this paper may be considered as criteria for designing or evaluating IV tools. The insights provided by this paper provide important contributions to Human Computer Interaction (HCI) and BI researchers and can assist with a deeper understanding of similar problems that novices face when working with enterprise systems. The use of quantitative and qualitative data analysis techniques provided insight into understanding how novices think while learning to use tools that aid in data analysis activities. This paper is part of a larger study whereby the design guidelines will form part of a framework for designing and evaluating IV tools. One limitation of this study is the small sample size and the fact that only one case study was used. Future research should include additional IV contexts and platforms and other case studies.

References

Bostock, M., & Heer, J. (2009). Protovis: A Graphical Toolkit for Visualization. IEEE Transactions on Visualization and Computer Graphics, 15(6), 1121–1128.

Calitz, A.P., Cullen, M. D.M., & Greyling, J. H. (2015). South African Alumni Perceptions of the Industry ICT Skills Requirements. In *Proceedings of the SACLA 2015 Conference, Johannesburg, South Africa, June 2-3, 2015*.

Card, S., Mackinlay, J. D., & Shneiderman, B. (1999). Information Visualization: Using Vision to Think. San Francisco: Morgan Kaufmann.

Chen, H., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS*, 36(4), 1165–1188.

Chi, E. H. (2000). A Taxonomy of Visualization Techniques using the Data State Reference Model. In Information Visualization, 2000. InfoVis 2000. IEEE Symposium, 69–75.

Chiang, R. H. L., Goes, P., & Stohr, E. A. (2012). Business Intelligence and Analytics Education, and Program Development: A Unique Opportunity for the Information Systems Discipline. ACM Trans. Manage. Inf. Syst., 3(3), 12:1–12:13.

DASIK. (2014). Retrieved July 7, 2015, from http://www.dasik.org/dasik-modules/bi

Elias, M. (2012). *Enhancing User Interaction with Business Intelligence Dashboards*. *Doctoral Thesis*. Ecole Centrale Paris.

Elias, M., Aufaure, M., & Bezerianos, A. (2013). Storytelling in Visual Analytics tools for Business Intelligence. In *Proceedings of the 14th IFIP TC13 International Conference on Human-Computer Interaction (Cape Town, South Africa, September 2-6, 2013). INTERACT 2013*. Springer Berlin Heidelberg.

Elias, M., & Bezerianos, A. (2011). Exploration Views : Understanding Dashboard Creation and Customization for Visualization Novices. In *Proceedings of the 13th IFIP TC13 International Conference on Human-Computer Interaction (Lisbon, Portugal, September 5-9, 2011). INTERACT 2011*. Springer Berlin Heidelberg.

Fan, W., & Bifet, A. (2013). Mining Big Data: Current Status, and Forecast to the Future. ACM SIGKDD Explorations Newsletter, 14(2), 1–5. doi:10.1145/2481244.2481246

Few, S. (2012). Criteria for Evaluating Visual EDA Tools. Visual Business Intelligence Newsletter. Perceptual Edge.

Grammel, L., Tory, M., & Storey, M. (2010). How Information Visualization Novices Construct Visualizations. IEEE Transactions on Visualization and Computer Graphics, 16(6), 943–952.

Gupta, B., State, C., & Goul, M. (2015). Business Intelligence and Big Data in Higher Education: Status of a Multi-Year Model Curriculum Development Effort for Business School Undergraduates, MS Graduates, and MBAs. Communications of the Association for Information Systems, 36(1), 449-476.

Hart, S. G. (2006). NASA-TASK LOAD INDEX (NASA-TLX): 20 YEARS LATER. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting,* 904–908. SAGE Publications.

Heer, J., Ham, F., Carpendale, S., Weaver, C. & Isenberg, P. (2008). Creation and Collaboration: Engaging New Audiences for Information Visualization. In Information Visualization, Springer-Verlag, Berlin-Heidelberg, 92–133.

Heer, J., Shneiderman, B., & Park, C. (2012). A taxonomy of tools that support the fluent and flexible use of visualizations. Interactive Dynamics for Visual Analysis, 10(2), 1–26.

Hilbert, M. (2013). Big Data for Development: From Information-to Knowledge Societies. Available at SSRN 2205145, 1–39.

Huron, S., Jansen, Y., & Carpendale, S. 2014. Constructing Visual Representations: Investigating the Use of Tangible Tokens. IEEE Trans. Vis. Comput. Graph. 20(2), (October 2013) 2102-2111.

Huron, S., Carpendale, S., Thudt, A., & Tang A. (2014). Constructive Visualization. In *Proceedings of The 2014 Conference on Designing Interactive Systems, Vancouver, Canada, June, 2014, DIS '14*. ACM. 433–442.

Jooste, C., Van Biljon, J., & Mentz, J. (2014). Usability evaluation for Business Intelligence applications : A user support perspective. South African Computer Journal, (53), 32–44.

Kienle, H. M., & Muller, H. A. 2007. Requirements of Software Visualization Tools: A Literature Survey. In Proceedings of the 4th IEEE International. Workshop on Visualizing Software for Understanding and Analytics (Banff, Alberta, Canada, June June 24-25). VISSOFT 2007. IEEE 2–9.

Letouzé, E. (2012). Big Data for Development: Challenges & Opportunities. Global Pulse Is a United Nations Initiative, (May), 47. Retrieved from http://www.unglobalpulse.org/sites/default/files/BigDataforDevelopment-UNGlobalPulseJune2012.pdf

Liu, S., Cui, W., Wu, Y., & Liu, M. (2014). A Survey on Information Visualization: Recent Advances and Challenges. Vis. Computing. 30, 12 (January). 1373-1393.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. H. (2011). Big Data: The Next Frontier for Innovation, Competition, and Productivity. Retrieved from (http://www.mckinsey.com/insights/mgi/research/technology_and_innovation/big_data_the_next_frontier_for_in novation.

Muriithi, G. M., & Kotzé, J. E. (2013). A conceptual Framework for Delivering Cost Effective Business Intelligence Solutions as a Service. ACM International Conference Proceeding Series, 96–100.

Nofal, M. I., & Yusof, Z. M. (2013). Integration of Business Intelligence and Enterprise Resource Planning within Organizations. Procedia Technology, 11, 658–665.

Pantazo, K., Kuhail, M.A., Lauesen, S., & Xu, S. 2013. uVis Studio: An Integrated Development Environment for Visualization. In Proceedings of the SPIE8654 Conference for Visualization and Data Analytics 2013 (Burlingham, USA, February 3, 2013). SPIE8654. IEEE Trans. Vis.

Patterson, R. E., Blaha, L. M., Grinstein, G. G., Liggett, K. K., Kaveney, D. E., Sheldon, K. C., & Moore, J. A. (2014). A human cognition framework for information visualization. Computers & Graphics, 42, 42–58.

Pitula, K., & Radhakrishnan, T. (2011). On eliciting requirements from end-users in the ICT4D domain. Requirements Engineering, 16(4), 323–351.

Global Pulse. (2015) Retrieved July 9, 2015, from http://www.unglobalpulse.org/about-new.

Ritsos, P. D., & Roberts, J. C. (2014). Towards more Visual Analytics in Learning Analytics, 9–13.

Sabherwal, R., & Becerra-Fernandez, I. (2013). Business Intelligence: Practices, Technologies and Management. John Wiley & Sons, Inc.

Sallam, R. L., Hostmann, B., Schlegel, K., Tapadinhas, J., Parenteau, J., & Oestreich, T. W. (2015). Magic Quadrant for Business Intelligence and Analytics Platforms.Gartner Group Inc.

Schröter, B. H. (2015). Helping Novices Explore Data: Facilitating Mental Model Creation of an Information Visualization System by Displaying Information Flows. Master's Thesis. Technische Universiteit Eindhoven.

Tobiasz, M., Isenberg, P., & Carpendale, S. (2009). Lark: Coordinating co-located collaboration with information visualization. IEEE Transactions on Visualization and Computer Graphics, 15(6), 1065–1072.

Toker, D., Conati, C., Steichen, B., & Carenini, G. (2013). Individual User Characteristics and Information Visualization: Connecting the Dots through Eye Tracking. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (Paris, France) ACM*, 295–304.

Wang, Y., & Harbert, R. J. (2015). Business Intelligence and Analytics Education : Hermeneutic Literature Review and Future Directions in IS Education. In *Proceedings of the 21st Americas Conference on Information Systems AMCIS (Puerto Rico, August 13),* 1–10.

Wixom, B., & Goul, M. (2014). The Current State of Business Intelligence in Academia : The Arrival of Big Data The Current State of Business Intelligence in Academia: The Arrival of Big Data. Communications of the Association for Information Systems, 34(1), 1–10.

Yigitbasioglu, O. M., & Velcu, O. (2012). A Review of Dashboards in Performance Management: Implications for Design and Research. International Journal of Accounting Information Systems, 13(1), 41–59.

Appendix E: SAICSIT Paper

Design Guidelines for Business Intelligence Tools for Novice Users

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ABSTRACT

The use of interactive dashboards has become a popular technique to aid users in Business Intelligence (BI) analysis and data discovery. The increase in the number of BI platforms on the market is driven by the expanding end-user population. A wider range of novice users, such as business users with minimal Information Technology (IT) or data science skills, are demanding BI tools that support rapid and easy dashboard development. Dashboard development is often a tedious process, involving a number of developers and software tools. Self-service BI tools are becoming prominent environments in which novice users can fulfil their BI requirements without the intervention of IT experts. However, the usability of BI tools has not fully matured to a level where novice users can utilise its features efficiently and effectively without the assistance from IT experts.

Limited research have been conducted in regarding usability criteria specific to BI tools that support novice users. The purpose of this paper is to expand on existing BI usability criteria for supporting novice users with their data analysis activities. Furthermore, the study proposes a set of design guidelines that can be used as a reference for designing, evaluating and selecting BI tools that aid novice users. Evaluations were carried out on current BI tools to investigate its usability and the extent to which these tools follow the proposed guidelines. Additionally, a field study was conducted with novice users to evaluate the difficulties of current BI tools. This study is concerned with the design of front-end features and usability of BI tools and not on the design of dashboards itself. The results indicated that the proposed design guidelines can be effectively used to select a BI tool for novices.

Categories and Subject Descriptors

Information systems~Decision support systems~Applied computing~Business intelligence

Keywords

Information Visualisation, dashboards, novice users, business intelligence

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1. INTRODUCTION

Business Intelligence (BI) is an umbrella term concerned with the development of processes, technologies, systems, practices, applications and methodologies that analyse valuable data to gain new insights about the organisation and markets [1]. The objective of BI is to support business analysts in understanding large data sets to retrieve and analyse information and to improve effective decision-making [2]. The increasing volume, velocity and variety of data generated by both internal and external sources emphasise a need for an effective method of conducting appropriate data analysis. A method to conduct effective data analysis is to develop well-designed, interactive Information Visualisation (IV) techniques that assist users to gain insights into their data, identify patterns, and make decisions [3]. Interactive IV facilitates the process of analysing large and complex data sets by allowing users to navigate, select, and display data using an easy-to-use interface that is often used as a component in data analytics and data exploration [4]. IV enhances human cognition by presenting large datasets visually, which enables humans to make sense of abstract information [5]. One of the most popular and useful interactive IV techniques in the field of BI and Business Analytics (BA) are dashboards [5], [6]. Dashboards comprise of multiple, linked visual displays, such as charts, on a single screen so that the most important information can be monitored at a glance [7].

A study by Gartner, has reported that the market for BI platforms grew by 9% in 2013 and is projected to grow at a compound annual growth rate of 8.7% by 2018 [8]. Commercial BI vendors have realised that their products need to support an easy development process, thereby providing users with effortlessly accessible and customisable dashboard environments. The numerous tools that are available for BI and BA support, vary in the amount of user interaction for specifying and controlling desired IV techniques. In this study the focus is on IV tools that support the novice user in exploring and analysing business data. Thus, the term BI tool or IV tool will be used for interchangeably as vendors of these products often target the BI and BA market under the terms: Business Intelligence, Business Analytics, Data Visualisation, Data Exploration or Data Discovery tools.

A number of studies have focussed on how novice users construct visualisations [3, 9, 10, 11, 12]. Heer, et al. [10] categorises users according to their skills and experience with IV as novice, savvy or expert users. Novice users have experience with operating a computer, but limited or no experience with programming. Novice users typically interact with visualisations within the boundaries offered, but hardly extend the existing functionality to suit their analysis needs. Grammel, et al. [9] define novice BI users as people who are not familiar with IV and data analysis beyond the charts and graphics encountered in everyday life.

The development and interpretation of moderately complex dashboards remains a challenge for novices [10, 11, 14]. Two main reasons can be attributed to this challenge. The first reason is that novices lack expertise to develop effective dashboards, such as mapping the data to appropriate visual attributes [9, 13] . The second reason relates to the usability of current BI tools [3, 11, 14]. Often novices are restricted by the technical expertise demanded by BI tools that require additional programming to develop a dashboard, synchronise them in a dashboard view, and connect the data sources to dashboards [3, 15]. Moreover, novice users are not expert programmers and must spend time to learn the specific grammar before developing visualisations. As a result, dashboards are generally still being developed by experts due to a long and complex development process, and involves a large amount of communication between business analysts and the end-users [6, 9]. This causes an intrinsic time delay as users provide feedback at different stages of the design or customisation of the dashboard [3]. The process to develop dashboards is often facilitated in a distributed development environment, requiring technical expertise to integrate various software tools with one another. Novice users do not have the technical experience to integrate the various software tools and find it challenging to learn the various software components involved in the process. Another problem is that novice users do not necessarily know how to select appropriate visualisations in their dashboards.

The primary aim of this paper is to investigate the usability of BI tools supporting dashboard development, with specific focus on novice users. A secondary aim of this paper is to propose a set of design guidelines for BI tools targeting novice users. The main research problem to be addressed by this paper is the complexity in the process of developing dashboards in traditional BI tools. In order to address the research problem of this paper several research questions (RQs) were identified, namely:

RQ1: What design guidelines can be used for BI tools that can support dashboard development by novices?

RQ2: What criteria can be used to evaluate the usability of BI tools supporting novice users?

RQ3: What BI tools can effectively support novice users in their dashboard development activities?

A literature review was conducted to investigate the typical IV process that users follow and the tools that can be used to support their activities (Section 2). In order to identify a BI tool that can support novice users, a set of design guidelines were identified and used as a criteria to evaluate existing BI tools (Section 3). The research methodology followed in this study is discussed in Section 4, where usability metrics for the field study are identified. A field study of BI tool usability was conducted with Information Systems (IS) students at the Nelson Mandela Metropolitan University (NMMU). The results of the field study were analysed (Section 5) and several conclusions and recommendations are presented (Section 6).

2. BACKGROUND

This section provides background on some of the issues in the process of developing dashboards and other types of visualisations (Section 2.1). A brief overview is provided of dashboards and their purpose (Section 2.2). Lastly, a number of existing IV toolkits are identified (Section 2.3).

2.1 Information Visualisation

Information Visualisation (IV) is an interdisciplinary field concerned with the visual representation of data so that the user can interpret the data with minimum effort [16]. Various IV techniques exist to visually present data. Some taxonomies have been developed to support the appropriate selection of suitable IV techniques [7]. IV is a process of forming a mental model of data [17]. There are several models of IV processes that describe a series of steps users follow to develop and configure visualisations to gain insights. A popular reference model for an IV process has been proposed by Card, et al. [16], and refined by Chi [18], Tobias, et al. [19] and Jansen and Dragicevic [20]. The reference model describes three steps for how users interpret and interact with visualisations namely: data transformations, visual mappings and view transformations (Figure 1). First, data tables are processed and transformed from raw data (Data transformation). Data tables can be further transformed by applying filters, adding calculations and merging tables [9]. The data tables are then mapped to visual structures (Visual mappings), which typically take the form of generic visualisation mechanisms such as bar graphs or line charts with their corresponding properties. Once visual structures are created from the data tables, views are rendered and displayed from the visual structures.

Views display different parts of the visual structures at varying levels of abstraction (View transformations). Selecting different views do not change the visual structure of the selected visualisation, but allow users to observe the data from different perspectives. The user transforms the views using operations such as zooming on a map, or zooming out or drilling down on different granularity levels. Finally, users interpret the views with a particular goal or task in mind, thereby interacting with the visualisation in an iterative process of data transformation, visual mapping and changing current views. This study will adopt the IV process represented by Card, et al.'s reference model [16].

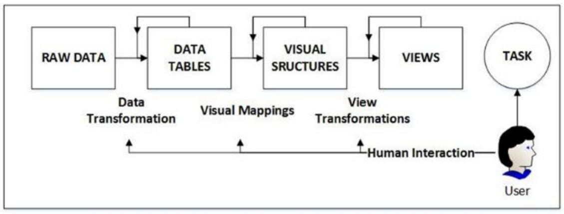

Figure 1: Visualisation Reference Model [16].

Several aspects of IV models have been researched, however, knowledge is still limited in terms of understanding how novice users construct visual mappings [3, 9, 13, 15]. Grammel, et al. [9] found three main challenges that novice users experience when creating visualisations. Novice face a selection barrier, where they try to find the correct data attributes for the questions they have regarding their data set. This step is particularly challenging since novice users are often unfamiliar with data set and do not have a proper understanding of the meaning of the attributes. The second barrier relates to visual mappings, where users struggle to select an appropriate visualisation for their selected data attributes. The reason for this is that novice users have partial specifications of how their data should be represented. This result was also confirmed by Elias [3]. For example, users select the correct visualisation type, but do not select enough data attributes. In contrast, some users would select all the attributes they would want to visualise, but do not select the appropriate visualisation type. The third barrier referred to interpretation, where users do not have the knowledge to make sense of the data visualisation. Other problems found related to not knowing how to filter or group data elements correctly.

