MOBILE BUSINESS INTELLIGENCE SUCCESS

AN EMPIRICAL EVALUATION OF THE ROLE OF MOBILE BI CAPABILITIES

By:

Twan Peters

Tilburg University
The Netherlands, Tilburg

July 2013

Colophon

Title:	Mobile business intelligence success
Subtitle:	An empirical evaluation of the role of mobile BI capabilities
Author:	Twan Peters
ANR:	690841
University:	Tilburg University
Faculty:	School of Economics and Management
Department:	Information Management
Supervisor:	Dr. Hans Weigand
Organisation:	Capgemini Nederland B.V.
Supervisor:	Marco de Ruiter
Place:	Tilburg
Date:	July, 2013

MANAGEMENT SUMMARY

The term business intelligence (BI) is first mentioned and described by Luhn (1958). BI is a system comprised of both technical and organisational elements that presents historical and/or real-time information delivered to its user's with the objective of making effective business decisions and for the overall purpose of increasing organisational performance. BI is a critical foundation of competition for many organisations, and has consistently been ranked among the top two agenda items of senior IT executives over the last several years. However, not all BI initiatives have been successful. Failure occurs when organisations deploy BI solutions without having a clear understanding of the BI capabilities which are important to achieve a successful BI implementation result.

Recently, a new BI innovation has been developed. Rapid technological developments in the last decade have changed the capabilities of mobile devices enormously. This has enabled BI vendors to develop an extension of BI which is designed and optimised for smartphones and tablets. This extension is called mobile BI. Mobile BI enables decision makers to access BI anytime and anywhere to support their decision-making. Although there were high expectations of mobile BI, it has had a slower adoption rate than initially anticipated.

Currently, no research has been performed on the relationship between the mobile BI capabilities and its success rates. By not having a clear understanding of the capabilities, organisations can spend a lot of time and money on mobile BI without it contributing to organisational success. It can lead to undesirable consequences such as financial losses and dissatisfaction among employees.

In the last decade, many researchers have addressed different aspects of information systems (IS) success. DeLone and McLean (2003) have performed an extensive research to review these aspects, and as a result they have built an IS success model. In this study, the DeLone and McLean 2003 IS success model is adapted to provide a better understanding of mobile BI success by examining the impact of mobile BI capabilities and its success from the user's perspective.

The service construct is removed from the DeLone and McLean (2003) IS success model, and the model is extended with engagement, top management support, time since adoption and four separated system quality constructs instead of one system quality construct as originally defined. An online survey is used to obtain data and PLS path modelling has been used to analyse the relationships in the extended DeLone and McLean (2003) IS success model.

The outcome of the performed research suggests that the mobile BI capabilities; accessibility, flexibility, attractive interface design, ease of use and information quality significantly impact mobile BI success. Whilst flexibility may be the most importation mobile BI capability, user's should easily be able to modify their attractively designed mobile BI solution to their high quality information needs. They should also have an appropriate user access to the required information resources and should quickly and easily be able to access the required information anytime and anywhere. Improving these mobile BI capabilities influences the engagement, use and user satisfaction levels which explain the variance in the perceived net benefits. Mobile BI adoption in organisations has enabled individuals to present their arguments more convincingly, make higher quality, and faster decisions, as well as to increase their job effectiveness and reduce the costs of business processes. Results also suggest that organisations should provide top management support on mobile BI projects. Their support can significantly impact the perceived net benefits by motivating greater user participation, and they can insist on the use of information-based decision making.

PREFACE

When I started to write this master thesis, I defined three goals; completing the study Master Information Management at Tilburg University, conducting research in an interesting, new and 'trendy' subject and finishing this master thesis in 3-5 months as the Information Management program dictates. The first two goals were found to be feasible or realistic.

Writing this thesis has gone through its ups and downs, as probably every master student experiences. In the beginning especially there were obstacles in finding case study organisations in the Netherlands and/or Belgium. Therefore, I eventually had two options; changing my research method, or choosing another subject. However, for me, there was only one option, to conduct a mobile business intelligence study. I convinced my Capgemini supervisor that I was 100% sure that I could find enough respondents for a questionnaire, and that changing the subject was not at all necessary. Thus, I changed my research method from a qualitative to a quantitative research method. In truth I was not 100% certain of my convictions. In fact, it was a very risky challenge, as there are more blogs that write about mobile business intelligence than there are actual organisations using it, sorry Marco for doing that. In the end, I really enjoyed writing this master thesis. Sometimes you have the feeling that you deserve a Nobel prize for a simple statistical analysis that a fresher could have done, and at others you cannot stop thinking about a new strategy to overcome the obstacles that have arisen on your research path. I didn't succeed in writing this master thesis in 3-5 months, but I'm convinced that the extra time has resulted in a high quality study that can be put into practice.

The results of this master thesis would have been impossible without the participation of a number of persons. I would hereby like to thank everyone who helped me with my research or was somehow involved in it. More specifically, I want to thank my supervisor at Capgemini, Marco de Ruiter, who gave me the opportunity to write this thesis at Capgemini, and who gave me the freedom there to shape my own research. He was always available for help and inspiration and took care of all the contract extensions I needed. I also thank my supervisor at Tilburg University, Hans Weigand. He was always available to provide feedback whenever I needed and helped me to think about how to continue my research. I would also like to thank him for the numerous times that he had to convince organisations that I really was a master student who was conducting a mobile business intelligence study for his master thesis. Many thanks also to all the respondents who took the time and effort to complete the questionnaire. Without their help I would not have been able to finish this research, sorry for the endless remainders I sent for your participation in this research. And finally, I thank all of my friends, family and my girlfriend who provided support and encouragement during the writing of my master thesis. I hope that you will enjoy this thesis as much as I did.

Twan Peters
Milheeze, July 2013

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

LIST OF ABBREVIATIONS	
BI	Business Intelligence
CFA	Confirmatory Factor Analysis
DSS	Decision Support Systems
EFA	Exploratory Factor Analysis
ETA	Extraction Transformation Load
EUCS	End-user computer satisfaction
IT	Information Technology
IS	Information Systems
IQ	Information Quality
OLAP	Online Analytical Processing
OIP	Organisational Information Processing
PLS	Partial Path modelling
RIM	Research In Motion
ROI	Return On Investment
VIF	Variance Inflation Factor

1 INTRODUCTION

1.1 PROBLEM INDICATION

Today, information and knowledge represent the fundamental wealth of an organisation. Organisations try to utilise this wealth to gain competitive advantage when making crucial decisions. Striving to achieve a competitive advantageous position and enhancing the firms' performance relative to their competitors should be the main business objective for business organisations (Raduan, Jegak, Haslinda, & Alimin, 2009). Organisations need to know as soon as possible what has happened, and what is currently happening, in order to determine and influence what needs to happen in the future (Farrokhi & Pokorádi, 2012). Therefore, many organisations continue to increase their investment in implementing various types of information systems (IS) e.g. business intelligence (BI) systems. BI systems make it possible for an organisation to extract useful information from enormous amounts of data from numerous sources. Organisations need BI to improve their performance, profit and to stay competitive in today's highly aggressive business world. Over the last decade BI systems have evolved into critical systems in organisations to provide decision-makers with actionable information, delivered at the right time and the right place and in the correct form, enabling effective decisions (Ghazanfari, Jafari, & Rouhani, 2011; Ramakrishnan, Jones, & Sidorova, 2012; Viaene et al., 2009). In 2010 and 2011, BI topped the list of most important application and technology developments in an annual survey that was held under senior IT executives from over 600 respondents located in US, Europe, Asia and Latin America (Luftman & Zadeh, 2011; Luftman et al., 2012). Added to that, Forrester research shows that most organisations should focus their IT investment plan on BI (Evelson, 2011).