Carpendale [21] provides an extensive discussion on various approaches for evaluating challenges associated with IV. However, Huron, et al. [13] suggests three approaches to investigating problems that which could be valuable for informing future tool design. The first approach is to investigate existing IV tools to determine possible improvements. The second approach relates to the design of a new technique, developing a software prototype and empirically comparing the results to existing tools. The third approach is to study the human behaviour independently from the design of specific software tools. This study follows the first approach.

2.2 Dashboards

Several problems with IV techniques have been identified in the previous section. These problems impact dashboard development. Dashboards are visual displays of the most important information that are consolidated and organised on a single screen to achieve one or more objectives [7]. The information embedded in dashboards are intended to be monitored at a glance allowing users to take appropriate action on issues and problems needing attention [5, 7].

Few [22] motivates that irrespective of how powerful a software tool is, a poorly designed dashboard would fail to communicate efficiently and effectively. It can be deduced that tools tailored towards novice users needs to provide highly practical defaults and support flexibility to customise the dashboard to their needs beyond the typical aesthetics. Dashboards can consist of a variety of different charts that are typically interactive and allowed to be explored for further analysis [5]. Users can interact with dashboards through features for filtering, linking or brushing, zooming up or drilling down, alerts and drag and drop [23].

2.3 Information Visualisation Tools

A variety of IV techniques are designed and selected for specific purposes and typically rely on software tools that support particular features. For this reason, one should consider the purpose for which an IV tool will be used before evaluating it, since no single IV tool will support all purposes equally [22]. IV tools can be used for either exploratory data analysis, descriptive or narrative statistics, monitoring and prediction [22, 23, 24] . A number of taxonomies have also been developed in recent years to categorise IV tools according to their features and level of expertise required [6, 10, 22, 24, 25, 26]. Additionally, Victor [27] distinguishes IV tools based on three fundamental paradigms that either support programming, pre-defined templates or free-hand drawing. Although each paradigm is tailored towards a different user group, all of these approaches are criticised. In this study, a distinction is made between two main categories namely Commercial Visualisation Tools (Section 2.3.1) and Custom Visualisation Toolkits (Section 2.3.2).

2.3.1 Commercial Visualisation Tools

The need to support novice users is reflected in the increasing focus of the IV research community and commercial IV vendors [6, 8, 9, 10]. Commercial tools are generally offered as a type of software suite that functions as a stand-alone, or integrate as add-ons; more or less seamlessly into an existing data infrastructures [24]. Commercial tools offer a variety of features to support easy visualisation development. Some features include data connection wizards, sophisticated chart typologies, design pallets, predefined calculations, drag-and-drop interaction, filters, chart comparisons and direct manipulations of dashboards. The benefit of commercial tools are that they require no, or limited, configurations or programming adjustment before users can become operational [24]. Moreover, users become proficient using commercial tools fairly easy since these tools attempt to facilitate the entire IV process in a single environment, requiring minimal programming effort, and provide immediate visual output. Users are typically guided by wizards when connecting to data sources such as databases, CSV files, spreadsheets, web services and so on.

Chart typologies allow for rapid data exploration by selecting data variables, a predefined chart type, and configuring its parameters such as colour, size and text labels with a limited number of clicks. An additional benefit is that commercial tools allow for coordinated and multiple views. Multiple views represent highly interactive visualisation environments that enable users to see different data sets in various forms, to manipulate the visual presentation in different ways, and also coordinate the interaction between different views [3]. However, the majority of commercial tools do not support the development of novel designs and are often criticised for being restrictive in terms of developing novel designs [3, 13, 26] and being platform specific [28]. As a result, commercial vendors are making their products accessible on mobile devices [1]. Some of the most popular BI tools on the market today are Tableau 9.0 [29], SAP Lumira [30], Microsoft (MS) PowerPivot [31] and TIBCO Spotfire [32].

2.3.2 Custom Visualisation Toolkits

In order to enable custom visualisations, a number of programming toolkits have been developed for IV [15, 26]. The toolkits are highly flexible for developing novel visualisations and unique BA solutions. However, they are not tailored towards novice users and are often limited to software engineers [3, 23, 24]. These tools offer open-source environments to create unique visualization applications, and have strong capabilities to display data on various devices [6, 24, 26]. Creating visualisations are not easy and require a high amount of programming expertise and effort to synchronise components into an existing system, or to feed data back into an existing data source [24, 25]. Multiple individual charts need to be linked together and can be a tedious process to configure navigation and interaction mechanisms between them. Custom toolkits also generally require high setup costs and have a steep learning curve[6, 12, 23]. A number of these toolkits incorporate their own declarative grammars that consists of high-level languages to specify how data should be mapped to visual elements [23, 33].

A number of lightweight programming toolkits have been developed to target novice programmers using web services

(HTML5, CSS, SQL, AJAX, Flash, J2E and JavaScript libraries) to manipulate elements in webpages [3, 26, 1, 33]. Some of the most popular custom toolkits are D3 [34], Prefuse [35], The InfoVis toolkit [36] and Google Charts [37]. Furthermore, Grammel, et al. [9] explain that novice users can be domain experts in their area of expertise (accounting, medicine, manufacturing, etc.) and that the data they wish to analyse can be from this area. This study adopts the definition offered by Grammel, et al. [9] that assumes that novice users have minimal experience with IV techniques, and zero to minimal experience with programming IV techniques.

3. THE DESIGN OF BI DASHBOARD TOOLS

A number of evaluation criteria, design guidelines and taxonomies of BI features have been proposed for IV and BI tools in literature [3, 9, 10, 15, 22, 23]. This section synthesises and categorises existing studies of BI design and provides a comprehensive set of eleven design guidelines for BI dashboard tools (Table 1). One of the most comprehensive taxonomies for interactive IV features are proposed by Heer, Schneiderman and Park [23], categorised 12 analytical tasks into three high-level categories namely: (1) data and view specification, (2) view manipulation, and (3) analysis process and provenance. Furthermore, the three categories include critical tasks that enable iterative visual analysis for visualisation creation, interactive querying, multi-view coordination, history tracking and collaboration. Although these are related to IV features in general, many of these can be used to support novice users. The first guideline (G1) for a BI dashboard is that it must support an easy dashboard development process [6, 9, 23]. The tool should also provide a guided development process (G2), allowing users to follow a systematic set of common steps [9, 13, 23]. These steps often occur in a workflow type of manner that enables users to keep track of what they have done.

Guides can include any type of wizard-like feature for connecting to a data source, selecting data, creating calculated columns or selecting a visualisation type. Guided development using wizards or other step-by-step approaches could lead to premature commitment to data or visualisations [9]. By following a bottom-up approach, where data attributes are selected first and then an appropriate visualisation would eliminate the problem [13]. Moreover, previews of visualisations can also assist this problem in allowing the user to view what the chart would look with the selected data before committing to a particular visualisation.

Users should have flexibility when they want to explore, for example, reverting back to selected data or skipping a step to select an alternative chart type [9, 13, 23, 38]. A flexible and easy customisation process is therefore the third guideline (G3) identified and is particularly important for iterative refinements, since users will search and explore visualisations and additional attributes that meet their goals [6]. The process facilitated in the dashboard tool needs to be interactive, allowing users to easily connect to, explore, correct, update and collect data in an iterative manner [20]. Moreover, users should be able to manipulate and navigate the selected visualisation [38]. Such interaction can be facilitated through immediate and continuous visual feedback (G4) on any changes that are made to the dashboard [3, 9, 15, 20]. User friendly data input for common data formats are essential for such changes (G5), especially when variables are transformed (counts or summations) or new attributes (calculations) are derived from existing values [10, 23]. It is particularly important that the tool can facilitate data transformation (manually or automatically), so that the user does not have to apply calculations prior to importing data [23]. Moreover, novice users tend to have a particular visualisation type in mind, but the visualisation may not be appropriate for the selected data.

The provision of automatic visualisations (G6) through chart typologies can assist novice users to visually map their data to appropriate visualisations [3, 9, 23]. The benefit of chart typologies are simplicity and familiarity since users are better at recognition rather than recall [23]. These typologies often include automatic chart generation based on the amount and nature of selected data attributes. Chart suggestions can also be helpful when selecting an alternative chart type based on the selected data types. Useful defaults refer to parameters or pre-sets that allow users to refine the appearance of the dashboard elements, for example predefined colours, sizes, scales, text labels [10].

Number (G1-10)	Description	Resource
1.	Easy development process	[6, 9, 23]
2.	Guided development process	[9, 12, 23]
3.	Flexible customisation process	[6, 9, 12, 23, 38]
4.	Immediate and interactive visual feedback	[3, 9, 15, 20]
5.	User friendly data input for common data formats	[10, 23]
6.	Automatic visualisations creation and suggestions with useful defaults	[6, 9, 10, 38]
7.	Search, filter and navigation facilities	[6, 9, 15, 38]
8.	Multiple coordinated views for comparison.	[3, 6, 22, 23]
9.	History tools and storytelling (undo and redo).	[3, 12, 23, 38]
10.	Promote learning through explanations	[3, 9, 10]
11.	Saving, Sharing and collaboration	[10, 22, 23, 39]

The seventh guideline (G7) states that search, filter and navigation facilities must be provided by a BI dashboard development tool. Search facilities assist users when they are looking for other data sources, a specific table, attribute or any text component on the dashboard [3, 9]. This is particularly useful when a user knows an attribute name for example “Sales” when wanting to select data. Moreover, search facilities are also helpful when aiming to filter a dashboard with dynamic queries that allow users to interactively explore and change parameters of representations [3]. Sufficient navigation mechanisms and interactions (bread crumbs, minimise icons, double click actions and back buttons) are highly important for novice users when exploring the interface and moving from or to different levels of data granularity during drill-down/up activates [3].

Dynamic queries are especially relevant to multiple coordinated views (G8) that will dynamically highlight all text components that match a text search across all other charts, or affect the data displayed across all charts if specific filters are applied [3]. Filters can be applied using radio buttons, checkboxes, dropdown menus or sliders [23]. Moreover, auto-complete functions are highly recommended when searching or querying from the BI tool [25]. Multiple coordinated views are multiple charts that contains multiple independent charts, each representing the same data set from different perspectives [22]. Coordinated views can also be linked together, allowing a change in the one chart to affect the other. Elias [6] explains that novice users often get confused between linking and filtering. Linking occurs when data items are selected in the one view to highlight (or hide) corresponding data in other views [23]. Filtering allows for removing unwanted data items from the entire display [23]. Moreover, sufficient hide/show tabs should be used not only for screens, but also for useful features to avoid dashboards from being cluttered.

The iterative process of dashboard development requires users to keep track of their analysis findings [3, 23]. The ninth guideline (G9) relates to the need for history tools (including undo/ redo) that allow users to re-view, re-visit or re-apply specific settings and analysis steps [3, 13, 23]. This is particularly relevant for novice users who are experimenting with various types of charts and also learning the features of a tool. A more recent development allows for users to incorporate storytelling in their analysis activities through annotations [13, 23, 39]. Annotations allow novice users to make notes or "tell a story" of their findings that enables users to quickly revise the situation depicted in the dashboard. These "stories" should be accompanied by features for highlighting, colouring and zooming [39]. The tenth guideline (G10) states that a BI tool should also promote learning through explanations [3, 9, 10]. These can be explanations of features in the tool, the particular use for a visualisation type (reasons for use, advantages or disadvantages), or provide details on demand when a user hovers a specific point on the visualisation. Sufficient explanations with appropriate terminology should be provided to enhance [3].

The last guideline (G11) relates to the importance of saving, sharing and collaboration. Novice users often have the need to share or publish their findings with others for follow-up analysis and share thoughts of the developed dashboards for refinement [22, 23]. Sharing dashboards go beyond static exports and screenshot type images. Users of dashboards require dashboards to keep their interactivity, even if they only extend to a few granularity levels.

4. RESEARCH METHODOLOGY

The Design Science Research (DSR) methodology was used in this study. DSR was selected as a suitable methodology as it offers an iterative process of conducting research. The research process begins with the awareness of the problem, which can be solved through iterations of suggestion, developing and evaluating an acceptable artefact [40]. The iterative nature of the DSR is evolutionary, allowing the initial research problem to be restated when necessary [40]. The research strategies used in this study were selected based on their ability to answer the RQs. In addition to literature reviews, three strategies were used to capture data and were a pilot study, one field study and informal evaluations (Section 4.1). The research instruments were designed based on those used in other studies and allowed for quantitative and qualitative feedback (Section 4.2). Students of an Enterprise Resource Planning (ERP) course were used as participants in the study to evaluate a selected BI tool, since they are novice BI users and are required to develop a simple dashboard as part of their course outcomes (Section 4.3).

4.1 Research Design

A set of design guidelines that can be used when designing BI tools for novice users (Table 1) was used to select an appropriate BI tool that could be evaluated in a field study. After an informal evaluation was conducted by the researcher on a number of BI tools, MS PowerPivot and Tableau were selected since they supported the greatest number of guidelines. Due to time constraints and licensing agreements, PowerPivot was selected as the BI tool to be used for an initial field study. This study forms part of a larger study where both Tableau and PowerPivot will be evaluated for usability as seen in a similar study by Ed et al. [4]. Participants were given three hours to complete a task-list and were expected to give feedback on the usability of the tool in the post-test questionnaire. Usability is increasingly recognised as an important quality factor for interactive software systems [41]. Usability focusses on measures for effective, efficient and satisfactory task execution and aims to support the ordinary and uninterrupted interaction between the user and the system [42]. Evaluating the usability of a system is particularly useful when aiming to improve the user interface or to establish the quality in use within a given context.

Prior to the field study participants were given a brief overview of the structure of BI in general and of PowerPivot. By providing a process of how dashboards are created can act as a type of mental model that enables better understanding of how the different software components work together [11, 43]. Teaching novice users the underlying structure of the software system is an effective method for increasing performance with, and understanding of the system [11]. Providing an overview of the system can also increase the mental model of novice users, which allows them to more easily infer the results of the interacting system [11].

4.2 Research instruments

Not all BI features that support the design guidelines could be tested with a student group in the field study. However, the features supporting the guidelines were identified by the researcher during the informal evaluations. The study participants were not expected to integrate the various visualisations or perform drill-up/down activities on different data levels, but should rather apply filtering, sorting and selecting of appropriate visualisations.. The field study required participants to complete four main tasks. The purpose of the field study was to test whether participants could create a dashboard with multiple visualisations, apply filters, and utilise the features of PowerPivot to select appropriate data attributes and visualisations. The outcome of the task-list was to derive at a dashboard displaying inventory information from the SYSPRO ERP system database such as cost prices, quantities, warehouses, product descriptions and sales.

The four main tasks could be mapped to each of the IV process steps (Figure 1). The first task required participants to create an SQL view programmatically in MS SQL Server by only selecting the raw data rows and columns (Data Transformations). The SQL view allows the user to create a virtual table, consisting of various rows and columns from different but associated tables. Heer, et al. [10] argue that novice users cannot be expected to understand file formats for more complex data types or write advanced queries that export data to a specific file format. Therefore, the SQL code was provided to participants since they were not familiar with the database. The second task required participants to connect to the SQL View from MS Excel, and import the rows and columns that are selected in the SQL statement to create a pivot tables. (Data Transformations). Once the table and additional calculations were prepared (Cost value on hand and selling value on hand), participants had to create four pivot charts using PowerPivot (Visual Mappings). Participants could select (or drag) attributes to the four pivot charts, which allowed them to experiment with pre-defined chart templates (bar, pie, column area, line), as well as different attributes to compare the selected data from multiple perspectives. The final task involved customising and arranging the elements of the entire dashboard. Participants were able to apply advanced filters based on product description, warehouse name, price ranges and so on. During the evaluation, participants were expected to take note of any problems that were encountered and to record the particular issue, as well as how they solved the problem.

The post-test questionnaire consisting of 10 sections (S1-S10) was administered to participants. The first section of the questionnaire addressed the participants' experience with a computer, general BI or IV tools, and MS Excel as this is consistent with a similar study conducted by Schröter [11]. Sections two to eight (S2-S8) consisted of usability metrics. Criteria for BI dashboard development tool usability are limited, particularly for novice users. Five usability metrics were selected from those recommended by Jooste, Van Biljon and Mentz [14]. Although it is beyond the scope of this study to discuss the usability guidelines in detail, a summary of each are provided (Table 2). These usability metrics related to visibility, flexibility, learnability, error control and helpfulness, and operability.

The three main usability metrics are satisfaction, efficiency and effectiveness [44]. Jooste, et al. [14] did not specifically list these three main metrics as usability metrics, however, they were added as additional metrics: task-completeness (effectiveness), task-times (efficiency) and satisfaction. The participants were required to give a subjective rating of their experience for each of the usability metric items using a five-point Likert scale. Participants were also required to rate which of tasks were the most difficult in chronological order (S9). Finally, students were provided with two open-ended questions to provide qualitative feedback on the best and worst aspects regarding the process and/ or software that they experienced during the usability evaluation (S10).

Several methods are used for testing the reliability and validity of the questionnaire. Face validity was established since the questionnaire was derived from literature, whilst content validity was confirmed by a pilot test conducted at NMMU which contributed to the refinement of the final research instruments.

Table 2: Usability guidelines for BI [14].

Functional grouping	**Usability guideline**
Visibility	Information, instructions, navigation options and system statuses should well-structured and clear at all times.
Flexibility	The user should feel in control and be able to customise the application for individual or collaborative usage.
Learnability	Learnability should be promoted using familiar terminology, mechanisms for limiting memory loads and provide cues that make the application accessible for infrequent usage.
Error Control and help	Provision should be made for features such as error prevention, recovery, help on demand and user support. Additionally, training should be available (initial training and refresher courses).
Operability	The application should display a hierarchical map to determine data granularity. Data attributes and dimensions should be easy to identify and access on all level of granularity. Data should be up-to date, allowed to be filtered and shared. Multiple views of different data should be accompanied by various IV techniques. The application should provide a rapid response rate and behave consistently.

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4.3 Participant Profile

The participative sample used throughout this study was selected through purposive sampling to ensure that the participants had minimal experience with dashboard development. Undergraduate Information Systems (IS) students from the Nelson Mandela Metropolitan University (NMMU) in South Africa were selected for the field study. The sample consisted of 32 students who were enrolled for the third year ERP course. This sample was purposively selected as the students are introduced to BI dashboards during the duration of the course. The ERP course only offered an introduction to BI dashboards and all participants could be regarded as novice users of BI tools. Moreover, the part pants had no particular experience with IV and were also novice programmers.

5. FIELD STUDY RESULTS

The results of a field study, consisting of a usability evaluation and a post-task questionnaire, were analysed in detail according to the identified usability metrics (Section 4.2). Information Systems (IS) students from the Nelson Mandela Metropolitan University (NMMU) in South Africa were selected for the field studies. The second field study consisted of 32 participants. The majority (84%) of the participants had more than 10 years of experience using a computer (n=27), while the (9%) of the participants have been using computers for between five and ten years (n=3). There were only a small portion of the participants (6%) that have been using computers for less than five years (n=2). Only a small total of 6% (n=2) of the participants have never had experience with BI or data analysis other than MS Excel (Table 3). The majority of participants (94%) had minimal experience with BI and data analysis tools. A couple of participants mentioned that they have used some BI tools in a second year module, known as Business Systems such as MS PowerPivot. Since all participants had experience with MS Excel, data was collected in terms of their experience with the tool.

		n	%
Experience with a computer in years	Less than five (5) years	2	6
	Between five (5) and nine (9) years	3	9
	More than 10 years	27	84
	Total	**32**	**100**
Experience with BI and data analysis.	No experience	2	6
	Novice	19	59
	Intermediate	11	34
	Total	**32**	**100**
Experience with MS Excel.	Novice	18	56
	Intermediate	14	44
	Total	**32**	**100**

An analysis of the data provided interesting results and is reported on according to the metrics identified (Table 2). All of the participants managed to complete the usability study using the task-list, as well as the post-task questionnaire. Item reliability was established for the Likert-scale type questions since the sections S3,S4, S5, S6, S7 and S8 have Cronbach's Alpha ratings between 0.76 and 0.87 (Appendix A: Table A) and are therefore considered acceptable [45]. The section on learnability initially scored a Cronbach's alpha of 0.43. This was due to two negatively stated questions which many of the participants did not interpret properly. The two questions were removed which improved the Cronbach's Alpha's for the learnability section to 0.86. Although the overall Cronbach's Alpha rating of 0.65 is slightly below the accepted standard of 0.7 it is still acceptable in an initial study and newly developed questionnaires [45]. The mean for each close-ended Likert scale item was classified according to the following ranges:

- Strongly disagree ($1.0 \geq \mu < 1.8$)
- Disagree ($1.8 \geq \mu < 2.6$)
- Neutral ($2.6 \geq \mu \leq 3.4$)
- Agree ($3.4 > \mu \leq 4.2$)
- Strongly agree ($4.2 > \mu \leq 5.0$)

5.1 Task Completeness

The results for task completeness were positive since all 32 participants completed all tasks successfully. Participants that required some assistance to complete tasks were requested to take note of the specific problems that were encountered. Nearly half (44%) of participants (n=14) required assistance at some stage of performing their tasks (Appendix A: Table B). The majority of the problems reported related to minor issues, such as not reading the task list properly, customising the dashboard appearance, finding specific tabs and options, and typing errors (Table 4). Two problems were encountered with the SQL server that timed out. The program had to be restarted and the data was recovered.

	n	%
Finding tabs and options	6	27
Typing errors (server name)	3	14
Customisation options (dashboard layout, colours, chart types, labels)	8	36
Reading errors/ clarifying instructions	3	14
SQL server timeout	2	9
Total	**22**	**100**

The participants were asked to upload their completed dashboard files to a repository where the researcher could view their final dashboards for completeness. All of the participants' dashboards were compared to the suggested solution. Participants were allowed to customise their dashboards as they desired. Although some users had different chart types, all participants' final dashboards were regarded as accurate when compared to the suggested solution (Figure 2). It can therefore be deduced that the development process supported in PowerPivot is effective for novice users to create dashboards in terms of effectiveness and, accuracy and task completeness. The mean ratings for each usability metric was calculated (Appendix A: Table F) and presented in Figure 2.

5.2 Efficiency

Efficiency is a subjective measurement of task time. The participants were satisfied with their overall task times and gave a mean rating in the "Strongly Agree" range (μ=4.34). The mean task time for all the tasks was 64 minutes and 45 seconds. The mean task times for each time were ranked according to the most time spent on task (Appendix A: Table C). The results indicated that participants spent the most time on Task 4, customising the dashboard, with a mean task time of 19 minutes and 22 seconds. This result is supported by the findings of Grammel et al. [9] and Elias and Bezerionaos [6], since novice users are not experts in selecting appropriate data attributes and display formats. The second longest task time was recorded for Task 1, creating the SQL view, with a mean time of 16 minutes and 22 seconds. Task 2, importing data in MS Excel, was performed in the least amount of time with a mean of 10 minutes and 45 seconds.

5.3 Satisfaction

Participants were satisfied with the layout and the appearance of their overall dashboard since the results were in the "Strongly Agree" range for the satisfaction of the final dashboard (μ=4.47). Participants were also satisfied with the overall dashboard development process as the mean rating was in the "Strongly Agree" category for the satisfaction of the overall development process (μ=4.57). The high satisfaction level of the development process can be partially attributed to the fact that an overview was provided to participants about the development process. Satisfaction was the item that scored the highest mean overall rating in the questionnaire (μ=4.46), which is in the Strongly Agree range (Figure 2). The high satisfaction levels indicate that the development process is not too complex when using PowerPivot, which is necessary for novice users according to guideline one (G1).

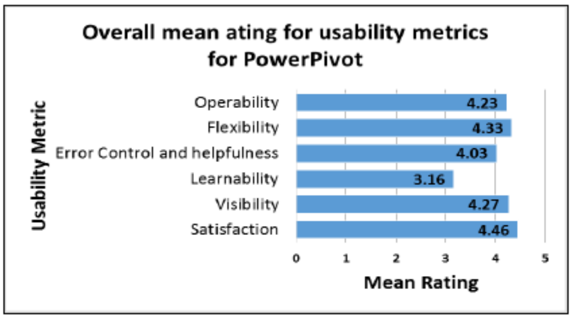

Figure 3: Overall mean rating for usability metrics for PowerPivot.

5.4 Visibility

The visibility metric received a mean rating of 4.27, which falls into the Strongly Agree category. Although the majority of the participants did not experience visibility issues, some participants (27%) still needed assistance due to features that were not found easily (Table 2). The participants perceived the features to be displayed in an uncluttered and well-structured manner (μ=4.38). The participants perceived the features to be self-explanatory (μ=4.22) and were fairly aware of the systems status during the duration of the evaluation (μ=4.22). The results also revealed that participants could easily navigate to the various features and screens within PowerPivot (μ=4.25).

The high visibility rating can be attributed to three evident design guidelines. Immediate visual feedback (G4) allowed participants to view the status of their dashboard at all times as changes were made. Promote learning through explanations (G10) was also verified as explanations of features and charts could be easily read and understood. Multiple coordinated views (G8) could also be verified as participants could derive at several individual charts from the same dataset with ease.

5.5 Learnability

The item that scored the lowest overall mean rating was learnability (μ=3.16). Since the mean rating is in the Neutral category, it can be deduced that that some participants experienced some learnability issues. The participants seemed to be familiar with the terminology that is used in PowerPivot and had a good understanding of the features (μ=4.22). This result is also complimented by the high mean learnability rating of PowerPivot's features (μ=4.28). Guideline 10 (G10), promote learning through explanations, was verified for learnability as participants stated that explanations helped them to understand which chart types can be used with certain variables. Immediate visual feedback (G4) and automatic charts and recommendations (G6) also assisted participants in learning how their action affect visualisations such as selecting particular variables, filtering, or changing colours and labels.

The second lowest usability item overall was error control and helpfulness (μ=4.03), however, its mean rating is still high and falls within the Agree category. Participants agreed that they could easily recover from errors that were made (μ=4.06) and received sufficient assistance through clear error messages and suggestions (μ=3.78). The explanations for the functionality through tooltips and other descriptive features were also considered helpful (μ= 3.78). The results also showed that participants favoured the automatic and recommended chart generation features (μ=4.06). The recommended charts were also helpful in determining its use and appropriateness, since they were supported by helpful explanations when the selected chart was not appropriate for the selected data (μ=4.16). The positive feedback about the helpful explanations and automatic generation verifies guideline 10. Not only do explanations assist in learning, but they are also helpful when explaining why particular features cannot be used, for example when a chart cannot be chosen when not enough attributes are selected. Moreover, participants found it helpful to connect to their created SQL view using a connection wizard (μ=4.31), which is particularly necessary for novice users and is supported by guideline 2, guided development.

5.6 Flexibility

The participants found PowerPivot to be highly flexible with a mean overall rating of 4.33, which falls into the Strongly Agree category. Considering that the participants were novices, they were able to experiment with different features and charts, customise the layout of overall dashboard effectively, and select desired attributes from the data set. The item with the lowest mean related to the control over the application (μ =3.97). Participants could easily customise the layout (or position) of PowerPivot's features (μ=4.31), as well as, the appearance of the overall dashboard (μ=4.47). Furthermore, the data attributes could easily be selected or "swopped" with other available data attributes in the data set (μ=4.28). The item that scored the highest mean rating for flexibility was the ability to easily change the chart type. This result supports those found for the operability metric and indicates that participants were able to experiment easily with different data attributes. These results support the flexible customisation process guideline (G3), as well as the user friendly data input (G5) as participants can easily derive at their own calculations or add additional data attributes. Flexibility is not only important for novice users to experiment with the features of the tool, but also to view which visualisations are suited for the data they would like to view. It can also be deduced that the helpfulness ratings of the recommended charts and explanations thereof had an influence on the mean overall rating of flexibility.

5.7 Operability

The mean overall rating for operability was 4.23. The high rating falls into the Strongly Agree category and indicates that participants could effectively use PowerPivot to develop dashboards and perform data analysis. Participants could easily use the various features to view data from various perspectives (μ=3.97), for example, identifying the unique dimensions: warehouse, quantity, product, year, price and so on. Moreover, participants could easily apply filters to see the immediate effects in the dashboard (μ=4.38). Participants were also able to easily experiment with various chart types if the recommended charts was desired (μ=4.28). This result indicates that PowerPivot is flexible in terms of changing a chart for the selected attributes. The different components (combination of charts and interactive slicers) could also be easily organised (μ=4.25), which enabled participants to customise the layout of their dashboard as they desired. This result reveals that participants had a high degree of control over the application. Although Jooste, et al. [14] classified control over the application under flexibility (Section 5.6), the International Organisation of Standardisation (ISO) motivates it as part of the definition of operability [44].

Participants perceived PowerPivot to behave in a consistent manner (μ=4.28). Having software that performs in a consistent manner is particularly important for learnability. A number of design guidelines were supported through operability. The flexible customisation process (G3), multiple coordinated views (G8), and automatic visualisations and suggestions (G6) allowed participants to easily create multiple charts from different data attributes, as well as easily apply filters to view data from different perspectives in a consistent manner.

None of the metrics received overall mean ratings in the Strongly Disagree or Disagree ranges (Figure 3). Satisfaction was the item that scored the highest overall mean rating (μ=4.46) and indicates that the participants were satisfied with using PowerPivot to develop dashboards. The item that scored the lowest overall mean was learnability (μ=3.16). It can be deduced that the participants had to spend some time to learn the development process and the features of the PowerPivot, however, the learning curve is not too steep. The mean usability rating for each individual metric, which was adapted from Jooste et al. [14] was calculated (Appendix A) and is presented in Figure 4.

The participants were also asked open-ended questions relating to their top three positive and negative features of PowerPivot. Some positive features cited by participants include: "Everything is automatically made for you", "Makes data analysis far less complex" and "Easy to change the look and feel of charts". However, the majority of the participants found PowerPivot's features were "easy to use" and "interactive and graphical". Moreover, some participants commented on the process steps and referred to it as an "Interactive and dynamic process" and stated that "dashboards were easy to customise". The majority of participants stated that PowerPivot was easy to learn and to understand as "everything is clearly visible and well explained". Several participants stated: "Selecting filters is really easy" and "Filters were helpful as some charts became cluttered".

The negative aspects that were reported related mostly to navigating between screens, charts and features. This typically created confusion between the pivot table with the entire data set and a secondary screen with the visualisations, or searching for particular customisation settings. Some comments were "changing something in the pivot table affected another chart unnecessarily" and one participant "was unsure whether in PowerPivot or normal Excel". Another found difficulty inserting pivot tables and customising the dashboard, while some thought that the process was difficult to follow as it was "intense without a guide". This result is consistent with the need for a guided development process as suggested for guideline two. Interestingly, one participant mentioned that there were no search facilities for attributes or features as required by guideline seven. This verifies that novice users would like to conduct searches. A few participants complained about the tedious process of typing the SQL statement. One participant mentioned that there were not enough explanations and tutorials in PowerPivot to support "newcomers". This result verifies that novice users expect a BI tool to be easy to learn (G10).

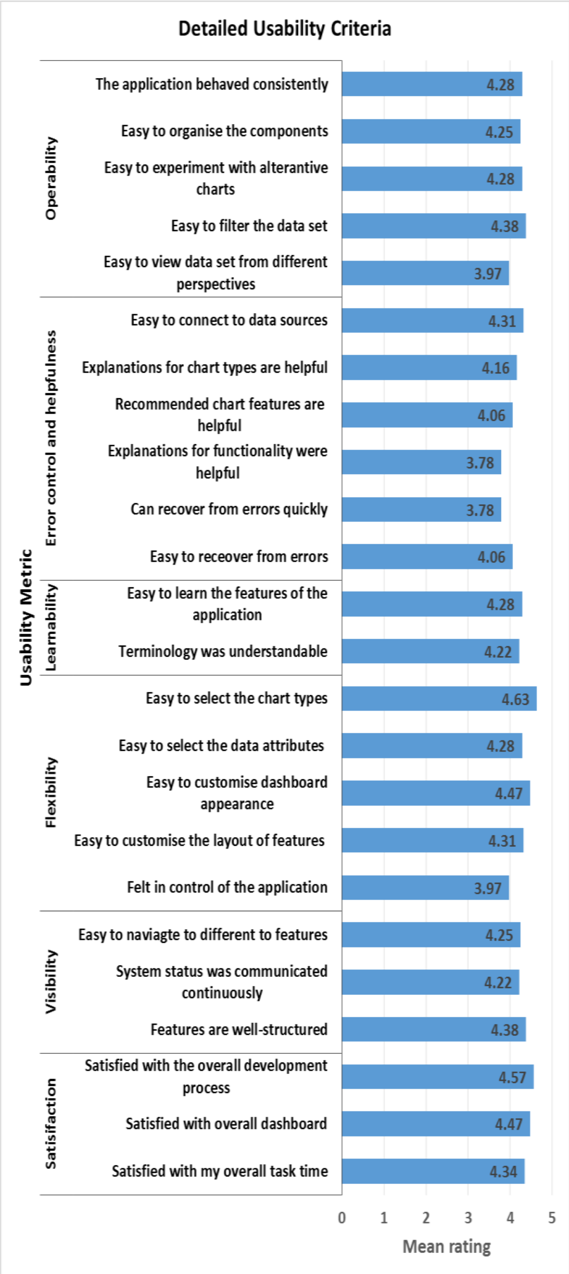

Figure 4: Detailed usability criteria.

6. CONCLUSIONS AND RECOMMENDATIONS

The purpose of this study was to develop a set of design guidelines for BI tools supporting novice users. The initial set of design guidelines for a BI tool was derived (Table 1) from previous work on novice users regarding IV. The first research question was therefore answered successfully. This initial set of guidelines were used as a criteria for selecting an appropriate tool that can support novice users in developing interactive BI dashboards. Metrics for evaluating BI tool usability for novice users were derived from a similar study by Jooste, et al. [15]. These metrics were supplemented by additional usability metrics and were used to evaluate the MS PowerPivot BI software tool in a field study. The second research question was therefore answered successfully. The results from the field study evaluations were positive and could develop dashboards efficiently. The quantitative results indicated that the participants were fairly satisfied with the usability of PowerPivot and could successfully develop dashboards following a logical development process in a reasonable amount of time. Participants were able to easily connect to data, select data attributes and experiment with different visualisations using PowerPivot. Furthermore, participants could also apply filters to view the data set from different perspectives. Moreover, participants perceived PowerPivot to be highly flexible as the dashboard could be easily customised. It can be deduced from the results that the features supported by PowerPivot require some time and effort to learn, but are not difficult to learn. The third research question was therefore answered successfully as PowerPivot can be used as a BI tool to support novice users in their analysis activities.