The current BI systems in most organisations are only available on desktop computers and/or laptops. Ten years ago, laptops, equipped with WiFi access were a boon to mobile productivity. Business travellers were able to access business intelligence and analytical functionality at locations outside of the organisation. Later, 3G USB sticks enabled laptop users to connect their laptop with the internet whilst they were on the move. However, that doesn't make the laptop an ideal travelling device for accessing BI systems; users have to boot up the laptop, which can take quite some time, and it is a relatively large device to carry around all the time. This doesn't increase the user satisfaction in using a BI system when being on the move. The more satisfied the user is, the more the BI system is used (Hou, 2012). With the increase in number and variants of mobile gadgets, both large and small organisations nowadays make extensive use of 'smart' devices such as smart phones and tablets. Compared to laptops, these devices are much more practical to carry around 24/7, anytime, anywhere. According to a survey among 768 IT professionals conducted by Dimensional Research (2012), 89% of IT professionals have mobile devices such as smartphones or tablets that are connected to corporate networks. Smart phones and tablets make it possible for employees to see and use important company data in a more revolutionary way. In 2003, Research In Motion (RIM) introduced its first BlackBerry smartphone, which enabled users to send and receive e-mail and text messages and use the internet to find and access data. Before the BlackBerry smart phone, systems could push data to mobile phones but the devices generally did not support anything beyond simple data alerts and basic displays. The BlackBerry was the first step to mobile business intelligence (mobile BI). Mobile BI could be defined as the extension of BI to smartphones and tablets. The development of mobile BI applications really improved with the introduction of the iPhone in 2007, the Android platform in 2007, and the iPad in 2010, together with a steady stream of technological advances in networks, memory and computing power for mobile devices (Stodder, 2012). Mobile BI is an emerging technology with high expectations. It has, according to a Dresner Advisory Services mobile BI study the highest priority in many organisations after email and personal information management applications (Dresner, 2011). Not only that, Gartner analysts believe that 33 percent of BI functionality will be utilised via handheld devices by 2013 (Tapadinhas, 2012). Mobile BI enables decision makers to access BI at anytime and anywhere to support their decision making. Although there were high expectations of mobile BI, it has had a slower adoption rate than initially anticipated (Dresner, 2011).

Despite interest and investments, not all BI initiatives are successful. BI success can be measured by an increase in organisations' profits, or enhancement to competitive advantage (Farrokhi & Pokorádi, 2012). Measuring the return on investment is a method that is sometimes used to measure BI success (Anderson-lehman, Watson, Wixom, & Hoffer, 2004). However, the return on investment of BI is often difficult to measure, because many benefits provided by BI are intangible and non-financial, such as improved decision-making and timely information. When these advantages transfer into financial benefits such as cost-savings or profit increase, the time lag between the actual production of intelligence and financial gain makes it difficult to measure the benefits of BI (Lönnqvist & Pirttimäki, 2006). Therefore, many organisations do not measure the benefits of their BI acquisition (Hannula & Pirttimaki, 2003). However, another approach to measure BI success is subjective measurement. Hou, (2012), Isık, Jones, & Sidorova, (2013) and Popovič, Hackney, Coelho, & Jaklič (2012) used subjective measurements to measure BI success and benefits. Subjective measurement enables researchers and organisations to understand the perceptions and the extent to which the user's realised their expected benefits with BI, and to investigate which BI capabilities are important to increase the perceived benefits. This enables organisations to take BI adoption decisions whilst having a clear understanding of the BI capabilities that define the success of BI systems from the user's perspective. It also increases the readiness of organisations to adopt BI which is a crucial element for a successful BI implementation (Farrokhi & Pokorádi, 2012). BI capabilities range from easy to use to flexibility in decision making support. Organisations that take advantage of these BI capabilities, have an increase in BI usage, and as a result the value derived from BI systems increases as well. They explain the BI success in an organisation (Isık et al., 2013). These capabilities are not researched for mobile BI. They could be different from BI, since the platform and devices differ from traditional BI. Mobile devices are easy to carry, have a smaller screen, provide a touch-screen interface and have lower performance and reduced memory, when compared to laptop and desktop computers.

1.2 PROBLEM STATEMENT

Failures occur when organisations make BI adoption decisions without having a clear understanding of the BI capabilities that define the success of BI (Isik, Jones, & Sidorova, 2011). At the present moment, no research has been performed on the relationship between the mobile BI capabilities and its success. By not having a clear understanding of these capabilities, organisations can spend a lot of time and money on mobile BI without it contributing to its' organisational success. It can lead to undesirable consequences such as financial losses and dissatisfaction among employees.

The success of Information systems depends on the system's user's. It is hard to deny the success of an information system whose user's say that they like it (DeLone & McLean, 1992). Decision makers have to use mobile BI in their decision making process before it can be successful. Subjective measurement based on the satisfaction of decision makers and their perceptions of the extent to which the expected benefits of BI were realised, indicate how effective BI is considered by its user's (Lönnqvist & Pirttimäki, 2006). Therefore we want to understand what the relationship between mobile BI capabilities and mobile BI success is from the user's perspective.

The results of this research allow organisations to better be prepared for implementing a mobile BI solution, since organisations can be made aware of the impact of mobile BI capabilities. Results also enable mobile BI vendors, like Capgemini, to improve the promotion of mobile BI solutions to potential customers.

1.3 RESEARCH QUESTIONS

The aim of the research is to investigate what the relationship between mobile BI capabilities and mobile BI success is from the user's perspective. There are three parts to solve in this research. (1) What are the mobile BI capabilities that can be measured from the user's perspective? (2) What is mobile BI success and how can it be measured from the user's perspective? (3) And what is the relationship between the first and second part?

1.4 SCOPE AND LIMITATIONS

This research focuses on the relationship between mobile BI capabilities and mobile BI success from the user's perspective. Not on organisational factors that may have an influence on mobile BI success, nor on how users use their mobile BI solutions; also not on the back end systems, and neither on financial methods to measure the benefits.

1.5 RESEARCH METHODOLOGY

In all academic studies, researchers need a strategy that guide them in development and execution of the scientific research, which is also known as research design or research strategy (Maimbo & Pervan, 2005). The research question to be answered is: What is the relationship between the mobile BI capabilities and mobile BI success from the user's perspective? This overall research question is a 'what' question. According to Yin (2003, p. 5) a survey or archival analysis is a suitable strategy for a research question that has a 'what' form. Secondly, Yin (2003, p. 7) states that when a 'what' question is to be the focus of study, a further distinction among survey and archival is the extent of the investigator's control over and access to actual behavioural events. To answer the research question of this study, it is not required to be able to have any influence to change the mobile BI solutions and to manipulate how users work with mobile BI solutions. Therefore, survey and archival are both possible. However, survey is the most practical choice, because archival requires access to computer files and records of organizations that are using of used mobile BI, which can be problematic due to privacy reasons and regulations. Thirdly, a survey is preferred when contemporary events are examined. For this study, mobile BI solutions will be examined, which is a recent innovation. Hence, a survey research strategy is preferred for this research, see table 1 (Yin, 2003, p. 5). Using a survey helps the researcher to gather information from a representative sample, and generalize those findings back to a population, within the limits of random error. Furthermore, a surveys' research is flexible, and can be used to reach respondents from a wide scope (Bartlett, Kotrlik, & Higgins, 2001a).

Table 1: Relevant situations for different research strategies

Strategy	Form of research question	Requires control of behavioural events?	Focuses on contemporary events?
Experiment	How, why?	Yes	Yes
Survey	Who, what, where How many, How much?	No	Yes
Archival analysis	Who, what, where How many, How much?	No	Yes/No
History	How, why	No	No
Case study	How, why	no	Yes

Source: Yin (2003, p. 5)

A research can be conducted as exploratory, descriptive or explanatory (Yin, 2003, p. 3). This research will be an explanatory research, because it is devoted to finding causal relationships amongst variables for example mobile BI capabilities with mobile BI success. Which is derived from theory-based expectations on how and why mobile BI capabilities should be related to mobile BI success. This research is not exploratory, because the objective is not to become more familiar with a topic, such as identifying problems that impede a successful BI implementation. This research is also not descriptive as the aim is not to describe a situation or context, such as e.g. documentation of the types of BI processes being used by small and large organisations (Malhotra & Grover, 1998).

Drawing on the research purpose, and based on the established arguments, this research begins with an explanatory literature review to theoretically answer the main research question. It ends with the empirical element, to test the theory-based expectations with the use of a survey.

Theory development

The data for the literature review has been collected by searching for relevant articles on all the available resources of Tilburg University and scientific search engines such as Science Direct and Google Scholar. Because there aren't at the present time any scientific studies of mobile BI available, use will also be made of mobile BI reports from research organisations such as Aberdeen, Dresner, Gartner, BeyeNETWORK and TDWI.