Positive feedback was received regarding the clear steps that assisted participants in understanding what they were doing. Although not all design guidelines could be verified in the field study, the results still support that they can be used to select BI tools for novice users. Design guidelines 2, 7, 8, 9 and 11 could only be partially verified in the field study with novice users. Although PowerPivot does support most of these guidelines as identified by the researcher, not all the features could be sufficiently tested in the field study. It is therefore recommended that a secondary is conducted to test more advanced features with novices such as creating linked charts for multiple views (G8), creating stories (or annotations) (G8), and performing drill-down/up activities, and searching for particular attributes or values with search facilities (G8). Although not evident in PowerPivot, it helps to visually depict a series of steps to users. It is therefore strongly recommended that a BI tool with a guided development process (G2) is evaluated with novice users for effectiveness.

Tableau was identified as one BI tool that supported a guided development process but could not be tested in the field study due to licensing agreements. Therefore, this paper is part of a larger study whereby more advanced BI features will be evaluated with novice and expert users using PowerPivot and Tableau. The objective is to report on how development practices differ in terms of experts and novices, which could provide valuable insights in the way BI tools are designed. Other future research could include the evaluation of dashboard development from a user perspective by analysing the mental processes formed during dashboard development. A BI tool could support multiple methods of developing dashboards, for example, supporting a stringent, guided method for novice users versus a more flexible approach for experts. When novice users progress, they can move from the stringent guided approach to the more flexible approach.

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8. REFERENCES

[1] Chen, H. and Storey, V. C. 2012. Business Intelligence and Analytics: From Big Data to Big Impact. MIS. 36, 4 (December 2012), 1165–1188.

[2] Işik, Ö., Jones M. C., and Sidorova A. 2013. Business Intelligence Success: The Roles of BI Capabilities and Decision Environments. Inf. Manag. 50, 1. (December 2012), 13–23.

[3] Elias, M. 2012. Enhancing User Interaction with Business Intelligence Dashboards, Doctoral Thesis. Ecole Centrale.

[4] Ed, J. A., Janvrin, D. J. R., Raschke, L., and Dilla, W. N. 2014. Making Sense of Complex Data Using Interactive Data Visualization. J. Account. Educ. 32, 4 (October 2014), 31–48.

[5] Yigitbasioglu, O. M. and Velcu, O. 2012. A Review of Dashboards in Performance Management: Implications for Design and Research. Int. J. Account. Inf. Syst. 13, 1 (August 2011), 41–59.

[6] Elias, M. and Bezerianos, A. 2011. Exploration Views: Understanding Dashboard Creation and Customization for Visualization Novices. In Proceedings of the 13th IFIP TC International Conference on Human-Computer Interaction (Lisbon, Portugal, September 05-09, 2011). Springer, Berlin-Heidelberg, 274–291.

[7] Few, S. 2006. Information dashboard design. O'Reilly Media Inc., Sebastopol, CA.

[8] Sallam, R. L., Hostmann, B., Schlegel, K., Tapadinhas, J., Parenteau, J., and Oestreich, T. W. 2015. Magic Quadrant for Business Intelligence and Analytics Platforms.Gartner Group Inc.

[9] Grammel, L., Tory, M., and Storey, M. 2010. How Information Visualization Novices Construct Visualizations. IEEE Trans. Vis. Comput. Graph. 16, 6 (October 2010), 943–52.

[10] Heer, J. Ham, F. Carpendale, S. Weaver, C.and Isenberg, P. 2008. Creation and Collaboration: Engaging New Audiences for Information Visualization. In Information Visualization, Springer-Verlag, Berlin-Heidelberg, 92–133.

[11] Schröter, B. H. 2015. Helping Novices Explore Data: Facilitating Mental Model Creation of an Information Visualization System by Displaying Information Flows. Master's Thesis. Technische Universiteit Eindhoven.

[12] Huron, S., Jansen, Y., and Carpendale, S. 2014. Constructing Visual Representations: Investigating the Use of Tangible Tokens. IEEE Trans. Vis. Comput. Graph. 20, 2 (October 2013) 2102-2111.

[13] Huron, S., Carpendale, S., Thudt, A., and Tang A. 2014. Constructive Visualization. In Proceedings of The 2014 Conference on Designing Interactive Systems (Vancouver, Canada, June, 2014) DIS '14. ACM. 433–442.

[14] Jooste, C., Van Biljon, J., and Mentz, J. 2014. Usability Evaluation for Business Intelligence Applications: A User Support Perspective. South African Computer Journal. 1, 53 (August 2014). 32–44.

[15] Pantazo, K., Kuhail, M.A., Lauesen, S., and Xu, S. 2013. uVis Studio: An Integrated Development Environment for Visualization. In Proceedings of the SPIE8654 Conference for Visualization and Data Analytics 2013 (Burlingham, USA, February 3, 2013). SPIE8654. IEEE Trans. Vis.

[16] Card, S., Mackinlay, J.D., and Shneiderman, B. 1999. Information Visualization: Using Vision to Think. Morgan Kaufmann, San Fransisco.

[17] Patterson, R. E., Blaha, L. M., Grinstein, G.G., Liggett, K.K., Kaveney, D. E., Sheldon, K. C., Havig, P. R. and Moore, J. A. 2014. A Human Cognition Framework for Information Visualization. IEEE Trans. Vis. Comput. Graph. 42, 1 (April 2014). 42–58, 2014.

[18] Chi, E. H. 2000. A Taxonomy of Visualization Techniques Using the Data State Reference Model. In Proceedings of the Information Visualization Symposium (Salt Lake City, USA, October 09-10, 2000). InfoVis 2000. IEEE Symposium. 69–75.

[19] Tobiasz, M., Isenberg, P. and Carpendale, S. 2009. Lark: Coordinating Co-Located Collaboration with Information Visualization. IEEE Trans. Vis. Comput. Graph. 15, 6 (December 2009). 1065–1072.

[20] Jansen, Y., and Dragicevic, P. 2013. An Interaction Model for Visualizations Beyond the Desktop. IEEE Trans. Vis. Comput. Graph.19, 12 (December 2013). 2396–2405.

[21] Carpendale, S. 2008. Evaluating Information Visualizations Challenges in Evaluating Information Visualizations. In Information Visualization. Springer, Berlin-Heidelberg, 19–45.

[22] Few, S. 2012. Criteria for Evaluating Visual EDA Tools. Visual Business Intelligence Newsletter. Perceptual Edge.

[23] Heer, J., Shneiderman, B., and Park, C. 2012. A Taxonomy of Tools that Support the Fluent and Flexible Use of Visualizations. Interact. Dyn. Vis. Anal. 10, 2. 1–26.

[24] Zhang, L., Stoffel, A., Behrisch, M., Mittelstadt, S., Schreck, T., Pompl, R., Keim, D., Weber, S., and Last, H. 2012. Visual Analytics for the Big Data Era - A Comparative Review of State-of-the-Art Commercial Systems. In Proceedings of the IEEE Conference on Visual Analytics Science and Technology (Seattle, USA, October 14-19, 2012). VAST 2012. IEEE. 173–182.

[25] Kuhail, M. A., Pantazo, K., and Lauesen, S. 2012. Customizable Time-Orientated Visualizations. In Advances in Visual Computing. Springer, Berlin-Heidelberg. 668-677.

[26] Satyanarayan, A. and Heer, J. 2014. Lyra: An Interactive Visualization Design Environment. Comput. Graph. Forum. 33, 3 (June 2014). 351–360.

[27] Victor, B. 2013. Drawing Dynamic Visualizations. (May 2013). Retrieved 16 June, 2015 from http://worrydream.com/DrawingDynamicVisualizationsTalkAddendum/

[28] Heer, J. and Bostock, M. 2010. Declarative Language Design for Interactive Visualization. IEEE Trans. Vis. Comput. Graph. 16, 6 (October 2010). 1149–1156.

[29] Tableau, Tableau Desktop. 2015. Retrieved 16 June, 2015 from http://www.tableausoftware.com/products/desktop.

[30] SAP, SAP Lumira, 2015. Retrieved 16 June, 2015 from http://go.sap.com/product/analytics/lumira.html.

[31] Microsoft, Microsoft PowerPivot Add-Inn. 2015. Retrieved 16 June, 2015 from https://support.office.com/en-nz/article/Power-Pivot-Add-in-a9c2c6e2-cc49-4976-a7d7-40896795d045.

[32] TIBCO, TIBCO Spotfire. 2015. Retrieved 16 June, 2015 from http://spotfire.tibco.com/products/spotfire-desktop.

[33] Liu, S., Cui, W., Wu, Y., and Liu, M. 2014. A Survey on Information Visualization: Recent Advances and Challenges. Vis. Comput. 30, 12 (January). 1373-1393.

[34] Data Driven Documents, D3. 2015. Retrieved 16 June, 2015 from http://d3js.org/

[35] Prefuse, The Prefuse Visualization Toolkit. 2015. Retrieved 16 June, 2015 from http://prefuse.org/

[36] The InfoVis Toolkit, JavaScript InfoVis Toolkit. 2015. Retrieved 16 June, 2015 from http://philogb.github.io/jit/

[37] Google Developers, Google Charts. 2015. Retrieved 16 June, 2015 from https://developers.google.com/chart/interactive/docs/gallery/controls.

[38] Kienle, H. M. and Muller, H. A. 2007. Requirements of Software Visualization Tools: A Literature Survey. In Proceedings of the 4th IEEE International. Workshop on Visualizing Software for Understanding and Analytics (Banff, Alberta, Canada, June June 24-25). VISSOFT 2007. IEEE 2–9. DOI=ieeexplore.ieee.org/10.1109/VISSOF.2007.4290693

[39] Elias, M., Aufaure, M., and Bezerianos, A. 2013. Storytelling in Visual Analytics Tools for Business Intelligence. Proceedings of the 14th IFIP TC13 International Conference on Human-Computer Interaction (Cape Town, South Africa, September 02-06, 2013). INTERACT 2013. Springer, Berlin-Heidelberg, 280–297.

[40] Johannesson, P. and Perjons, E. 2012. A Design Science Primer, 1st ed. CreateSpace, Lexington. 2012.

[41] Seffah, A., Donyaee, M., Kline, R. B., and Padda, H. K. 2006. Usability Measurement and Metrics: A Consolidated Model. Softw. Qual. J. 14, 2 (June 2006). 159–178.

[42] Tsakonas, G. and Papatheodorou, C. 2008. Exploring Usefulness and Usability in the Evaluation of Open Access Digital Libraries. Inf. Process. Manag. 44, 3 (May 2008). 1234–12508.

[43] Sears, A. and Jacko, J. A. 2009. In Human-computer Interaction: Design Issues, Solutions, and Applications. CRC Press. Boca Raton.

[44] ISO/IEC 25010, “Systems and software Quality Requirements and Evaluation (SQuaRe).” 2011.

[45] Gravetter, F. and Wallnau, L. 2009. In Statistics for the Behavioral Sciences, 8th ed. Wadsworth, Belmont, CA.

Appendix A

Table A: Cronbach's alpha coefficients for the factors

Factor	Item total correlation (α)
2. Satisfaction	0.83
3. Visibility	0.84
4. Flexibility	0.87
5. Learnability	0.86
6. Error Control and helpfulness	0.76
7. Operability	0.81
Overall Rating	0.65

Table B: Frequency Distributions: for task completeness (n = 32)

	Yes		No	
Tasks	**n**	**%**	**n**	**%**
I could complete all tasks successfully.	32	100%	0	0%
I could complete all the tasks without assistance.	14	44%	18	56%

Table C: Central tendency and dispersions for task times (n = 32)

Time	Rank	Mean	S.D.	Minimum	Quartile 1	Median	Quartile 3	Maximum
Time 1	2	16.69	6.87	7.00	13.75	15.50	17.00	46.00
Time 2	1	10.84	4.03	2.00	8.00	10.50	13.25	22.00
Time 3	3	17.84	6.34	7.00	12.00	18.00	22.25	29.00
Time 4	4	19.38	12.29	3.00	11.50	16.00	24.25	63.00
Time		64.75	20.68	30.00	48.00	61.50	74.00	116.00

Table D: Central tendency and dispersions of aggregated usability metric ratings (n = 32)

Item	Mean	S.D.	Minimum	Quartile 1	Median	Quartile 3	Maximum
2. Satisfaction	4.46	0.52	3.33	4.00	4.50	5.00	5.00
3. Visibility	4.27	0.47	3.50	4.00	4.00	4.50	5.00
4. Flexibility	4.33	0.56	2.40	4.00	4.60	4.80	5.00
5. Learnability	3.16	1.08	1.00	2.38	3.50	4.00	5.00
6. Error Control and helpfulness	4.03	0.49	3.00	3.83	4.00	4.33	5.00
7. Operability	4.23	0.46	3.00	4.00	4.20	4.60	5.00
2-7. Rating	4.08	0.39	2.87	3.92	4.07	4.31	4.66

Table E: Frequency distributions of individual usability metric ratings (n = 32)

Satisfaction	Mean	S.D.	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
I am satisfied with my overall task time.	4.34375	65%	0	0%	0	0%	3	9%	15	47%	14	44%
I am satisfied with my overall dashboard.	4.46875	62%	0	0%	0	0%	2	6%	13	41%	17	53%
I am satisfied with the overall dashboard creation process.	4.566667	50%	0	0%	0	0%	0	0%	13	43%	17	57%
Visibility	Mean	S.D.	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
The functions are displayed in an uncluttered and well-structured manner	4.375	49%	0	0%	0	0%	0	0%	20	63%	12	38%
The functions are easy-to-use and are self-explanatory.	4.21875	61%	0	0%	0	0%	3	9%	19	59%	10	31%
The application communicated the system status in an understandable manner	4.21875	55%	0	0%	0	0%	2	6%	21	66%	9	28%
I could easily navigate to different screens and functions.	4.25	62%	0	0%	0	0%	3	9%	18	56%	11	34%
Flexibility	Mean	S.D.	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
I felt in control of the application at all times	3.96875	78%	0	0%	2	6%	4	13%	19	59%	7	22%
I could easily customise the layout of functions in the application.	4.3125	64%	0	0%	1	3%	0	0%	19	59%	12	38%
I could easily customise and manipulate the appearance of the dashboard.	4.46875	62%	0	0%	0	0%	2	6%	13	41%	17	53%
I could easily select and change the data attributes I needed from the data set.	4.28125	81%	0	0%	1	3%	4	13%	12	38%	15	47%
I could easily change the chart type.	4.625	55%	0	0%	0	0%	1	3%	10	31%	21	66%
Learnability	Mean	S.D.	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
The terminology used within the application was understandable and familiar.	4.21875	49%	0	0%	0	0%	1	3%	23	72%	8	25%
It was easy to learn the data analysis functionality to create dashboards	4.28125	52%	0	0%	0	0%	1	3%	21	66%	10	31%
I have to learn a lot of functions to use this application again in the future.	3	119%	3	9%	9	28%	9	28%	7	22%	4	13%
I felt that that it was mentally challenging to create an analysis dashboard.	2.6875	112%	4	13%	12	38%	8	25%	6	19%	2	6%

Error Control and helpfulness	Mean	S.D.	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
I could easily recover from any errors.	4.0625	84%	0	0%	2	6%	4	13%	16	50%	10	31%
The application helped me to recover from error quickly (error versus suggestion).	3.78125	83%	0	0%	2	6%	9	28%	15	47%	6	19%
The application provided helpful explanations for functionality.	3.78125	79%	0	0%	2	6%	8	25%	17	53%	5	16%
The recommended charts function were helpful.	4.0625	62%	0	0%	0	0%	5	16%	20	63%	7	22%
The explanations for chart types are helpful in understanding its use.	4.15625	63%	0	0%	0	0%	4	13%	19	59%	9	28%
It was helpful using a wizard to connect to my data source (SQL view)	4.3125	59%	0	0%	0	0%	2	6%	18	56%	12	38%
Operability	Mean	S.D.	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
I could easily identify, select and view the different dimensions in the created data cube.	3.96875	65%	0	0%	1	3%	4	13%	22	69%	5	16%
I could easily filter the data displayed in the dashboards	4.375	61%	0	0%	0	0%	2	6%	16	50%	14	44%
I could easily experiment with alternative charts based on the selected data	4.28125	63%	0	0%	0	0%	3	9%	17	53%	12	38%
I could easily organise the charts and data in my dashboard	4.25	57%	0	0%	0	0%	2	6%	20	63%	10	31%
The application behaved in a consistent manner	4.28125	58%	0	0%	0	0%	2	6%	19	59%	11	34%

Appendix B


InventoryValuation.xlsx - Excel
Total Quantity On Hand
Total Cost Value Vs Sales Value
Top 10 Sales Products for 2013
Total BackOrders
PivotChart Fields
Pivot Charts

Appendix F: Task-list with a Suggested Solution for Field Study 2

Participant Number: ____________

PC Number: __________

Dashboard Development Workshop___________________________

Objective:

The objective of the workshop is to create an executive dashboard that updates its contents in real-time. The dashboard will mainly display data from the SYSPRO database and allow for data analyses to be performed.

Pre-requisites

- SYSPRO 7 with Demo data (SQL database);
- Microsoft SQL Server Management Studio 2014;
- Microsoft (MS) Excel 2013.

Steps to create a dashboard:

Step 1: Create an SQL View (SQL Server Management Studio 2014)

Step 2: Import and transform the SQL View (Microsoft Excel 2013)

Step 3: Create a PivotTable and Pivot Charts for a dashboard

Step 4: Customise the entire dashboard

Remember to record the start and end time for EACH STEP in the task list.

1. Open Excel and check if the PowerPivot tab is visible.
2. If NOT, click on File>Options>Add-Ins.
3. On the drop-down menu, select COM Add-ins and click “Go…”
4. Select Microsoft Office PowerPivot for Excel 2013
5. Click “OK”.
6. It should appear as a tab now (if it does not please ask for assistance before starting).