1.6 SCIENTIFIC AND SOCIETAL BENEFITS OF THE RESEARCH

This study is relevant for both researchers and (business) organisations. This study proposes to extend the current research in BI with a mobile BI study about the relationship between mobile BI capabilities and mobile BI successes on the individual level. The results of study allow organisations to better be prepared for a mobile BI implementation, as they are more aware of the mobile BI capabilities that are important for a successful mobile BI implementation. It may also help organisations to improve their mobile BI solution, in order to derive more value from their implementation. From a vendor point of view, for mobile BI vendors such as Capgemini, this research provides valuable information which can be used in promoting mobile BI to potential customers, and to improve already deployed mobile BI solutions. Results may help to increase the adoption rate of mobile BI.

1.7 THESIS OUTLINE

This study starts with a review of current literature. Chapter 2 gives a definition of BI and mobile BI, describes what mobile BI is and how (mobile) BI improves decision-making. Chapter 3 discusses the DeLone and McLean 1992 and 2003 information systems success framework. The relationships between mobile BI capabilities and mobile BI is discussed in chapter 4, and ends with a conceptual model and proposed hypotheses.

Chapter 5 and 6 represent the empirical part of the research, wherein chapter 5 contains a description of the research design and survey methodology. Chapter 6 describes the data screening, validity and reliability measures, and the outcome of the hypotheses analysis.

Chapter 7 gives an interpretation of the results discussed in chapter 6, and the limitations of the study as well as its implications for both managers and academics. Recommendations are provided for future research directions to be conducted in the BI field.

2 BUSINESS INTELLIGENCE

This research investigates the relationship between mobile BI capabilities and mobile BI success from a user's perspective. It is, therefore, important to know more about BI in general and mobile BI in particular. Section 2.1 defines BI from various perspectives, resulting in a definition that will be used in this research. The definition of BI will then be used as a basis to define mobile BI in section 2.2. Which in turn is followed by a discussion about the primary purpose of BI and mobile BI in organisations in section 2.3. This chapter ends with a short conclusion in section 2.4.

2.1 BUSINESS INTELLIGENCE

The term business intelligence is first mentioned and described by Luhn (1958). Luhn described BI as a system that is designed to disseminate information to various sections in an organisation (Luhn, 1958). Nowadays, BI has various definitions in the science and professional literature. In European literature, BI is considered as a broad umbrella concept for competitive, market, customer, competitor, strategic, and technical intelligence (Lönnqvist & Pirttimäki, 2006). In the academic literature, some researchers approach BI from a more technical point of view, others define BI as a holistic and sophisticated approach to cross-organisational decision support. Table 2 provide some of the BI definitions.

Table 2: BI definitions

BI Definition	Author(s)	Definition Focus
Organized and systemic processes which are used to acquire, analyse and disseminate information to support operative and strategic decision making.	Hannula & Pirttimaki (2003)	Technological
A system that combines data collection, data storage and knowledge management with analytical tools so that decision makers can convert complex information into competitive advantage.	Negash (2004)	Technological
The ability of an organisation or business to reason, plan, predict, solve problems, think abstractly, comprehend, innovate and learn in ways that increase organisational knowledge, inform decision processes, enable effective actions, and help to establish and achieve business goals	Popovič et al. (2012)	Organisational
A managerial philosophy and tool that helps organisations manage and refine information with the objective of making more effective decisions	Pirttimäki & Lönnqvist (2006)	Organisational
An umbrella term for decision support.	Alter (2004)	Organisational
Results obtained from collecting, analysing, evaluating and utilising information in the business domain.	Chung et al. (2004)	Organisational

Even the BI term has been defined from several perspectives, the most BI definitions share the same referent, they all include the idea of analysing data and information, which eventually is used to enhance organisational decision-making. Isik et al. (2011) combined several technological and organisational BI definitions into one BI definition. This definition will be used in this study as definition of BI. Isik et al. (2011) defined BI as 'a system comprised of both technical and organisational elements that presents historical and/or real-time information delivered to its users with the objective of making effective business decisions and for the overall purpose of increasing organisational performance'.

Decision Support Systems
BI is often used as a synonym for decision support system (DSS), and vice versa. However, are they the same? DSS's are designed to assist a decision maker with systematically analysed complex semi-structured decision problems. By integrating complex mathematical models into user-friendly software that is able to transform business data into numerical and graphical reports, a DSS alleviates cognitive limitations that may restrict and bound a decision makers ability to make rational decisions (Lilien et al., 2004; Williams et al., 2007).

Early DSSs were typically a single solution, they supported a particular decision making process for a particular part of an organisation. The underlying data was specific to the application and the user interfaces were often customized for a particular purpose. In a later stadium, more data sources were used for one single decision support solution. That was difficult because there was no uniform or integral view on the data. This is the point when BI was introduced. BI made it possible, with data warehouses and analytical tools, to integrate and analyse the growing accumulation of organisational data whereby the centre of the architecture represents integral data sources and analytical decision-taking. This data oriented approach enables a DSS to provide a uniform and integral view on the data (Frolick & Ariyachandra, 2006), and which makes BI an area of the current DSS's, BI is just another phase in the progression of DSS (Khan, 2012). However, not all researchers agree with this description. Negash (2004) describes BI as a natural outgrow of a series of previous systems that were designed to support decision making, and pointed out that DSS is just one of these systems. According to Negash (2004), BI is a term that has replaced decision support systems, executive information systems and management information systems. This suggests that BI is not the exactly the same as DSS, but that they are very closely related to each other.

2.2 MOBILE BUSINESS INTELLIGENCE

Mobility is certainly the most visible, if not the most important computer technology development in the first part of this century. Research in Motion (RIM) introduced the first BlackBerry smartphone in 2003, which enabled users to send and receive e-mail and text messages and to use the internet to find and access data. This area of smart phones enabled BI software vendors to create analytical applications that could run on BlackBerry smart phones and competing devices. It was the first step to mobile business intelligence (mobile BI), using BI applications that are designed and optimised for mobile devices such as smartphones and tablets (not laptops) (Stodder, 2012). These systems have to be able to produce BI content that delivers the touchscreen experience, whilst minimising the drawbacks of smaller screens, low performance and reduced memory, and that can also take advantage of some of the unique capabilities of mobile devices such as location awareness (Tapadinhas, 2012). Therefore, for the purpose of this study, the BI definition of Isik et al. (2011) is used to define mobile BI:

Mobile BI refers to a system comprised of both technical and organisational elements that presents historical and/or real-time information to its user's for analysis on mobile devices such as smartphones and tablets (not laptops), to enable effective decision making and management support, for the overall purpose of increasing organisational performance.

The development of mobile BI applications really improved with the introduction of the iPhone in 2007, the Android platform in 2007, the iPad in 2010 (tablet), and the steady stream of technological advances in networks, memory and computing power for mobile devices. Even though organisations have a longer history with RIM smartphones, at the present time there are more plans to establish a mobile BI platform for Apple and Android products than for RIM products (Stodder, 2012). The increasing technological capabilities of mobile devices are a major factor in the evolving process of mobile BI applications. Mobile BI applications are constantly evolving as mobile BI vendors gain experience in mobility (Tapadinhas, 2012). Tapadinhas (2012) categorised the most important characteristics of the current mobile BI solutions into seven categories in a Gartner report, see table 3.

Table 3: Mobile BI characteristics

Categories	Sub categories
Information display and interaction	Rich visual experience, touchscreen experience, responsiveness, ease of use dashboards.
Information exploration	Guided information exploration, table manipulation, manipulation of graphical visualisations, map manipulation (such as drilling down into the underlying levels of data), report development on the device.
Analytics	Ad hoc information exploration, packaged analytics, scenario simulations, analytic model development on the device.
Context awareness	GPS integration, camera integration, voice integration, sensor integration.
Offline mode exploration	Offline information navigation, automatic information download, on-demand information download.
Rich application functionality	Collaboration features, alert features and multimedia support.
Multiple device support	Apple, Android, Blackberry, Microsoft.

Source: Tapadinhas (2012)

The current mobile BI solutions have a rich, interactive touch-centric and screen form factor friendly user interface (Tapadinhas, 2012). We have selected a few examples of Roambi mobile BI solutions, see figure 1, to give a broader understanding of how mobile BI looks.