Step 1: Create an SQL View in SQL server

Start Time:_________

1. Open Microsoft SQL Server Management Studio 2014.
2. Write down the name of the Server name (You will need this later): ___________

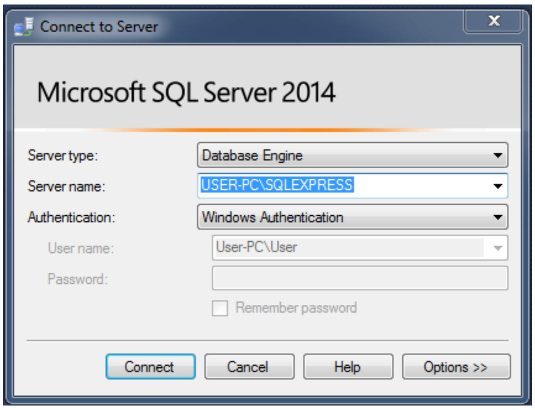


Figure 1 - Server name

3. Click on the “Connect” button.
4. Create a SQL view from the SYSPROCompanyEdu1 database to evaluate inventory information (Table 1). *Hint: first test the SQL query without the Create View statement. If successful with all fields, add the Create View statement and execute.*

Table 1, SQL View code for inventory evaluation.

```
Create View vw_invValYourparticpantNumber

SELECT InvWarehouse.StockCode,
InvMaster.Description AS StockDescription,
InvWarehouse.QtyOnHand,
InvWarehouse.QtyOnOrder,
InvWarehouse.QtyOnBackOrder,
InvWarehouse.Warehouse,
InvWhControl.Description AS WarehouseName,
InvWarehouse.UnitCost,
InvPrice.SellingPrice,
InvWarehouse.PrevYtdSalesVal,
InvWarehouse.YtdSalesValue

FROM InvWarehouse INNER JOIN
InvWhControl ON dbo.InvWarehouse.Warehouse = InvWhControl.Warehouse LEFT OUTER JOIN
InvMaster ON InvWarehouse.StockCode = InvMaster.StockCode LEFT OUTER JOIN
InvDocument ON dbo.InvWarehouse.StockCode = InvDocument.StockCode LEFT OUTER JOIN InvPrice
ON dbo.InvWarehouse.StockCode = InvPrice.StockCode AND InvPrice.PriceCode = 'A'
```

5. Once the View is executed successfully you will receive a message “Command(s) completed successfully”.
6. Save the SQL view as vw_invValYourParticipantNumber in the appearing folder (Something similar to this C:\Users\User\Documents\SQL Server Management Studio\vw_InvValYourPnumber.sql) - Testers please provide feedback on directory

End time: _________

Step 2: Import SQL View and transform data in Excel

Start time:_________

Step 2a: Import

1. Open Microsoft Excel 2013.
2. Click on the PowerPivot tab.
3. Click on the Manage button (A blank PowerPivot workbook appears in a separate screen).

4. In the “Get External category” click on the “From Database” button and select “From SQL Server” (A Table Import Wizard appears to assist in connecting to a data source).
5. Enter the Server name that you have recorded in step 1.
6. Ensure that the “Use Windows Authentication” option is checked.
7. Select the “SysproCompanyEdu1” database from the “Database name” drop-down menu.
8. Click next.
9. Ensure that that the “Select from a list…” option is ticked.
10. Click next.
11. Search and select the SQL view that you created in step 1 – “vw_invValyourParticipantNumber”.
12. Click Finish. You will receive a success message.
13. Click OK (You should see a table in the PowerPivot workbook).

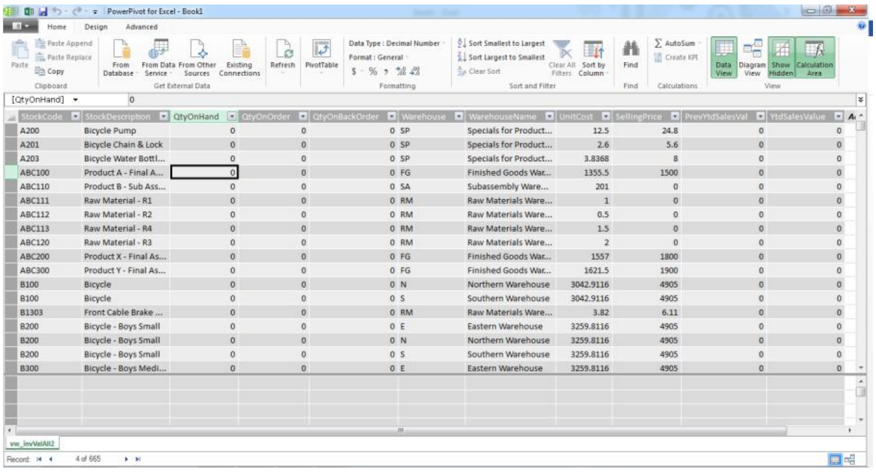


Figure 2, PowerPivot Workbook

Step 2b: Transform (add calculations and fields)

1. Add two additional columns to the table as in the figure 3:
   a. CostValueOnHand Formua - *fx* =[QtyOnHand]*[UnitCost]
   b. SellingValueOnHand Formula - *fx* =[QtyOnHand]*[SellingPrice]
   c. Round both columns to two decimal places.

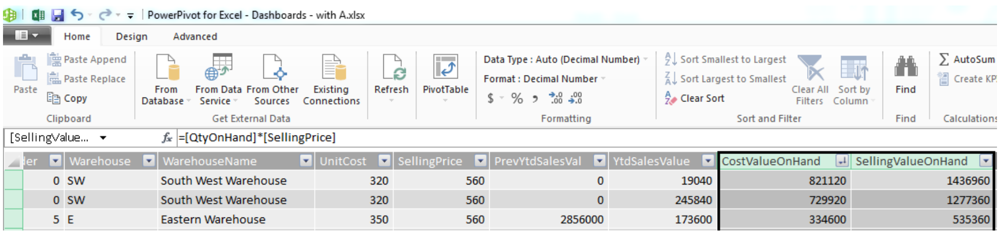


Figure 3, Two additional columns

2. Save the PowerPivot Workbook as YourName_InventoryValution on your desktop.

End time:____________

Step 3: Create Pivot table and Pivot charts

Start time: ___________

1. Click on insert PivotTable dropdown from within the PivotChart workbook and select the "Four Charts option" (figure 4).
2. You will receive an option to insert the charts in a new workbook click "OK". Rename the workbook sheet from "sheet 2" to "Pivot charts".

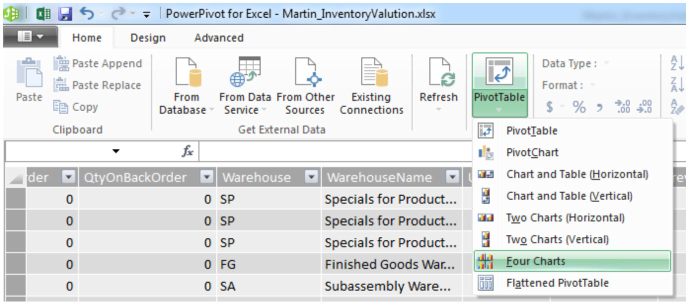


Figure 4, Insert a PowerPivot Chart from the PowerPivot workbook into the Excel workbook.

3. You will now see four chart containers in the middle of the screen and a "PivotChart Fields" column on your left with multiple attributes.

Excel has automatically create a PivotTable for you which is based on the same concept as a multi-dimensional cube. You will be able to select or drag-and-drop attributes from the created table to view the data from multiple perspectives.

Chart 1

The first chart will compare the Sum of CostValueOnHand and the Sum of Selling Value on hand on inventory across all the warehouses.

a. Click on the Chart 1 container and select the following attributes for chart 1 in the PivotCharts Fields container:
   i. *WarehouseName*
   ii. *CostValueOnHand*
   iii. *SellingValueOnHand*

b. Notice how Excel automatically calculates the sum of these values for you and creates a charts.

c. Take a few seconds to experiment with alternative charts, but stick to the bar chart (Insert tab).

d. Apply filters to the chart by clicking on the WarehouseName drop-down to view only specific warehouse data (figure)

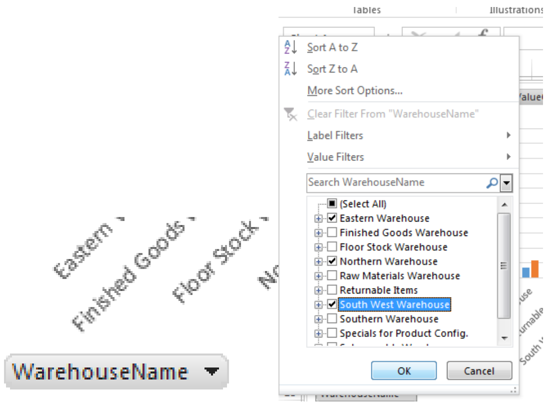


Figure 5, filters for charts

Chart 2

The second chart will list the top ten products sold for this year, or Year to date (YTD).

a. Click on the second chart container and select the following attributes:

   i. StockDescription

   ii. YtdSalesValue

b. Filter the chart to display the top ten products by clicking on the StockDescription drop-down, and click on value filter, then top ten (figure 6).

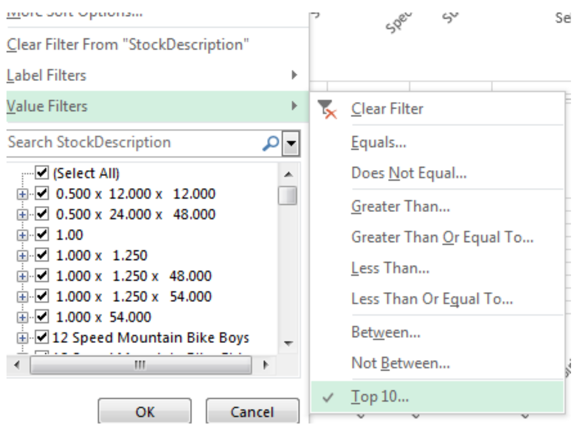


Figure 6, filter chart to display top ten products sold this year

Chart 3

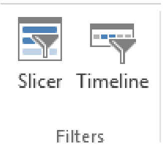
The third chart must display the total QtyOnHand for all warehouses. However, you are specifically interested in viewing the QtyOnHand for men's bicycles.

a. Click on the third chart container and select the following attributes:
   i. WarehouseName
   ii. StockDescription
   iii. QtyOnHand
b. Filter the chart by clicking on the StockDescription drop-down and type "men" in the search box. Click "Ok" to accept the filter.

Chart 4

You have noticed that some purchase order are on a backlog. Instead on using a chart, you would like to add a pivot table and a slicer to quickly sieve through the particular products that are on the back log.

a. Delete the 4 container.
b. Click in cell L:24
c. Go to the PowerPivot Workbook and click on the insert "PivotTable" option (similar to figure 4).
d. Select existing worksheet and click "Ok" (A pivot table container will appear).
e. Select the following attributes (Notice that a long table is now inserted):
   i. WarehouseName
   ii. StockDescription
   iii. QtyOnBackorder
f. Click anywhere in the pivot table and insert a Slicer from the Insert tab (filters category).



g. Select Warehouse name as the slicer.
h. In order to remove stock items from the pivot table that are not on the backorder, right click on any stock description, select Filter, then click "Value Filters…".
i. Set the items to show only backorder values greater than zero (figure 7).

j. Experiment with the slicer to view the backorders for different warehouses.

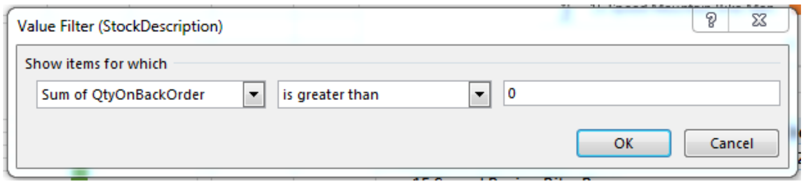


Figure 7, Set the pivot table to display backorder values greater than 0.

End time:___________________

Step 4: Customise the dashboard

Refresh

In this final step you are able to customise the appearance of the charts you have created.

1. Attempt to replicate how the charts are customised in figure 8.
2. Experiment with themes, colours, fonts, size, axis while using the following instructions as a guideline:
    i. To choose a theme, or add additional chart elements select the chart and click on the Design tab.
    ii. Right-Click on the bars or axis to format data series, text, add data labels, or select to change colours, width, gaps, currency, decimals etc.
    iii. Resize any contents of the charts to suit your needs.
    i. Right-click to filter the bars from largest to smallest.

3. To ensure that you are working with the most current data, click on the Data tab (a Workbook connections window will appear).
4. Select SQLServer option…SysproCompanyEdu1 and click on the “properties…” button (Connection properties window appears).
5. From the Usage tab, set “Refresh every” to 10 minutes.
6. Remember to SAVE and submit your Excel file on Moodle.

End time:________________

Figure 8, Final dashboard with Style 7 theme

END

Appendix G: Statistics for Field Study 2

Table A: Central tendency and dispersions for task times (n = 32)

Time	Rank	Mean	S.D.	Minimum	Quartile 1	Median	Quartile 3	Maximum
Time 1	2	16.69	6.87	7.00	13.75	15.50	17.00	46.00
Time 2	1	10.84	4.03	2.00	8.00	10.50	13.25	22.00
Time 3	3	17.84	6.34	7.00	12.00	18.00	22.25	29.00
Time 4	4	19.38	12.29	3.00	11.50	16.00	24.25	63.00
Time		64.75	20.68	30.00	48.00	61.50	74.00	116.00

Table B: Central tendency and dispersions of aggregated usability metric ratings (n = 32)

Item	Mean	S.D.	Minimum	Quartile 1	Median	Quartile 3	Maximum
2. Satisfaction	4.46	0.52	3.33	4.00	4.50	5.00	5.00
3. Visibility	4.27	0.47	3.50	4.00	4.00	4.50	5.00
4. Flexibility	4.33	0.56	2.40	4.00	4.60	4.80	5.00
5. Learnability	3.16	1.08	1.00	2.38	3.50	4.00	5.00
6. Error Control and helpfulness	4.03	0.49	3.00	3.83	4.00	4.33	5.00
7. Operability	4.23	0.46	3.00	4.00	4.20	4.60	5.00
2-7. Rating	4.08	0.39	2.87	3.92	4.07	4.31	4.66

Table C: Cronbach's alpha coefficients for the factors

Factor	All **(n = 32)**
2. Satisfaction	0.83
3. Visibility	0.84
4. Flexibility	0.87
5. Learnability	0.86
6. Error Control and helpfulness	0.76
7. Operability	0.81
2-7. Rating	0.65

Table D: Frequency Distributions: 1. Task Completeness (n = 32)

	Yes		No	
1.1. I could complete all tasks successfully.	32	100%	0	0%
1.2. I could complete all the tasks without assistance.	14	44%	18	56%

Table E: Frequency Distributions: 2. Satisfaction

	Mean	S.D	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
2.1. I am satisfied with my overall task time.	4.343	65%	0	0%	0	0%	3	9%	15	47%	14	44%
2.2. I am satisfied with my overall dashboard.	4.468	62%	0	0%	0	0%	2	6%	13	41%	17	53%
2.3. I am satisfied with the overall dashboard creation process.	4.566	50%	0	0%	0	0%	0	0%	13	43%	17	57%

Table F: Frequency Distributions: 3. Visibility (n = 32)

	Mean	S.D.	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
3.1. The functions are displayed in an uncluttered and well-structured manner.	4.375	49%	0	0%	0	0%	0	0%	20	63%	12	38%
3.2. The functions are easy-to-use and are self-explanatory.	4.218	61%	0	0%	0	0%	3	9%	19	59%	10	31%
3.3. The application communicated the system status in an understandable manner.	4.218	55%	0	0%	0	0%	2	6%	21	66%	9	28%
3.4. I could easily navigate to different screens and functions.	4.25	62%	0	0%	0	0%	3	9%	18	56%	11	34%

Table G: Frequency Distributions: 4. Flexibility (n = 32)

	Mean	S.D.	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
4.1.I felt in control of the application at all times.	3.96875	78%	0	0%	2	6%	4	13%	19	59%	7	22%
4.2. I could easily customise the layout of functions in the application	4.3125	64%	0	0%	1	3%	0	0%	19	59%	12	38%
4.3. I could easily customise and manipulate the appearance of the dashboard.	4.46875	62%	0	0%	0	0%	2	6%	13	41%	17	53%
4.4. I could easily select and change the data attributes I needed from the data set.	4.28125	81%	0	0%	1	3%	4	13%	12	38%	15	47%
4.5. I could easily change the cart type.	4.625	55%	0	0%	0	0%	1	3%	10	31%	21	66%

Table H: Frequency Distributions: 5. Learnability (n = 32)

	Mean	S.D.	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
5.1. The terminology used within the application was understandable and familiar.	4.21875	49%	0	0%	0	0%	1	3%	23	72%	8	25%
5.2. It was easy to learn the data analysis functionality to create dashboards	4.28125	52%	0	0%	0	0%	1	3%	21	66%	10	31%
5.3. I have to learn a lot of functions to use this application again in the future.	3	119%	3	9%	9	28%	9	28%	7	22%	4	13%
5.4. I felt that that it was mentally challenging to create an analysis dashboard.	2.6875	112%	4	13%	12	38%	8	25%	6	19%	2	6%

Table I: Frequency Distributions: 6. Error Control and helpfulness (n = 32)

	Mean	S.D.	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
6.1. I could easily recover from any errors.	4.0625	84%	0	0%	2	6%	4	13%	16	50%	10	31%
6.2. The application helped me to recover from error quickly (error versus suggestion).	3.78125	83%	0	0%	2	6%	9	28%	15	47%	6	19%
6.3. The application provided helpful explanations for functionality.	3.78125	79%	0	0%	2	6%	8	25%	17	53%	5	16%
6.4. The recommended charts function were helpful.	4.0625	62%	0	0%	0	0%	5	16%	20	63%	7	22%
6.5. The explanations for chart types are helpful in understanding its use.	4.15625	63%	0	0%	0	0%	4	13%	19	59%	9	28%
6.6. It was helpful using a wizard to connect to my data source (SQL view)	4.3125	59%	0	0%	0	0%	2	6%	18	56%	12	38%

Table J: Frequency Distributions: 7. Operability (n = 32)

	Mean	S.D.	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
7.1. I could easily identify, select and view the different dimensions in the created data cube.	3.96875	65%	0	0%	1	3%	4	13%	22	69%	5	16%
7.2. I could easily filter the data displayed in the dashboards	4.375	61%	0	0%	0	0%	2	6%	16	50%	14	44%
7.3. I could easily experiment with alternative charts based on the selected data	4.28125	63%	0	0%	0	0%	3	9%	17	53%	12	38%
7.4. I could easily organise the charts and data in my dashboard	4.25	57%	0	0%	0	0%	2	6%	20	63%	10	31%
7.5. The application behaved in a consistent manner	4.28125	58%	0	0%	0	0%	2	6%	19	59%	11	34%

Table x: Frequency Distributions: 8. Task difficulty (n = 32)

	Mean	S.D.	Least challenging		Neither least nor most		Most challenging	
Step 1: Creating the query and importing it as a data set into Excel.	1.84375	68%	10	31%	17	53%	5	16%
Step 2: Transforming the data set (adding calculations, additional fields	1.625	49%	12	38%	20	63%	0	0%
Step 3: Selecting appropriate charts, inserting pivot tables, attributes and applying filer	1.96875	65%	7	22%	19	59%	6	19%
Step 4: Manipulating and customising the selected chart (editing labels, colours, size etc.	1.6875	54%	11	34%	20	63%	1	3%

Appendix H: Task-List for the Final Evaluation with Tableau

Practical Assignment for WRER302/ WRBA202

Business Intelligence tools for visualising data: Tableau software

Total marks: 20

Name: _____________________

Participant Number (provided by the researcher): ______________________

Purpose:

The purpose of this assignment is to determine what participants experience when conducting data analysis using Business Intelligence (BI) tools. The problems as well as the advantages of using the BI tool will be documented. More specifically, you will create a performance dashboard in a popular BI software tool known as Tableau 9.0. The assignment guides participants through an entire data analysis process. The case study used in this assignment is based on a fictitious retail company known as the Global Superstore. You are expected to follow the steps provided in the task-list and to answer questions based on their sales data. Some of the main outcomes are to:

- Analyse data surrounding market segments, products, sales, profits and geographic locations of stores;
- Identify trends in data,
- Setup features to filter and sort data,
- Setup drill-down paths to analyse finer details of data,
- View data from different perspectives using pivot tables and charts,
- Synthesise individual visualisations into a single dashboard,
- Create a story of data analysis findings.

Instructions

- Complete all tasks on the task-list using the *Global SuperStore.xls* file (Provided by the researcher).
- Save your Tableau workbook as *StudentNr_Tableau*.
- Record the task-times in the space provided on the printed task-list.
- Answer all questions on the answer sheet provided.
- Fill in the consent form before you start the task-list.
- Upon completion of the task-list, complete the usability questionnaire.

Deliverables (Due Wednesday 3 September)

- Printed Task-list and Answer Sheet
- Consent form: https://docs.google.com/forms/d/1seADlLIbbCvY-cRM2zEbpMTAtwa9SqQx-TSJUnOHk7A/viewform
- Questionnaire: https://docs.google.com/forms/d/1WDRaFeMoscbBWdYLJYQya-5RJ66HgtRMDG8c28RJd_k/viewform

Scenario

You have been appointed as a data analyst for the Global Superstore. The company supplies to three different market segments across the globe. They specialise in three main categories of products: furniture, office supplies and technology. The following task-list provides a task-description and the purpose of the task.

Start time: _________

Task Number	**Task description:**	**Purpose**
1.	1.1. Open the Tableau 9.0 software. Connect to the Excel spreadsheet provided (Global Superstore.xlsx). 1.2. There are three table sheets: *Orders*, *People and Returns.* You can select tables by dragging the names onto the sheet. Tables and attributes can also be searched for larger data sets and previews of queried data can be seen in a table (Figure 1). **Note:** Tableau automatically creates default queries to join tables. You can change these queries by clicking on the blue-coloured circles and selecting the type of joining operator. 1.3. Merge three tables for the purpose of this practical. Leave the data source a live connection. 1.4. Click on the *Sheet 1* tab below the *Go to Worksheet* icon to start analysing data with visualisations. A blank worksheet opens with the *Dimensions (data attributes)* and *Measures (calculated values) from the Orders table*.	Connecting to a data source

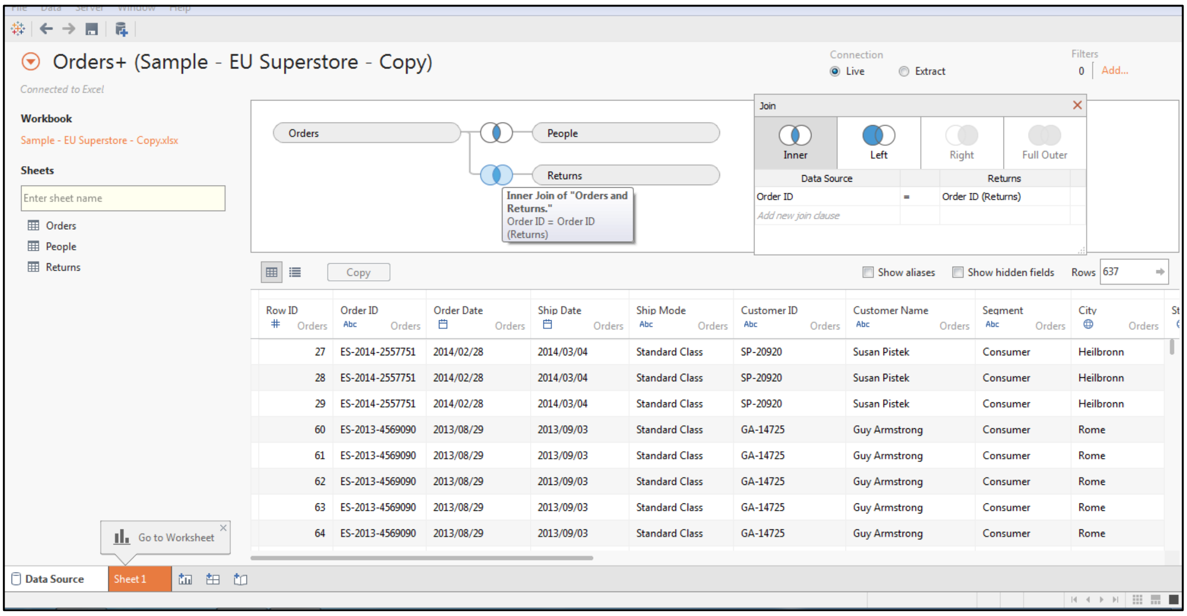
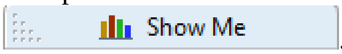


Figure 1, selecting data tables and creating queries.

End time:______________

Start time: _____________

Task Number	**Task description:**	**Purpose**
2.	Assume you have been asked to view the sales totals according to the product category, market and market segments. 2.1. Save the workbook as *StudentNr_Tableau* (remember to save regularly). 2.2 Drag the following Dimensions and Measures to the *Rows* and *Columns* shelves (as per Figure 2): 2.2.1 Category 2.2.2 Segment 2.2.3 Market 2.2.4 Sales **Note:** Tableau automatically applies the SUM measure. You can at any time change the measure with right-click on the measure you have added> Select Measure>. 2.3 Drag the *Market* dimension for a second time (from the Dimensions shelf) to the Color icon  . You can do the same with any dimension or measure to apply colour-coding.	Selecting Attributes Automatic charts Adding Calculations

2.4 Take a few seconds to experiment with alternative charts from the “Show me” tab .

2.5. Add an additional measure (calculation) as *Profit Ratio*. Right click anywhere in the *Measures* window and click *Create Calculated field… option. Add the calculation below:*

```
SUM([Profit])/SUM([Sales])
```

Note: You will see your newly added measure in the *Measures* window.

Question 1: Which market is clearly still an emerging market in terms of sales?

Answer: ____________________

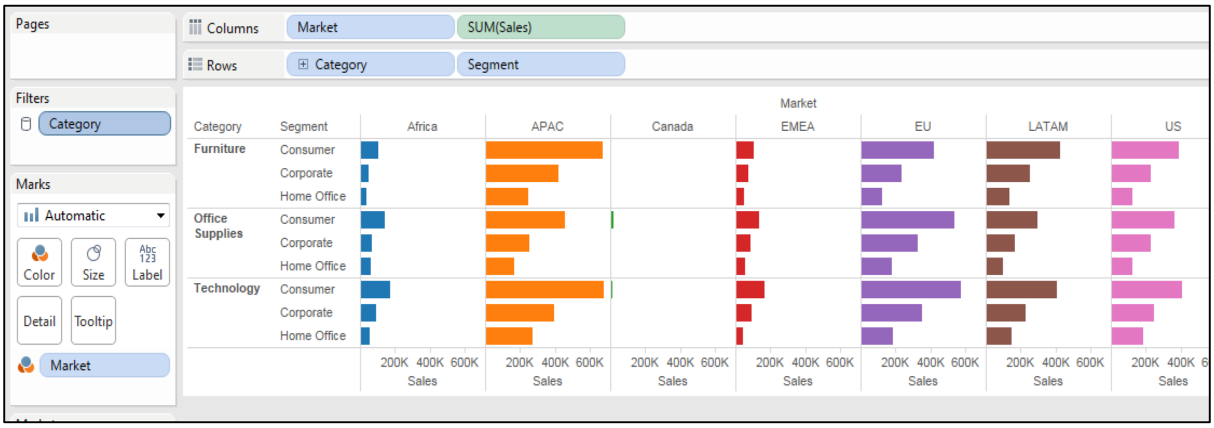
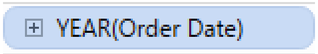
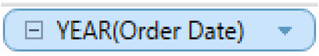


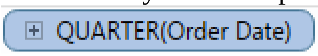
Figure 2, Sales quantities according to market segments

<table>
<tr><th>Task
Number</th><th>Task description:</th><th>Purpose</th></tr>
<tr><td>3.</td><td>Click on the Clear Sheet icon  on the ribbon to clear the work sheet BEFORE continuing with this task only. Starting on a blank sheet, you would like to view the total sales over time.

3.1. Drag the Sales measure to the Rows shelf.

Note: The total sales value is for four years combined (2011-2014).

3.2. To view the total sales over time for each year, drag the Order date dimension to the Columns shelf.
3.3. Click on the expand icon in  to drill-down into more details regarding sales data for each quarter. You can even go further up to viewing the monthly and daily sales.
3.4. Ensure that you are viewing sales per quarter. Drag  into the  icon.
(You will now see quarterly sales comparisons on a single chart).

3.5. To view a monthly sales comparison for each year, Right-click on the  and select Month.

Note: Your view should look similar to Figure 3.</td><td>Drill-down</td></tr>
<tr><td colspan="3">Question 2: Write down the Sales total, Year and Month in which the company had the highest sales to date.

Answer: ____________________</td></tr>
</table>

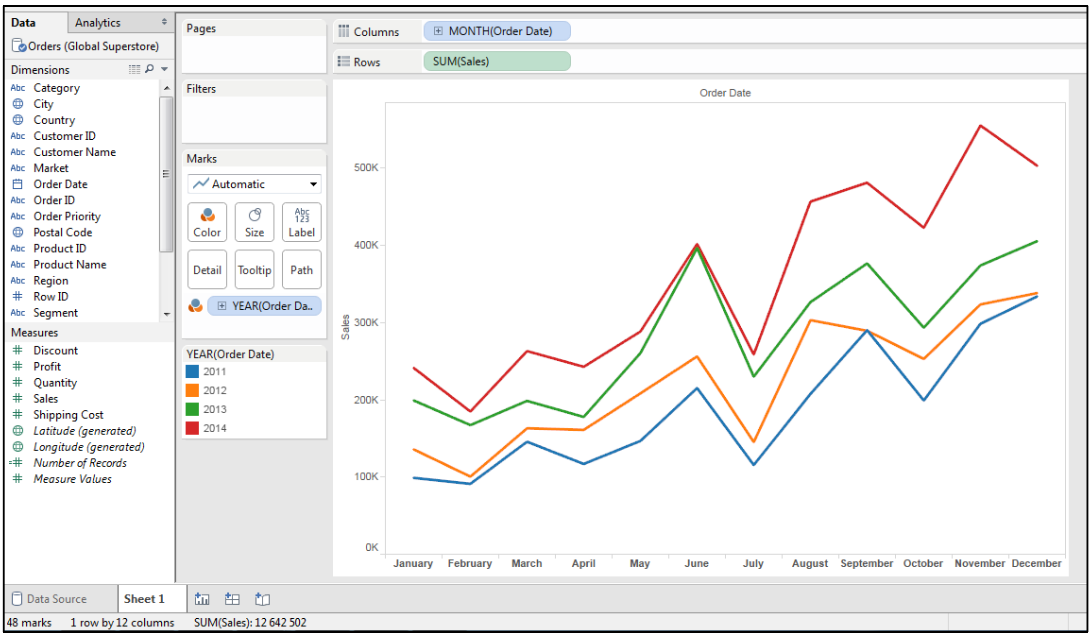


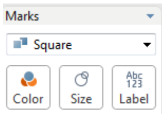
Figure 3, yearly sales comparison from January to December.

Task Number	**Task description:**	**Purpose**
4.	You would like to compare how your different product categories are performing. Assuming you were informed that the company is experiencing an annual dip in sales due to a holiday. 4.1. Drag the *Category* dimension to the *Rows* shelf. (Three categories for furniture, office supplies and technology). 4.2 Identify the month in which the company experiences a constant dip in sales across all categories for each year. 4.3 Once you have identified the month, Right click on any data point in that particular month where the dip occurs and select Annotate>Area. 4.4 Type the following in the text box: *"We are experiencing a constant dip in [MONTH IDENTIFIED] due to holidays."* 4.5 Click OK. 4.6 Expand the grey text box across all three charts for the identified month only. 4.7 Rename Sheet 1 to *Sales Seasons*.	Chart comparisons Annotations Sharing charts

<table>
<tr><td colspan="3">Question 3: Copy the chart into the answer sheet provided the heading “Question 3”. NB: Right click on the chart, select Copy>Image. You can easily share your charts with colleagues in other documents, emails, Skype etc.</td></tr>
<tr><th>Task Number</th><th>Task description:</th><th>Purpose</th></tr>
<tr><td>5.</td><td>You would like to view which of the company’s products are generating profits/ losses. To do so, you need to view the actual data behind the sales.

5.1. Right click on the Sales Season sheet you renamed and select “Duplicate as Crosstab”. (You will view the data as a table)
5.2. You can pivot the table by clicking on the Swap icon  .
5.3. Drag the Profit measure to the  icon.

Note: the highlighted colours are very pale.

5.4. Click on  and select Edit colors.
5.5. Check the Use Full Color Range and change the Stepped Color to 6 Steps.
5.6. Click Ok. Note: the colours are still pale.
5.7. Make the values more visible and change the Marks type to Square. 

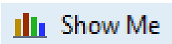
5.8. Add labels to chart.

Note: The Furniture category is not as profitable as the Office supplies and Technology categories.

5.9. Rename Sheet 2 to Crosstab.</td><td>Pivot Data

Formatting (Colours, Labels, size etc.)</td></tr>
<tr><td colspan="3">Question 4: In which Year and Month did the company incur a loss?</td></tr>
</table>

<table>
<tr><th>Task Number</th><th>Task description:</th><th>Purpose</th></tr>
<tr><td>6.</td><td>You would like to determine how all the retail stores are performing globally. However, you are not sure how to view the data in an appropriate chart.

6.1. Click on the create *New Sheet* icon at the bottom . Click on the *Show Me* tab to expand a list of available charts 
.

Note: *Show Me* indicates the required amount of dimensions and measures necessary for a specific chart.

6.2. Hold down the Ctrl-key and select the *Sales* measure and the *Country* dimension. Notice how *Show Me* suggests charts based on your selected data.
6.3. Select the *Symbol Map* option as suggested.

Note: A global map of all retail stores will be displayed with circles – larger circles indicate larger sales volumes.
6.4. Hover over the circles to view some of the sales values.</td><td>Chart Suggestions</td></tr>
<tr><td colspan="3">**Question 5A: Which country has the most sales?**</td></tr>
<tr><td></td><td>6.5. Drag the *State* dimension onto the map to view the different retail stores for each country. (Hundreds of smaller circles appear).

6.6. Edit the size of the circles using the size icon 

6.7. Edit the transparency and add a border for circles with 
.

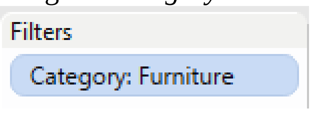
6.8. Drag the *Profit* measure to the Color icon to color code profits and losses. (Green circles are profitable stores and red represents those incurring losses).

6.9. Use the search feature to determine whether Gauteng is profitable (in the left corner of the map).
6.10. Use the unpin icon to return to the full map view .</td><td>Search

Zoom

Highlight</td></tr>
<tr><td colspan="3">**Question 5B: Is the Gauteng store profitable? How much is the profit/ loss?**</td></tr>
</table>

<table>
<tr><td colspan="3"></td></tr>
<tr><td></td><td>You have noticed earlier that the Furniture category is not as profitable compared to Office Supplies and Technology. You would like to investigate whether this trend occurs across all the retail stores.