Figure 1: Mobile Business Intelligence. Source: Roambi.com

Mobile BI applications can be split into three technological categories, (1) native applications (2) Web-based solutions and (3) hybrid solutions; rendering HTML content inside a native application container and behaving largely like their web-based counterparts (Tapadinhas, 2012; Stodder, 2012). Native applications open up the full functionality of the device and the operational system of a mobile device. The mobile BI application on mobile devices can take full advantage of native navigation controls, touchscreen/gesture capabilities, unique graphics/screen solution, connectivity, security and features for mixing different types of content and data that may not be available for web-bases solutions. Stodder (2012) argues that native applications are proving the most popular solution because they provide users with everything that the device has to offer. However, he also states that the downside for native applications is that expertise is also needed to develop, maintain and enhance applications running on each mobile device. Also, mobile devices vary in how they handle security, which is a critical issue whenever data is involved. Stodder (2012) states that when more organisations choose to make 'write once, deploy anywhere' a high priority, hybrid solutions will likely evolve as the main alternative to fully native applications and web-based solutions. Hybrid solutions use standards as HTML 5 and run primarily as embedded browser components. However, the reviewed organisations of Stodder (2012) are not confident in the maturity of HTML 5 to employ it for all BI and analytical applications. Therefore, time will tell which solution will become eventually the standard for mobile BI applications.

Any Time, Anywhere

Probably the biggest advantage of mobile BI compared to BI is that users can access BI information any time, and anywhere. By any time and anywhere we mean in a situation where the mobile BI solution can make use of the mobile connectivity, or supports an offline information navigation capability. This enables executives, field employees, sales people etc. to access the latest information (with the exception of offline solutions), monitor events, keep track of key performance indicators and receive alerts at any hour and/or location (web-based solutions always need a wireless data connection) (Watson & Leonard, 2011). A more practical example is that executives can use mobile BI to understand the company's current sales, profitability and performance trends over time (Watson, Wixom, & Bruce, 2013). Store managers can receive current sales results for theirs' and other stores in the region on their mobile device, enabling them to adjust their decisions about best sellers, floor displays and inventory to match current demand, all whilst walking around the shop floor, or travelling between stores. Furthermore, sales personnel can immediately access customer data, to show them how products and services could enable them to save or make money, without opening their laptop (Stodder, 2012).

Data security

The negative part of mobile BI is that users can easily lose their mobile devices, or their mobile devices could be stolen. Data security is then also an important part of mobile BI. According to Stodder (2012) it's one of the first cautionary notes about mobile BI. Data security is not only an important, but also a subject also a complex subject of mobile BI. Stodder (2012) divided mobile BI security into three levels which explains why it is so complex.

1. Mobile devices can be lost or stolen. Organisations have to take measures to protect the data on mobile devices from unauthorised access. In general mobile devices have their own embedded or operational system-level security features (Stodder, 2012). However, as security controls have an impact on the ease of use of the mobile BI solution, a balance should therefore be found between the risks and the security controls (Watson, Wixom, & Bruce, 2013).
2. Measures have to be taken to project the data transmission to and from the mobile devices. Data transmission can be protected by Secure Socket Layer protocols, encryption virtual private networks, lightweight directory access protocol directories etc.
3. The database where the data resides has to be protected against unauthorized access, extraction, replication etc. Organisations should address specific regulatory or privacy policies.

Three levels, and each one has different methods to protect the data. Co-ordinating the policies and technological implementation can be a difficult part of mobile BI (Stodder, 2012).

Architecture & infrastructure

Because of the characteristics of the mobile devices, the mobile BI infrastructure design and architecture differs from traditional BI. Yamakami (2008) states that the challenges for software engineers to cope with the characteristics of mobile devices can be arranged into three categories; constraints, diversity and changes. Constraints are the limited hardware characteristics such as minimal storage, battery, CPU power, display size and so forth. However, we must note that Yamakami discussed these constraints in 2008; currently, in 2013, a lot of these hardware characteristics have improved. However, a laptop is obviously more powerful. The screen size of a tablet and smartphones is small compared to laptops or desktop monitors. This limitation affects not only the software engineers, but also the organisations. Organisations have differing requirements, and they need to reconsider how some reports and charts are configured (Stodder, 2012).

Alongside diversity, there is not only one platform for mobile BI systems such as Windows for BI, but there are four different platforms for mobile devices; iOS, Android, Windows Phone and BlackBerry OS. This can be challenging for software engineering in terms of coding and testing. Yamakami (2008) argued that due to rapid changes in hardware, software and networking, it is difficult to design the mobile BI architecture.

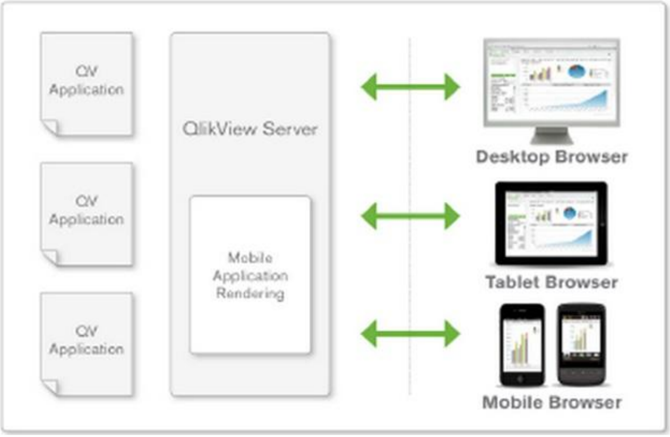

Figure 2: Qlikview architecture. Source: QlikTech UK (2011)

Although there are a lot of challenges to overcome in developing a mobile BI solution, there are at the moment many mobile BI solutions. Tapadinhas (2011) classified the mobile BI solutions into two groups; BI platforms and Information aggregators. Tapadinhas (2011) categorised the mobile BI vendors under the 'BI platforms' who have been delivering traditional BI, without mobility capabilities, and who are now making mobile BI solutions available, often integrated into the existing server infrastructure. Qlikview and MicroStrategy are two examples of BI vendors that also have a mobile solution, and where the mobile solution is integrated in the BI server. See figure 2 and 3 for an overview of the mobile BI architecture of Qlikview and MicroStrategy, both mobile BI services are in the main BI server integrated. Mobile BI vendors in the 'Information aggregators' are vendors that draw most of their value from solutions that are capable of connecting to existing BI platforms from other vendors, and (just as traditional vendors do) to other sources such as online analytical processing (OLAP) cubes, databases or flat files, rendering BI content to mobile devices. Tapadinhas (2011) argued that some of them are newcomers to the BI space, acting as pure mobile BI vendors. An example of an 'Information aggregator' is CompentArt. It only has a mobile BI server that is directly connected to the data sources and mobile devices, without a server for traditional BI; BI on desktop/laptops, see figure 4.

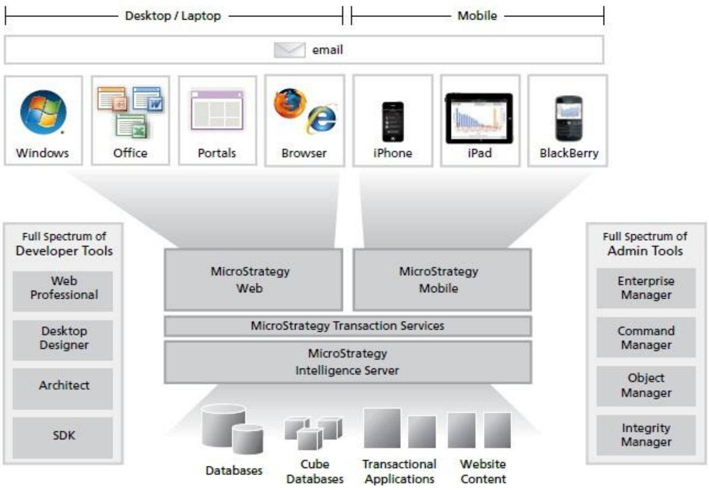

Figure 3: MicroStrategy architecture. Source: MicroStrategy (2011)