6.11. Drag the Category dimension to the Filters window.


6.12. Check the Furniture option in Filter window pop-up. Click Ok.

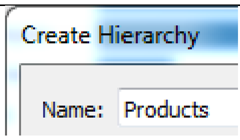
6.13. To add additional filters, right-click on the new Category filter you just added above and select Show Quick Filter.

Note: You should see a new filter window on the right with checkboxes for each of the three categories.

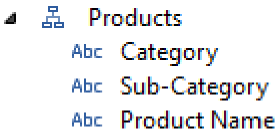
6.14. Click on the drop-down arrow on the right of the newly added Category filter window and select Single Value(list) to select radio buttons.
6.15. Rename the sheet to Global Sales and Profits.</td><td>Filter</td></tr>
<tr><td colspan="3">Question 5C: Take a screen shot of the current sheet and paste it in the answer sheet.</td></tr>
<tr><th>Task Number</th><th>Task description:</th><th>Purpose</th></tr>
<tr><td>7.</td><td>You need to establish which products from the Furniture category are causing the losses. In order to do so, you will create a hierarchy that allows you to drill-down from the Categories to Sub-categories dimensions, and then to the Product Name dimension.

7.1. Create a new sheet.
7.2. Expand the Show Me tab once again.
7.3. Hold down the Ctrl-key and select Sales, Category and Sub-category.
7.4. Select the Horizontal bars chart option.
7.5. In the Dimensions Window on the left side of the screen, drag the Sub-category dimension ONTO the Category dimension to start creating a hierarchy.
7.6. Type a name for the hierarchy as Products:</td><td>Drill-down

Sorting</td></tr>
</table>



7.7. Additionally, drag the *Product Name* dimension below the Sub-category dimension in the hierarchy. **Ensure that your hierarchy is structured as seen on the next page.**



7.8. Click on the ABC icon  to enable labels.

7.8. Pivot the chart to display vertical bars .

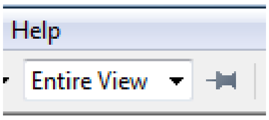
7.9. Click on (do not expand) the  dimension and click sort in descending order .

7.10. Drag the *Profit* measure to the Color icon.

Note: Take note of the sub-category causing a loss. You would like to view whether this loss occurs across all markets.

7.11. Drag the *Market* dimension to the *Rows* column.

7.12. Select the Entire View option to make all charts fit to the screen



.

Question 6A: Which sub-category is generating the loss?

Question 6B: Which Markets are not incurring a loss for the sub-category identified above?

<table>
<tr><th>Task Number</th><th>Task description:</th><th>Purpose</th></tr>
<tr><td>8.</td><td>
After you have answered the questions above (6A and 6B):

8.1. Remove the *Market* dimension.
8.2. Click the swap icon .
8.3. Rename the sheet to *Sales by Category*.

You have created a number of sheets with charts. You would like to synthesise all of them on a single dashboard.

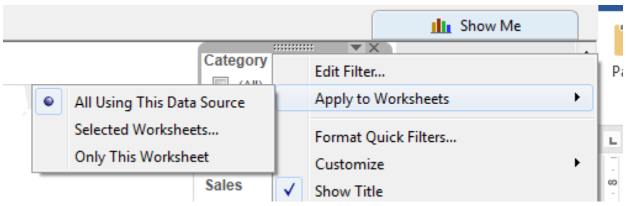
8.4. Click on the New Dashboard icon .
8.5. Drag the *Global Sales and Profit* Sheet on the dashboard.
8.6. Drag the *Sales by Category* sheet to the lower part of the dashboard. (You should be able to view these two sheets on a single screen).

Note: If the sheets do not fit properly you can adjust the size in the lower left hand corner.

To create an effective dashboard, each individual chart must be coordinated and linked to each other.

8.7. Click on the drop-down arrow in the right corner of the *Category filter* window and select *Apply to All worksheets> All using this data source*.

Note: You will be able to filter the entire dashboard based on these filters. Try it out.



8.8. Do the same for the *Sales and Profit (window with map)* and the *Sales by Category (window with bar chart) windows* by clicking on the drop-down arrow and selecting *Use as filter*.
8.9. Filter the dashboard by the *Technology* category.
8.10. Rename the dashboard to *Sales Dashboard*.
</td><td>Coordinated views</td></tr>
<tr><td colspan="3">

Question 7: How much profit was generated by Phones?

NB: After you answered this question change the filter back to Furniture.
</td></tr>
</table>

Task Number	**Task description:**	**Purpose**
9.	Now that you have created a number of charts in different sheets, you would like to share your findings with others. Create a story that will lead your readers to follow your analysis process. 9.1. Click on the New Story icon . 9.2. Drag the *Global Sales and Profit* sheet to start your story. 9.3. Do not filter the view (ensure the "All" option is selected in the filter window). 9.4. Add a caption "*Overall, the profits look strong.*" 9.5. Click Update.  9.6. Duplicate the first sheet and add the caption *"But not across all the categories. Furniture is generating a loss."* 9.7. Filter the chart by the Furniture category. 9.8. Click on the *New Blank Point* button. 9.9. Drag the *Sales by Category* sheet to show the profits relating to the furniture category. **Note:** If the Furniture sub-category is not shown, Go back to the original *Sales by Category* sheet and change the filter to Furniture and NOT technology. 9.10. Add the caption "Here's the biggest problem". 9.11. Click on the *New Blank Point* button. 9.12. Add the *Sales Dashboard*. 9.13. Add the caption *"Behind the scenes"*. 9.14. Rename the title of the story "Profitability: The full Story". 9.15. Rename the story sheet "Profitability". 9.16. Remember to save your workbook.	Creating a Story

End time:______________

REMEMBER: Complete the online questionnaire:

https://docs.google.com/forms/d/1WDRaFeMoscbBWdYLJYQya-5RJ66HgtRMDG8c28RJd_k/viewform

Answer Sheet: Tableau Assignment

Name: _______________

Student Number: ____________

Participant Number: ______________

	Marks (20)
Question 1: Which market is clearly still an emerging market in terms of sales? **Answer:**	**1**
Question 2: Write down the Sales total, Year and Month in which the company had the highest sales to date**.** **Answer:** Year: Month Sales total:	**3**
Question 3: Paste your visualisation here. **NB:** Right click on the chart, select Copy>Image. You can easily share your charts with colleagues in other documents, emails, Skype etc.	**3**
Question 4: In which Year and Month did the company incur a loss? **Answer:**	**2**
Question 5A: Which country has the most sales **Answer:**	**1**
Question 5B: Is the Gauteng store profitable? How much is the profit/ loss? **Answer:**	**2**
Question 5C: Paste your screen shot here	**3**
Question 6A: Which sub-category is generating the loss? **Answer:**	**1**
Question 6B: Which markets are not incurring a loss for the sub-category identified above? **Answer:**	**3**
Question 7: How much profit was generated by Phones? **Answer:**	**1**

Appendix I: Questionnaire for the Final Evaluation with Tableau Evaluation

Usability Evaluation for Tableau

Welcome to the survey for the Tableau Desktop application. Please answer the following questions accurately.

*Required

Particpant Number *

e.g. P02

Background Information

The following questions relate to some of your demographic details.

Age group *

- 18 -19 years
- 20-24 years
- 25-29 years
- 30+ years

Gender *

- ○ Male
- ○ Female

How long have you been using a computer? *

- ○ <2 years
- ○ 2-4 years
- ○ 5-9 years
- ○ 10+ years

Current year of study? *

- ○ 1st year
- ○ 2nd year
- ○ 3rd year
- ○ 4th year
- ○ 5th year

How much experience do you have with dashboards? *

- ○ None
- ○ Low
- ○ Moderate
- ○ Moderately high
- ○ High

How much experience do you have with Business Intelligence tools? *

- ○ None
- ○ Low
- ○ Moderate
- ○ Moderately high
- ○ High

How much experience do you have with spreadsheet tools like Micrsoft Excel tools? *

- ○ None
- ○ Low
- ○ Moderate
- ○ Moderately high
- ○ High

If you have used any Business Intelligence or other visual analysis tool in the past, list below.

Usability Evaluation

Please answer the following questions accurately based on your experience with Tableau.

Please indicate whether you could complete the following tasks successfully *

	Successfully without assistance	Successfully, but with assistance	Not Successfully
Task 1: Selecting a data source	○	○	○
Task 2: Viewing market segments, adding calculations	○	○	○
Task 3: Drill-down to sales per month	○	○	○
Task 4: Annotating and sharing visualizations	○	○	○
Task 5: Format colours, labels, size of visualisations	○	○	○
Task 6: Using the Show me, search and filtering features	○	○	○
Task 7: Creating a hierarchy for drill-downs	○	○	○
Task 8: Integrating visualizations into a single dashboard	○	○	○
Task 9: Creating a story.	○	○	○

Visibility

The user interface is well-structured (worksheet, menus, icons, buttons, layout) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The user interface was interactive. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

Information was easy to find onscreen. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The onscreen instructions are visible. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The system status was communicated adequately (loading, processing, idle etc.). *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

Flexibility

The system can be adjusted to suit individual needs (position of windows, menus, charts, filters, annotations etc.) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to customise the dashboard (colours, size, labels, fonts etc.) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to connect to a different data source (Excel, SQL server, etc.) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to select different data attributes (dimensions and measures) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to manipulate data (add calculations or additional measures). *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to select alternative chart types *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

« Back   Continue »

42% completed

Learnability

It was easy to learn the steps to create a dashboard *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to learn the features of the system. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The terminology used in the system was easy to understand *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

Error Control

It was easy to recover from errors (undo, redo) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The system prevented me from making errors (applying undesired options, selecting inappropriate charts, etc.) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

Making mistakes was not a problem knowing that I could learn from them (exploring how features worked) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

« Back　　Continue »

57% completed

Helpfulness

The system helped me to recover from errors (explanations, messages) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The system provided adequate help on-demand (tooltips, explanations) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The automatic chart generations and suggestions were helpful *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The guided development process was helpful (select data source, querying, select data attributes, visual mapping, formatting views) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

Adequate learning materials are provided in the system (tutorials, videos etc.) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

Operability

I felt in control of the system *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The system provided a rapid response rate *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The system behaved consistently *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

I could easily create visualisations. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

I could easily synthesise seperate visualisations into a single dashboard. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to select measures and dimensions. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to find information using search features (e.g. searching a country, dimensions, tables etc.) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to use the drill-down features *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to filter visualisations *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to sort the data. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to create a data story. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

It was easy to share the visualisations with peers (copy the visualisation). *

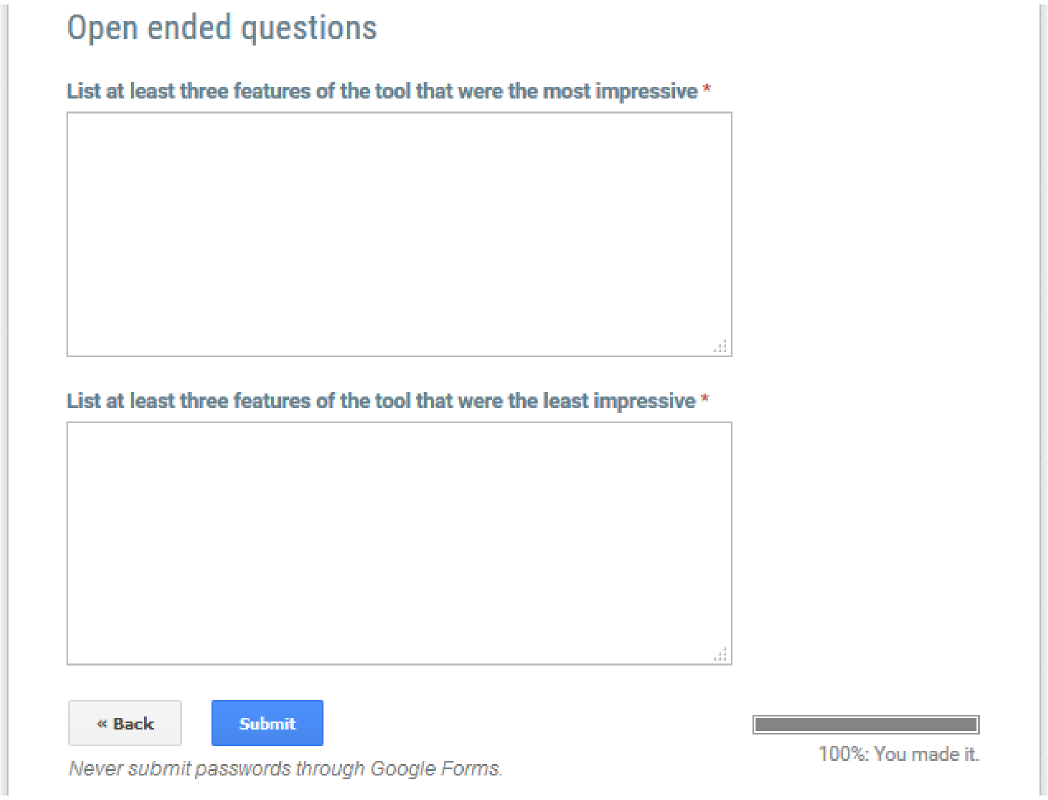
	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

I could create a dashboard in a reasonable amount of time *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

« Back   Continue »

85% completed



Open ended questions

List at least three features of the tool that were the most impressive *

List at least three features of the tool that were the least impressive *

« Back

Submit

Never submit passwords through Google Forms.

100%: You made it.

Appendix J: The BI Scorecard

Guidelines number/ description	Features for each guideline	Rating scale for each feature (Bad "-", acceptable "~" and good "+")
Easy development process (G1)	Integrated environment	- Different software tools need to be integrated manually to develop and render dashboards. ~ Components are mostly integrated in a single environment, but require some manual effort to develop and render dashboards. + Components are integrated in a single environment and functions are automated and interactive.
Guided Development Process (G2)	Guides	- None/ few general wizards. ~ Supports only few guides and wizards for IV process, but user needs to be familiar with IV process. + Support guides and wizards to assist user through the entire IV process.
Flexible customisation process (G3)	Flexible data selection	- Selecting a new data source is unintuitive, complex and time consuming (new visualisation is often created for new data source). ~ Data sources and attributes can be de/reselected, but takes practice. + Data sources and attributes can be easily de/reselected with almost no learning curve.
	Chart Formatting (reasonable defaults)	- Changing chart settings is tedious. ~ Changes are made for settings with a few clicks. + Important parameters may be changed instantly.
	Chart selection	- A new chart has to be made ~ Selecting alternative charts can be selected with a few clicks, but filters have to be re-applied. + Selecting alternative charts can be done instantly, maintaining filters that have been applied.
	Positioning of menus and visualisations in work areas (minimising, moving).	- None / no ability to position the layout of menus and windows. ~ Limited – can only position menus and visualisations in designated areas. + Good – flexible to position menus and visualisations freely.
Dynamic, immediate and interactive visual feedback (G4)	Feedback	- Unintuitive, limited interaction and feedback during changes made (programming is often required). ~ Interaction shows immediate visual feedback when changes are applied, but only have a few GUI options to interact and change visualisations. + Interaction shows immediate visual feedback when upon changes, with highly flexible and intuitive GUI to interact and change.
	Interaction with visualisations	- None/ limited interaction with visualisations ~ Good visualisation interaction (selection of data attributes, functions and formatting options) + Highly interactive; appearance can be directly manipulated and navigated to different levels of aggregation (drag and drop, double click, drop downs etc.).

Search, filter, sort and drill-down for navigation (G5)	Sorting	- Few, basic sorting options (ascending, descending, newest to oldest). ~ Sorting options are derived from selected attributes. + Sorting options are derived from selected attributes and can be applied both locally and globally.
	Drill-down/ up hierarchy	- No drill-down/ up hierarchies and navigation are supported. ~ Drill-down/up hierarchies are supported, but needs to be setup manually. + Drill-down/up hierarchies are automatically created based on smart data discovery, but is also customisable.
	Filters	- Basic, local filters are derived from attributes only a single filter is applied. ~ Multiple global and local filters are derived from attributes and applied. + Highly customisable global and local filters can be derived and set by the user from multiple attributes.
	Search facilities	- None search facilities ~ Basic search facilities for data attributes or text. + Advanced search facilities for data attributes, text in visualisations, searches can be used to highlight or filter data points.
	Navigation	- Poor navigation (menu items difficult to identify, lack of navigation paths) ~ Good navigation (Adequate layout of menu items and navigation paths) + Excellent navigation (customisable layout of menu items; navigation options are flexible)
Multiple Coordinated Views and dynamic queries (G6)	Coordinated views setup	- None/ charts cannot link. ~ Reasonable chart linking, but with some effort to specify relationships between charts. + Highly flexible chart linking can occur automatically or managed with a few clicks.
	Coordinated views scope	- None/ charts do not link ~ Linked charts are limited to specific functions and visualisations only (sort, filter, or drill-down). + Linked charts are flexible and can be set to affect all visualisations and worksheets (a wide range of functions can be used)
	Dynamic queries	- Setting up dynamic queries is tedious (programmatically). ~ Dynamic queries limited to filters, sorting or selection. + Dynamic queries derived from filters with interactive objects.
Automatic charts and suggestions (G7)	Automatic creation	- None/ only programmatically. ~ Charts are created automatically with predefined defaults. + Charts are created automatically with predefined, customisable defaults.
	Chart suggestions	- No chart suggestions. ~ Chart suggestions with limited advice for alternatives. + Chart suggestions with adequate advice for alternatives.
	Chart diversity	- Only few/ basic charts with predefined settings. ~ Reasonable amount of charts with predefined settings. + Many/ highly customisable charts to create novel designs.
	Chart Previews (not necessary if good undo o revert function)	- No Preview ~ Previews are limited, but easy to apply charts and use undo as preview. + Comprehensive previews

User friendly data input and Smart Data Discovery (G8)	Ease of data Selection	- Selecting data attributes is complex and highly unintuitive. ~ Data selection takes practice but is quickly understood + Data selection is intuitive with (almost) no learning curve.
	Ease of data import (or connection to data source)	- Connection to data source is unintuitive (manually or programmatically) ~ Connection to data source is somewhat intuitive, but requires manual tasks. + Connection to data source is intuitive, minimal manual tasks.
	Supported Import Data Formats or sources	- Requires a very specific file format. ~ Supports common file types and databases. + Supports multiple file formats which can be freely integrated.
	Functions for data transformation	- Too few functions to cover all use cases. ~ Large set of predefined functions for different data types. + Diverse set of pre-defined formulas that are highly customisable.
	Versatility of Formula Application	- Formulas only ever apply to the entire data set. ~ Predefined limits and predicates may be set. + Limits and Predicates may be customised to user's needs.
	Smart Data Discovery	- None/ users need to manually categorise data. ~ Data types are automatically categorised and aggregated (dimensions and measure). + Data types are automatically categorised and aggregated new measures are automatically calculated.
	Merging and join	- Relationships between data tables need to be set manually. ~ Relationships between data tables are identified, can be linked and merged using predefined functions with a few clicks with no data preview. + Relationships between data tables are identified, is linked and merged automatically, providing flexibility to create relationships and queries from predefined functions or programmatically.
	Previews of data	- No previews are shown based on data selected. ~ Previews of data are shown, but no features to transform the data. + Previews of data are shown, with features to transform the data.
History tools and Annotations (G9)	Undo and redo	- Undo and redo is limited to certain tasks only (some tasks need to be redone from scratch). ~ Undo and redo can be used to recover to a previous state with a few clicks. + Advance version control options are incorporated to recover a previous state (in addition to undo and redo).
	History tools	- No histories are provided of analysis findings. ~ Limited history tools indicating visualisations and filters that have been used. + Advanced history tools to review, re-visit and retrieve previous analysis steps.
	Storytelling (update explanation with playback)	- No storytelling features are available. ~ Story telling features are static showing only the analysis steps and findings. + Storytelling features are interactive with story templates for playback features showing analysis steps, findings and explanations how to interpret results.
	Annotations	- Basic text boxes. ~ Textual annotations can be linked to multiple charts and data points. + Annotations with interactions (dynamic, time horizons, visual indicators, expand/collapse, linked on different granularity levels during drill-down).

Sharing and collaboration (G10)	Export dashboards	- Cannot export data or dashboards ~ Only supports few export variants + Support different export variants in interactive, graphical and textual formats.
	Dashboard sharing	- Cannot share dashboards ~ Dashboards can be shared freely + Dashboards can be shared with permissions (read/write/data access)
	Saving a dashboard or workbook	- Basic saving, but cannot be re-used or edited. ~ Saved as multiple formats and can be re-used or edited. + Saved as multiple formats and for re-use and editing on multiple devices.
Promote learning through explanations (G11)	Explanations for features	- No explanation ~ Reasonable explanations with tooltips, but limited cues how to use the feature. + Good explanations with tooltips for how to utilise the feature.
	Explanations for visualisations	- No explanation ~ Reasonable explanation about the visualisation, but not on the attributes used. + Good explanation, with cues how on to select appropriate data attributes.
	Built-in tutorials and demos	- No learning materials ~ Limited learning material such as sample workbooks. + Comprehensive learning materials such as demos, tutorials and samples.
Additional	Licence Availability (cost)	- No free licence s are available (product must be purchased - expensive) ~ Reasonably priced trial licence / needs to be purchased once + Extensive trial licence for evaluation 0 effectively free (generally in the form of academic licence for a few months)
	Commercial vs trial licence	- Trial licence includes only a few features. ~ Trial licence includes all features included in a commercial licence. + Trial licence includes all features in a commercial licence plus free support.

Appendix K: Statistics for the Final Evaluation with Tableau

Table A: Frequency distribution - Age group

18 -19 years	5	8%
20-24 years	45	70%
25-29 years	13	20%
30+ years	1	2%
Total	64	100%

Table B: Frequency distribution – Gender

Female	18	28%
Male	46	72%
Total	64	100%

Table C: Frequency distribution - Year of Study

2nd Years	35	55%
3rd Years	22	34%
H & M	7	11%
Total	64	100%

Table D: Frequency distribution - Years using a computer

<2 years	1	2%
2-4 years	8	13%
5-9 years	14	22%
10+ years	41	64%
Total	64	100%

Table E: Frequency Distributions: Experience Items (n = 64)

	Mean.	S.D	None		Low		Moderate		Moderately high	
Dashboards Experience	2.3125	88.86%	12	19%	25	39%	23	36%	3	5%
BI Tools Experience	2.0312	92.53%	21	33%	24	38%	16	25%	2	3%
Spreadsheet Tools Experience	4.0156	72.36%	0	0%	1	2%	13	20%	34	53%

Table F: Frequency Distributions: Tasks Completeness Items (n = 64)

	Mean	S.D.	Not Successfully		Successful, but with assistance		Successfully without assistance	
Task 1: Selecting a data source	2.90625	29.38%	0	0%	6	9%	58	91%
Task 2: Viewing market segments, adding calculations	2.859375	35.04%	0	0%	9	14%	55	86%
Task 3: Drill-down to sales per month	2.796875	44.29%	1	2%	11	17%	52	81%
Task 4: Annotating and sharing visualizations	2.84375	36.60%	0	0%	10	16%	54	84%
Task 5: Format colours, labels, size of visualisations	2.828125	38.03%	0	0%	11	17%	53	83%
Task 6: Using the Show me, search and filtering features	2.828125	41.99%	1	2%	9	14%	54	84%
Task 7: Creating a hierarchy for drill-downs	2.8125	46.72%	2	3%	8	13%	54	84%
Task 8: Integrating visualizations into a single dashboard	2.703125	55.43%	3	5%	13	20%	48	75%
Task 9: Creating a story.	2.71875	60.34%	5	8%	8	13%	51	80%

Table G: Frequency Distributions: Visibility Items (n = 64)

	Mean	S.D.	Strongly disagree		Disagree		Neutral		Agree	
The user interface is well-structured (worksheet, menus, icons, buttons, layout)	4.375	74.54%	0	0%	1	2%	7	11%	23	36%
The user interface was interactive.	4.375	80.67%	1	2%	1	2%	4	6%	25	39%
Information was easy to find onscreen.	3.90625	93.81%	1	2%	4	6%	13	20%	28	44%
The onscreen instructions are visible.	3.96875	79.62%	0	0%	1	2%	18	28%	27	42%
The system status was communicated adequately (loading, processing, idle etc.).	4.234375	83.08%	1	2%	1	2%	7	11%	28	44%

Table H: Frequency Distributions: Flexibility Items (n = 64)

	Mean	S.D.	Strongly disagree		Disagree		Neutral		Agree	
The system can be adjusted to suit individual needs (position of windows, menus, charts, filters, annotations etc.)	4.140625	88.85 %	0	0%	4	6%	9	14%	25	39%
It was easy to customise the dashboard (colours, size, labels, fonts etc.)	4.15625	85.85 %	0	0%	3	5%	10	16%	25	39%
It was easy to connect to a different data source (Excel, SQL server, etc.)	4.5	71.27 %	0	0%	1	2%	5	8%	19	30%
It was easy to select different data attributes (dimensions and measures)	4.53125	64.16 %	0	0%	0	0%	5	8%	20	31%
It was easy to manipulate data (add calculations or additional measures).	4.203125	73.85 %	0	0%	1	2%	9	14%	30	47%
It was easy to select alternative chart types	4.546875	75.45 %	0	0%	2	3%	4	6%	15	23%

Table I: Frequency Distributions: Learnability Items (n = 64)

	Mean	S.D.	Strongly disagree		Disagree		Neutral		Agree	
It was easy to learn the steps to create a dashboard	4.328125	90.95 %	1	2%	3	5%	4	6%	22	34%
It was easy to learn the features of the system.	4.171875	80.78 %	0	0%	3	5%	7	11%	30	47%
The terminology used in the system was easy to understand	4.03125	94.23 %	0	0%	6	9%	9	14%	26	41%

Table J: Frequency Distributions: Error control Items (n = 64)

	Mean	S.D.	Strongly disagree		Disagree		Neutral		Agree	
It was easy to recover from errors (undo, redo)	4.15625	108.70 %	2	3%	4	6%	9	14 %	16	25%
The system prevented me from making errors (applying undesired options, selecting inappropriate charts, etc.)	3.53125	112.64 %	3	5%	8	13%	20	31 %	18	28%
Making mistakes was not a problem knowing that I could learn from them (exploring how features worked)	4.15625	85.85 %	1	2%	2	3%	7	11 %	30	47%

Table K: Frequency Distributions: Helpfulness Items (n = 64)

	Mean	S.D.	Strongly disagree		Disagree		Neutral		Agree	
The system helped me to recover from errors (explanations, messages)	3.437	97.39%	1	2%	9	14%	25	39 %	19	30%
The system provided adequate help on demand (tooltips, explanations)	3.515	103.88%	3	5%	6	9%	21	33 %	23	36%
The automatic chart generations and suggestions were helpful	4.359	78.41%	0	0%	2	3%	6	9%	23	36%
The guided development process was helpful (select data source, querying, select data attributes, visual mapping, formatting views)	4.125	78.68%	0	0%	1	2%	13	20 %	27	42%
Adequate learning materials are provided in the system (tutorials, videos etc.)	3.453	105.30%	3	5%	7	11%	23	36 %	20	31%

Table L: Frequency Distributions: Operability Items (n = 64)

	Mean	S.D.	Strongly disagree		Disagree		Neutral		Agree	
I felt in control of the system	4.109375	79.92%	0	0%	2	3%	11	17%	29	45%
The system provided a rapid response rate	4.234375	81.15%	1	2%	0	0%	9	14%	27	42%
The system behaved consistently	4.4375	66.37%	0	0%	0	0%	6	9%	24	38%
I could easily create visualisations.	4.46875	64.16%	0	0%	0	0%	5	8%	24	38%
I could easily synthesise separate visualisations into a single dashboard.	4.328125	81.76%	0	0%	3	5%	5	8%	24	38%
It was easy to select measures and dimensions.	4.5	69.01%	0	0%	0	0%	7	11%	18	28%
It was easy to find information using search features (e.g. searching a country, dimensions, tables etc.)	4.328125	79.79%	0	0%	1	2%	10	16%	20	31%
It was easy to use the drill-down features	4.234375	77.14%	0	0%	0	0%	13	20%	23	36%
It was easy to filter visualisations	4.390625	63.29%	0	0%	0	0%	5	8%	29	45%
It was easy to sort the data.	4.4375	70.99%	0	0%	1	2%	5	8%	23	36%
It was easy to create a data story.	4.375	88.19%	1	2%	2	3%	5	8%	20	31%
It was easy to share the visualisations with peers (copy the visualisation).	4.4375	70.99%	0	0%	1	2%	5	8%	23	36%
I could create a dashboard in a reasonable amount of time	4.203125	80.04%	0	0%	2	3%	9	14%	27	42%

Table M: Frequency Distributions: Factors (n = 64)

	Very Negative [0 to 20)		Negative [20 to 40)		Neutral [40 to 60]		Positive (60 to 80]		Very Positive (80 to 100]	
Experience	1	2%	35	55%	26	41%	2	3%	0	0%
Tasks Completeness	0	0%	3	5%	18	28%	43	67%	0	0%
Visibility	0	0%	3	5%	18	28%	43	67%	0	0%
Flexibility	0	0%	1	2%	17	27%	46	72%	0	0%
Learnability	0	0%	4	6%	28	44%	32	50%	0	0%
Error control	1	2%	6	9%	30	47%	27	42%	0	0%
Helpfulness	1	2%	6	9%	35	55%	22	34%	0	0%
Operability	0	0%	1	2%	19	30%	44	69%	0	0%
Overall	0	0%	4	6%	19	30%	41	64%	0	0%

Table N: Central tendency & Dispersion: Factors (n = 64)

	Mean	S.D.	Minimum	Quartile 1	Median	Quartile 3	Maximum
Experience	35.73	13.19	13.33	26.67	33.33	41.67	80.00
Tasks Completeness	60.36	9.37	22.22	55.56	62.96	66.67	66.67
Visibility	63.44	13.22	20.00	59.00	64.00	72.00	80.00
Flexibility	66.93	11.00	33.33	60.00	68.33	76.67	80.00
Learnability	63.54	15.02	20.00	60.00	63.33	75.00	80.00
Error control	58.96	15.41	13.33	53.33	60.00	66.67	80.00
Helpfulness	55.56	13.73	16.00	48.00	56.00	64.00	80.00
Operability	66.90	11.31	36.92	59.62	69.23	76.92	80.00
Overall	62.55	10.98	32.26	56.33	64.09	70.39	80.00

Table O: Central tendency & Dispersion: Factors (n = 64)

	Mean	S.D.	Minimum	Quartile 1	Median	Quartile 3	Maximum
Experience	2.43	1.53	1.53	2.07	2.33	2.67	4.20
Tasks Completeness	3.41	1.37	1.89	3.22	3.52	3.67	3.67
Visibility	3.54	1.53	1.80	3.36	3.56	3.88	4.20
Flexibility	3.68	1.44	2.33	3.40	3.73	4.07	4.20
Learnability	3.54	1.60	1.80	3.40	3.53	4.00	4.20
Error control	3.36	1.62	1.53	3.13	3.40	3.67	4.20
Helpfulness	3.22	1.55	1.64	2.92	3.24	3.56	4.20
Operability	3.68	1.45	2.48	3.38	3.77	4.08	4.20
Overall	3.50	1.44	2.29	3.25	3.56	3.82	4.20

Table P: One-sample t-Tests: Factors (n = 64)

Variable	**Mean**	**S.D.**	**t**	**p (μ=3.4; d.f.=63)**	**Cohen's d**	**Conclusion**
Experience	2.79	0.66	-7.44	<.0005	0.93	Neutral
Tasks Completeness	2.81	0.28	-16.77	<.0005	2.10	Neutral
Visibility	4.17	0.66	9.34	<.0005	1.17	Positive
Flexibility	4.35	0.55	13.76	<.0005	1.72	Positive
Learnability	4.18	0.75	8.28	<.0005	1.03	Positive
Error control	3.95	0.77	5.69	<.0005	0.71	Positive
Helpfulness	3.78	0.69	4.41	<.0005	0.55	Positive
Operability	4.34	0.57	13.37	<.0005	1.67	Positive
Overall	4.13	0.55	10.60	<.0005	1.32	Positive

Table Q: Pearson Product Moment Correlations - Experience to Overall

	Experience	Tasks Completeness	Visibility	Flexibility	Learnability	Error control	Helpfulness	Operability	Overall
Experience	-	.213	.166	***.309***	.220	.273	.081	***.352***	.276
Tasks Completeness	.213	-	.261	***.575***	***.342***	***.421***	***.367***	***.592***	***.503***
Visibility	.166	.261	-	***.631***	***.737***	***.484***	***.651***	***.691***	***.841***
Flexibility	***.309***	***.575***	***.631***	-	***.662***	***.588***	***.539***	***.813***	***.834***
Learnability	.220	***.342***	***.737***	***.662***	-	***.608***	***.681***	***.612***	***.875***
Error control	.273	***.421***	***.484***	***.588***	***.608***	-	***.546***	***.554***	***.776***
Helpfulness	.081	***.367***	***.651***	***.539***	***.681***	***.546***	-	***.565***	***.808***
Operability	***.352***	***.592***	***.691***	***.813***	***.612***	***.554***	***.565***	-	***.833***
Overall	.276	***.503***	***.841***	***.834***	***.875***	***.776***	***.808***	***.833***	-

Table R: t-Tests: Factors by Year of Study - 2nd Years (n =35) vs 3rd Years & Post Graduate (n = 29)

Factor	Year of Study	Mean	S.D	Difference	t	d.f.	p(d.f.=62)	Cohen's d
Experience	2nd Years 3rd Years & PG	2.62 2.99	0.62 0.66	-0.37	-2.31	62	**.024**	**0.58 Medium**
Tasks Completeness	2nd Years 3rd Years & PG	2.77 2.86	0.34 0.19	-0.09	-1.23	62	.222	n/a
Visibility	2nd Years 3rd Years & PG	4.05 4.32	0.75 0.50	-0.28	-1.70	62	.094	n/a
Flexibility	2nd Years 3rd Years & PG	4.25 4.47	0.59 0.49	-0.22	-1.60	62	.115	n/a
Learnability	2nd Years 3rd Years & PG	3.95 4.45	0.79 0.61	-0.50	-2.76	62	**.008**	**0.69 Medium**
Error control	2nd Years 3rd Years & PG	3.75 4.18	0.82 0.64	-0.43	-2.31	62	**.024**	**0.58 Medium**
Helpfulness	2nd Years 3rd Years & PG	3.67 3.91	0.67 0.69	-0.24	-1.41	62	.162	n/a
Operability	2nd Years 3rd Years & PG	4.18 4.54	0.63 0.40	-0.35	-2.60	62	**.011**	**0.65 Medium**
Overall	2nd Years 3rd Years & PG	3.98 4.31	0.58 0.45	-0.34	-2.54	62	**.013**	**0.64 Medium**