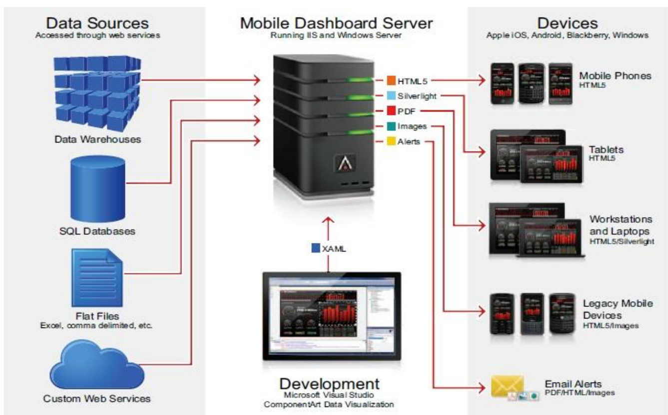

Figure 4: CompentArt architecture. Source: ComponentArt (2012)

2.3 DECISION MAKING

BI has the capability to collect, organise and analyse information from enormous amounts of data from different sources. With this capability, organisations are using BI to provide timely and superior information that enables them to analyse trends in market share, changes in customer behaviour and spending patterns, customer preferences, company capabilities and market conditions. For example, sales people need to have knowledge of market conditions, competitor offerings and special offers; BI can be used to gain this kind of knowledge. Furthermore, it helps analysts and managers to determine which adjustments are more likely to respond to changing trends. It has emerged as a concept for analysing data with the purpose of supporting decision makers with a more comprehensive knowledge of an organisation's operations which enables them to make more informed business decisions (Khan, 2012). BI is then also meant for all three levels of decision making within an organisation: strategic, tactical and operational (Negash, 2004).

On a strategic level, BI makes it possible to set objectives precisely and to follow realization of such established objectives. BI provide information in support of strategic decision related to the development of future results, based on historical performance, competitors, profitability of offers etc. (Olszak & Ziemba, 2007).
On a tactical level, BI provide information to support decisions that are related to planning and rely on real-time data and forecasting, to direct the future actions of marketing, sales, finance and capital management (Olszak & Ziemba, 2007).
On a operational level, BI support decisions that are related to the on-going operations of an organisation. These decisions are generally based on up-to-date financial data, sales and co-operation with suppliers and customers (Olszak & Ziemba, 2007).

Every decision has its own information requirements. According to Galbraith (1974), specific structural characteristics and behaviours can be associated with information requirements. Galbraith (1974) has proposed an Organisational Information Processing (OIP) theory, whereby organisations are structured around information. He uses the model to explain why organisations process information. The OIP theory identifies three concepts; information processing needs, information processing capability, and the fit between them to obtain the best possible performance in an organisation (Galbraith, 1974; Premkumar & Ramamurthy, 2005). In the OIP theory by Galbraith (1974), the amount of information that is needed by the decision makers to execute a task is explained with uncertainty. Uncertainty is the difference between information acquired and information needed to complete a task. Task characteristics, task environment and task interdependence are among the sources of uncertainty (Galbraith, 1974; Isik et al., 2013). Daft and Macintosh (1981), suggest that organisations not only process information to reduce uncertainty, but also to reduce equivocality. Equivocality can be described as multiple interpretations of a situation, which results in a messy, unclear field. A situation where new data may be confusing, and may even increase uncertainty. Hence, new data does not clarify anything when the equivocality is high. High equivocality means confusion and lack of understanding. In other words, decision makers reduce equivocality by defining an answer. However this answer is not 'totally' based on the processed data, because they do not clearly understand what it means or how to use it. For example, a problem may be perceived differently by managers from different functional departments in an organisation; an accounting manager may interpret specific information differently than a systems analyst. Both uncertainty and equivocality impact information processing in an organisation and should be minimized to achieve performance (Daft & Lengel, 1986; Daft & Macintosh, 1981). BI can be referred to as an 'uncertainty reduction process', which consists of increasing information-processing capabilities. As information increases, uncertainty decreases (Blanco & Lesca, 1998). Uncertainty exists in every business decision (Hostmann et al., 2007), and BI helps the decision maker to reduce that doubt. Minimising uncertainty results in better decisions. It is not surprising that most of the BI users value the BI capabilities that allow them to deal with uncertainty and changes in the environment (Isik et al., 2013). The advantage of mobile BI is that it not only helps the user to make better decisions, it also helps the user to make them more quickly than with traditional BI. Mobile BI has the advantage that users can make decisions anytime and anywhere. Which would suggest that mobile BI users can make decisions faster than BI users. Borg & White (2012) compared in an Aberdeen study, the characteristics and performance of 68 organisations that were using mobile BI against data collected from 132 organisations that were not using mobile BI. They concluded that managers in organisations using mobile BI were able to make decisions in almost one-third of the time that it takes managers not using mobile BI, see figure 4, and that the majority of the participants were users that were time-sensitive, who needed information within the hour, see figure 5. Borg & White (2012) argue that mobile BI puts information at the fingertips of front-line personnel anytime, anywhere, to make operational decisions that keep the organisation running smoothly without stalling. It enables them to make informed decisions in lost minutes between meetings and appointments, or even in furtive moments during them. However, Borg & White (2012) did not specify on which kind of decision making level the managers are working that completed their survey. There could be an improved decision time difference between for example mobile BI users on strategic or operational level. Especially highly mobile employees such as sales representatives require an on-the-go instant access to BI to be able to make informed decisions (Watson et al., 2013). Furthermore, in another research report Aberdeen, Lock (2012) concluded that 66% of the business managers found their ‘decision-window’ shrinking in 2011. This conclusion was based on 293 executives across the globe. It indicates that the timeframe a manager has to respond after business events have occurred, is getting steadily shorter, which could explain why mobile BI users need more information within the hour in order to make improved and faster decisions.

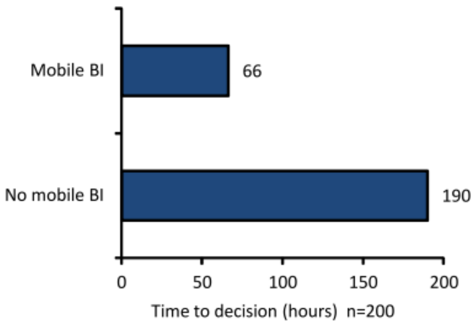

Figure 4: Faster decisions. Source: Borg & White (2012)

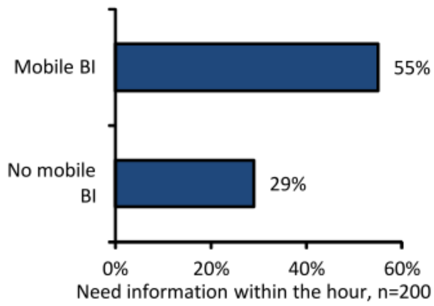

Figure 5: Time-Sensitive. Source: Borg & White (2012)

2.4 CONCLUSION

A BI system consist of both technical and organisational elements that presents historical and/or real-time information delivered to its users with the objective to support and improve decision making and for the overall purpose of increasing organisational performance. It has emerged as a concept for analysing data with the purpose of supporting decision makers with a more comprehensive knowledge of an organisation’s operations that enables them to make effective business decisions. It reduces the uncertainty in the decision making process. BI can be used for operational, tactical and strategic levels in an organisation. The difference between BI and mobile BI, is that for the technological part, mobile BI is optimized to work on smartphones and tablets, where BI works on a laptop or desktop computer. Mobile BI enables decision makers to access their mobile BI solution anywhere and anytime, which gives them the freedom to access required information whenever and wherever needed to make informed decisions.

3 INFORMATION SYSTEMS SUCCESS

The success of BI is the positive value an organisation obtains from its BI investment. BI success may represent benefits such as improved efficiency, reduced costs and improved profitability (Isik et al., 2013). Although the BI concept was first introduced in 1958, there is still a lack of research in the success of BI (Isik et al., 2013). However, BI is a class of information systems (IS), and in the IS area there is more research conducted about assessing IS success (Chau, Kuan, & Liang, 2007). As DeLone & McLean (1992) state, there are nearly as many measures as there are studies about the measuring of IS success, but there is no ultimate definition. Many of those measures are difficult to use and as a result, much of the work on IS success has focused on system use as a proxy for IS success (Dedrick, Gurbaxani, & Kraemer, 2003; Gordon, 1999; Information, 1988; Sabherwal et al., 2006).

If one the objectives of this study is to understand mobile BI success, it is important to understand the research that has previously looked at models and measures of IS and/or BI success to understand its' relevance and potential usage for this study. However, DeLone and McLean (1992 & 2003) have already done that. DeLone and McLean (1992) evaluated nearly 200 articles that included some measures of IS success. DeLone and McLean (1992) used their extensive research to build an IS success model and updated that model in 2003. Which makes the relevance questionable to study all those IS success models and measures again, while DeLone and McLean (1992 & 2003) already have done that, and used it as a basis for their IS success model. However, that doesn't mean that the DeLone and McLean (2003) IS success model is the right model to choose, and if the model is valid. Therefore, we discuss in this chapter the DeLone and McLean 1992 and 2003 IS success models in order to conclude if they can be used for this study.

3.1 DELONE AND MCLEAN IS SUCCESS MODEL

In the nineties attempts to define information systems (IS) success were ill-defined due to the complex, interdependent and multi-dimensional nature of IS. To address this problem DeLone and McLean (1992) performed a review of articles published during the period 1981 – 1987, and created, based upon this review a taxonomy of IS success (Petter & McLean, 2009). The DeLone and McLean (1992) model of IS success is a widely adopted, cited and criticised model (Delone & McLean, 2003; Lee & Chung, 2009; Seddon & Kiew, 1996; Wang & Liao, 2008). DeLone and McLean (1992) proposed, but did not empirically test a six-factor IS success model as a taxonomy and framework for measuring the complex dependent variables in IS research. The model emphasises the understanding of the connections between the different constructs of IS success. The six interrelated factors of success are; (1) system quality (2) information quality (3) use (4) user satisfaction (5) individual impact and the final factor, (6) organisational impact, see figure 5 (Delone & McLean, 1992).

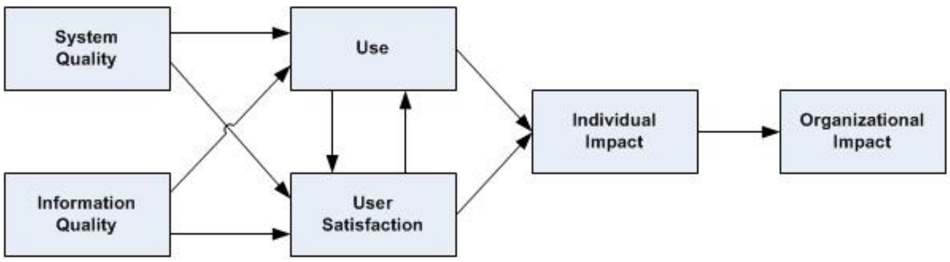

Figure 5: Information Success Model. Source: Delone & McLean (2003)

DeLone and McLean (1992) suggested that while many researchers used a single criterion, or just a few criteria's, one must understand all six constructs in order to effectively measure the success of an information system. System quality and information quality affect both use and user satisfaction, each being antecedents of individual impact, and this individual impact should ultimately affect the organisational impact. System quality refers to the technical measures such as reliability of the IS, response time, usability, adaptability and availability. Information quality refers to the level of the IS output in terms of accuracy, timeliness, accessibility and adaptability. System quality and information quality affect both use and user satisfaction. Use is measured in terms of queries by time, connected time and number of IS functions utilised. User satisfaction refers to measuring how information affects the user. Use and user satisfaction are both antecedents of individual impact, which deals with how the IS modifies the user experience with the system. Individual impact should ultimately affect the final construct; organisational impact. This contains measures about how the system and the information provided influence the organisation (DeLone & McLean, 1992). The DeLone and McLean (1992) IS model make two important contributions to the understanding of IS success. Firstly it provides a scheme for categorising the multitude of IS success measures which have been used in the research literature. Secondly, it suggests a model of temporal and causal interdependencies between the categories (Wang & Liao, 2008). Since DeLone & McLean 1992 proposed their IS success model, a number of studies have undertaken empirical research to test this model. Seddon & Kiew (1996) replaced 'use' with 'usefullness' and added a new component called 'user involvement' to the model. Their results partially supported the DeLone and McLean's (1992) IS success model. Seddon (1997) was among the first to test the model and proposed an adapted DeLone and McLean's (1992) model. Seddon (1997) also claimed that IS use is a behaviour pattern rather than a success measure, and replaced the 'use' factor with perceived usefulness. Rai, Lang, & Welker (2002) empirically and theoretically assessed DeLone & McLean (1992) and Seddon's (1997) IS success models in a quasi-voluntary IS context. They concluded that both models had an exhibited reasonable fit with the collected data; however, the DeLone and McLean (1992) IS success model outperformed the model of Seddon (1997). Furthermore, McGill & Hobbs (2003) adapted the Delone & McLean (1992) model in an user-developed application domain and concluded that the model was only partially supported by their data. Of the nine hypothesised relationships tested, only four were found to be significant: Information Quality → User Satisfaction, System Quality → User Satisfaction, User Satisfaction → Intended Use, and User Satisfaction → Individual impact. This paradox is repeated throughout other studies that attempted to validate the model; some studies found significant relationships while others did not.

After ten years of validation attempts and criticism, DeLone and McLean (2003) updated their model with several changes, such as (1) adding a third construct called 'Service Quality', to the two original system characteristics, 'system quality' and 'information quality' see figure 6.

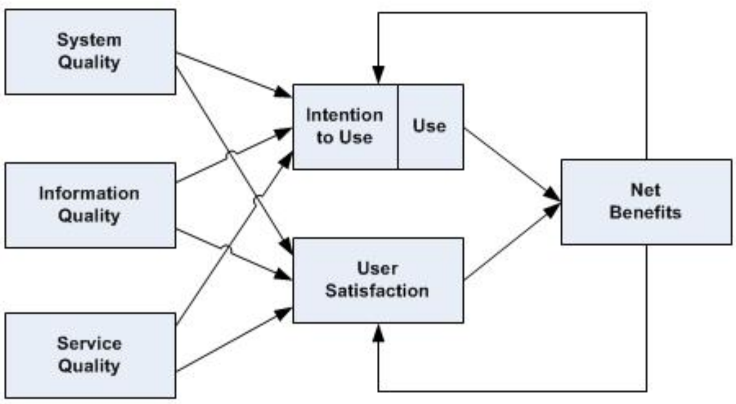

Figure 6: Information Systems Success Model. Source: Delone & McLean (2003)

Service quality was added because the changing nature of IS requires the service quality to be assessed when evaluating IS success. They described service quality as the overall support delivered by the service provider. Other changes were (2) adoption of 'intention to use' with the construct 'use' and (3) 'individual impact' and 'organisational impact' are grouped into a single measure called 'Net benefits'. Net benefits is the final success construct in the updated DeLone and McLean (2003) model. It refers to the impact of a system at an operational or organisational level. According to the authors, net benefits are the most important success measures as they capture the balance of positive and negative impacts of IS. Net benefits and the other constructs are context specific. This means that the items of the constructs depend on the type of IS that is being measured and the stakeholder to whom the benefits are being measured. Different types of IS require specific success measures (Delone & McLean, 2003). Furthermore, a feedback loop from (4) "Net Benefits" to "Intention to use/Use" and "User Satisfaction" was added. The feedback loops reflects the continuation or discontinuation of use and user satisfaction of an information system, as influenced by the net benefits. They explained that the arrows demonstrate associations amongst constructs in a process sense. Finally, (5) the researchers clarified that, in a processional sense 'use' must precede 'user satisfaction'. A positive experience with 'use' will lead to greater 'user satisfaction', and similarly, increased 'user satisfaction' will lead to an increased 'intention to use' which ultimately will increase 'use', and, as a result, certain 'net benefits' will occur (Delone & McLean, 2003). In the end, the model of DeLone and McLean (2003) suggests that the use of an IS, and user satisfaction with that IS leads to net benefits attributed to that system, which explains the success of an IS. It states that the antecedents to intention to use and satisfaction are information quality, system quality and service quality. DeLone and McLean (2003) argued that the three quality constructs have different weights, which depend on the context and application of the model. To measure the success of a single IS system, information quality and system quality may be the most important quality constructs. However, to measure the overall success of the IS department, service quality, may become the most important quality construct (Delone & McLean, 2003).

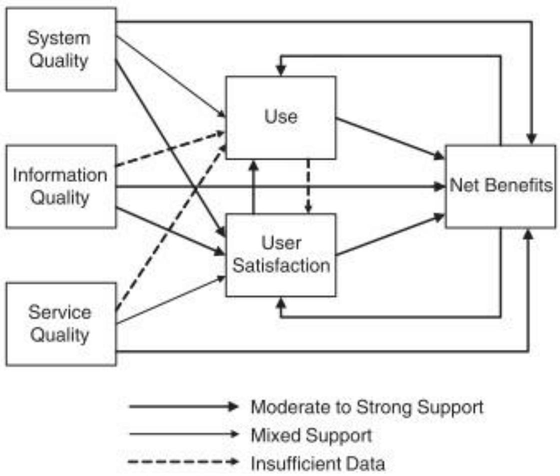

Figure 7: Support for interrelationships between D&M success constructs at an individual level of analysis. Source: Petter et al. (2008)

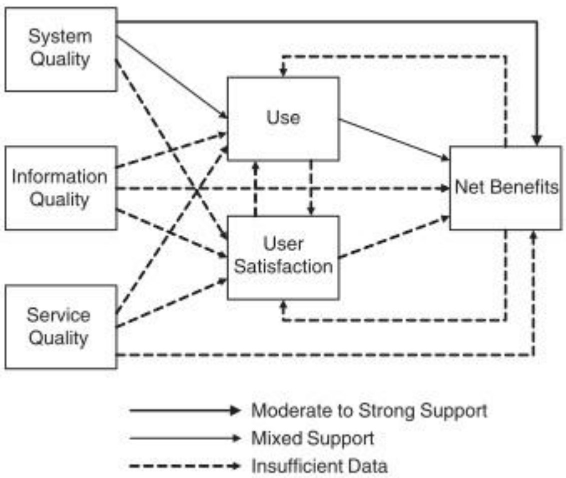

Figure 8: Support for interrelationships between D&M success constructs at an organisational level of analysis. Source: Petter et al. (2008)

Petter et al. (2008) studied the updated DeLone and McLean (2003) IS success model. They used a qualitative literature review and examined 90 empirical studies that were published in the time period 1992 – 2007, and reported only empirical results, both quantitative and qualitative studies of interrelationships among the DeLone and McLean success dimensions. Petter et al. (2008) analysed the model at both the individual and organisational contexts. They found significant results at the individual level of analysis for all the relationships in the model except for System Quality → Use and Service Quality → User satisfaction, see figure 7. These are different when compared to the organisational level of analysis. The researchers did only find a significant relationship between 'system quality' and 'net benefits', see figure 8. Because of the insufficient data, Petter et al. (2008) could not analyse the rest of the relationships in the DeLone and McLean (2003) IS success model at the organisational level.

Pérez-Mira (2010) extended the research of Petter et al. (2008) at the organisational level. Pérez-Mira (2010) applied the DeLone and Mclean model in the E-commerce environment. They gathered website features from 448 top retailers, categorised them according to DeLone and Mclean's taxonomy, and introduced them as the independent variables in their model. Pérez-Mira (2010) tested 12 hypotheses, three of these hypotheses are an extension of the original model, namely three direct paths from all three qualities to net benefits, which was also done by Petter et al. (2008). Of the twelve hypotheses, only six were found to be significant, and two hypotheses were direct relationships between qualities and net benefits, see table 4. Interesting is that none of the three qualities, (information quality, system quality and service quality), affect user satisfaction significantly. That is also the case between satisfaction and net benefits. Pérez-Mira (2010) argued that it is difficult to find a good surrogate for satisfaction because the construct is so closely related to individual perceptions and individual behaviours. They also questioned who is satisfied at the organisational level and how an organisation may be satisfied.

Table 4: Summery of hypothesis testing of the DeLone and McLean model at the organisation level.

Hypotheses		Result
H1. Use	← System Quality	Strong support
H2. Use	← Information Quality	Not Significant
H3. Use	←Service Quality	Strong support
H4. Satisfaction	←Use	Moderate support
H5. Net Benefits	←Use	Strong support
H6. Net Benefits	←Satisfaction	Not Significant
H7. Net Benefits	←Information Quality	Moderate support
H8. Net Benefits	←System Quality	Strong support
H9. Net Benefits	←Service Quality	Not Significant
H10. Satisfaction	←Information Quality	Not Significant
H11. Satisfaction	←System Quality	Not Significant
H12. Satisfaction	←Service Quality	Not Significant

Source: Pérez-Mira (2010)

Petter and McLean (2009) empirically evaluated the strength of the relationships within DeLone and McLean's (2003) model at the individual level of analysis, using the quantitative method of meta-analysis. Petter and McLean (2009) aggregated the results of 52 empirical studies that were published in the time period 1992 to mid-2007, and that examined the relationships between the IS success model at the individual level of analysis. The researchers developed 14 hypotheses which are consistent with the updated DeLone and McLean model. 11 hypotheses are specifically stated in the updated model, and 3 were additional hypotheses that were implied in the original DeLone and McLean 1992 model, but are no longer part of the updated model. Petter & McLean (2009) found that the majority of the relationships posited in the updated Delone and McLean (2003) IS success model were significant, see table 5 (next page). Interestingly enough, only the service quality construct was found to be unsupported or not measurable amongst the relations; service quality → intention to use, service quality → user satisfaction and service quality → use are not supported or measurable (Petter & McLean, 2009).

Sabherwal et al. (2006) used another model to test the relationships amongst constructs that are connected to information systems (IS) success, as well as the determinants of IS success. They developed a new IS success model and tested the constructs of the model with 612 findings, from 121 studies published between 1980 and 2004. The model was analysed at the individual context, and four constructs of the model are the same as in the model of DeLone and McLean (2003), namely: system quality, user satisfaction, system use and net benefits. Sabherwal et al. (2006) found a relation between system quality → use and user satisfaction → net benefits. However, they couldn't find a relationship between user satisfaction → use.

We have summarised the results of the relationships between the constructs of DeLone and McLean (2003) IS success model at the individual level of analysis from Sabherwal et al. (2006), Petter et al. (2008) and Petter et al (2009) results in table 5.

Table 5: Empirical studies testing DeLone & McLean model constructs at the individual level of analysis

Relationship	Empirical studies	Study Result
System Quality → Use	Petter et al. (2009)	Moderate support
	Petter et al. (2008)	Mixed support
	Sabherwal et al. (2006)	Significant
System Quality → User Satisfaction	Petter et al. (2009)	Strong support
	Petter et al. (2008)	Strong support
	Sabherwal et al. (2006)	Significant
System Quality → Net Benefits	Petter et al. (2009)	Not examined
	Petter et al. (2008)	Moderate support
	Sabherwal et al. (2006)	Significant
Information Quality → Use	Petter et al. (2009)	Moderate support
	Petter et al. (2008)	Insufficient data
	Sabherwal et al. (2006)	Not examined
Information Quality → User Satisfaction	Petter et al. (2009)	Strong support
	Petter et al. (2008)	Strong support
	Sabherwal et al. (2006)	Not examined
Information Quality → Net Benefits	Petter et al. (2009)	Not examined
	Petter et al. (2008)	Moderate support
	Sabherwal et al. (2006)	Not examined
Service Quality → Use	Petter et al. (2009)	Not significant
	Petter et al. (2008)	Insufficient support
	Sabherwal et al. (2006)	Not examined
Service Quality → User Satisfaction	Petter et al. (2009)	Not significant
	Petter et al. (2008)	Mixed support
	Sabherwal et al. (2006)	Not examined
Service Quality → Net Benefits	Petter et al. (2009)	Not examined
	Petter et al. (2008)	Moderate support
	Sabherwal et al. (2006)	Not examined
Use → User Satisfaction	Petter et al. (2009)	Weak support
	Petter et al. (2008)	Insufficient data
	Sabherwal et al. (2006)	Not examined
Use *(intention)* → Net Benefits	Petter et al. (2009)	Strong support*
	Petter et al. (2008)	Moderate support
	Sabherwal et al. (2006)	Significant
User Satisfaction → Use *(intention)*	Petter et al. (2009)	Strong support*
	Petter et al. (2008)	Moderate support
	Sabherwal et al. (2006)	Not significant
User Satisfaction → Net Benefits	Petter et al. (2009)	Strong support
	Petter et al. (2008)	Strong support
	Sabherwal et al. (2006)	Not examined
Net Benefits → Use *(intention)*	Petter et al. (2009)	Strong support*
	Petter et al. (2008)	Moderate support
	Sabherwal et al. (2006)	Significant
Net Benefits → User Satisfaction	Petter et al. (2009)	Strong support
	Petter et al. (2008)	Strong support
	Sabherwal et al. (2006)	Not significant

**Petter et al. (2008) chose to consider both intention to use and use as the same construct. While Petter et al. (2009) distinguished between intention to use and use.*

3.2 CONCLUSION

DeLone and McLean's (2003) IS success model is extensively tested by various researchers, and the majority of the inter-relationships between the constructs are found to be significant by Petter et al. (2008), Petter & McLean (2009) and Sabherwal et al. (2006) at the individual level of analysis. However, more research is needed to investigate the relationships of the model at the organisational level of analysis. The construct 'user satisfaction' especially needs more research to conclude if it can be used at the organisational level of analysis. Pérez-Mira (2010) argues that it is a construct that is problematic to measure at the organisational level, and questions if the proposed measurements of DeLone and McLean (2003) for satisfaction are adequate for the model. Even so, when the DeLone and Mclean (2003) model of IS success is used at the individual level, it provides a good basis to identify specific characteristics of an IS that affects the success of an IS. Therefore, we have adapted in this study the DeLone and McLean (2003) IS success model as a basis to research the relationship between mobile BI capabilities and mobile BI success from the user's perspective.

4 CONCEPTUAL MODEL

The conceptual model shows how we theorise the inter-relationships between the variables that are considered integral to the situation being investigated. The conceptual model is based on the DeLone and McLean (2003) IS success model. In order to adapt and use this model, each construct of DeLone and McLean's (2003) model is discussed with the use of the literature review in chapter 2 and 3, and, when needed, extended with (BI) scientific literature. Every section in this chapter contains a construct with its discussion and ends with the conceptual model and a summary of the developed hypotheses. Hypotheses are formulated based on the relationships between constructs of the conceptual model.

4.1 NET BENEFITS

Net benefit is the most important construct in order to determine if an IS is successful, and contains the most important measures that determine the success of information systems, as they capture the balance of positive and negative impacts of the IS. Net benefits of an IS are always the same, but are context specific (Delone & McLean, 2003; Grover et al. 1996; Seddon et al. 1999). In other words, in this study, the benefits that can be realised need to be based on mobile BI, at the individual level of analysis. The output of (mobile) BI is processed information (Moody & Walsh, 1999). Information is a crucial factor in decision-making. With high quality information, uncertain decision-making conditions can evolve into certainty. Information is then a crucial role in the success or failure of organisations (Citroen, 2011). Information has to be used to actually have an impact on the organisation's ultimate performance, otherwise it has no value (Moody & Walsh, 1999). In other words, (mobile) BI must be utilised before it can deliver performance effects (Hou, 2012). Williams (2004) states that the business value of BI lies in its ability to improve the effectiveness of the core business processes that drives business performance. For example, BI enables line managers to access relevant and timely information, such as daily customer and product updates, and to make better and instantaneous decisions. However, Negash (2004) states that BI is not only beneficial for operational business processes, but also for making decisions at the tactical and strategic level. It increases value by providing intelligence to support strategic decisions (Olszak & Ziemba, 2007).

Elbashir et al. (2008) studied which kind of performance benefits organisations were able to achieve with the use of BI. They modelled the effects of BI systems on both business process performance and organisational performance. Elbashir et al. (2008) used Porter's value chain framework to identify the business activities within organisations that are supported by BI systems. Porter's framework partitions value chain activities that are involved in the physical creation of the product, marketing and delivery to buyers, that is, primary activities. Also supporting activities that provide the inputs and infrastructure that allow the primary activities to take place (Porter & Millar, 1985). Guided by Porter's framework, Elbashir et al. (2008) defined with the use of a broad review of the scientific and professional literature (50 cases), an initial list of 26 measurement items. These 26 items were assessed by different academics, BI experts and senior managers. Based on their feedback, four items were removed. Elbashir et al. (2008) tested the remaining 22 items with the use of a questionnaire that was completed by 419 respondents, representing 202 organisations, with a maximum of three respondents per organisation, who were asked to answer the survey on behalf of their strategic business unit or on behalf of the whole organisation. Elbashir et al. (2008) applied two factor analyses to examine the underlying constructs that group the 22 measurement items. Of the 22 items, 18 were found reliable and valid, the remaining 18 items were loaded onto four constructs; (1) organisational benefits, (2) business supplier/ partners relation benefits, (3) internal processes efficiency benefits, and (4) customer intelligence benefits, see table 6.

Hou (2012) examined the effect of user satisfaction on system usage and individual performance with BI systems. He used 14 individual performance measures, four of which were taken from Igbaria & Tan (1997) and ten from Leidner & Elam (1993). Hou (2012) used 330 questionnaires which were completed by 330 key-end users of 330 organisations who were considered to have abundant experience and knowledge in BI systems at all levels in an organisation. All of the 14 individual performance measures were found to be significant, see table 6 for these measures. Hou (2012) concluded that higher levels of user satisfaction can lead to increased BI system usage and improved individual performance, and that higher levels of BI system usage will lead to higher levels of individual performance (Hou, 2012). Furthermore, it also indicates that even if the study of Hou (2012) is user perception-based, BI can provide business benefits, such as, quality decision making benefits, job performance benefits, problem identification speed benefits etc.

Popovič et al. (2010) developed a conceptual model to assess the business value of BI systems through an extensive literature review, in-depth interviews with three Slovenian organisations and case study analysis of the three Slovenian organisations, see figure 9. They argued that the true business value of BI systems is hidden in improved business processes and thus in improved business performance. Popovič et al. (2012) adapted this model, see figure 10, and used it to obtain a comprehensive understanding of the interrelationships between BI systems success constructs.

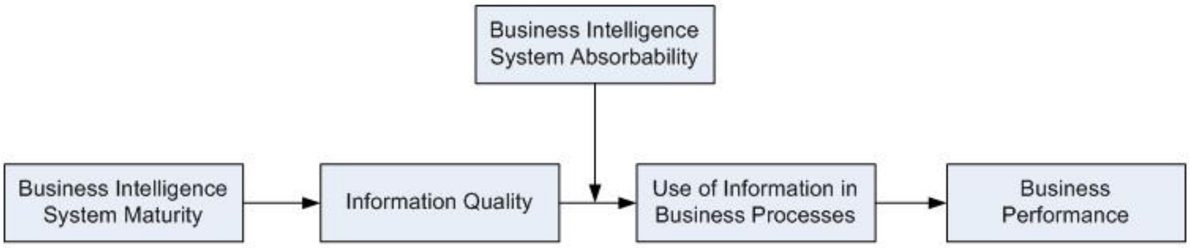

Figure 9: Conceptual model for researching business value of BIS. Source: Popovič et al. (2010)

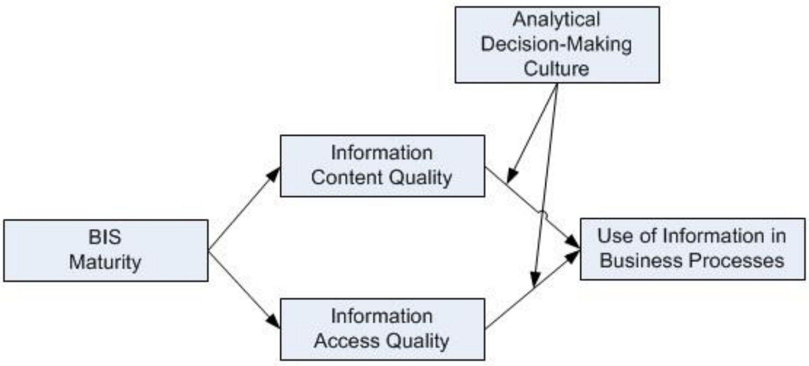

Figure 10: BIS success model. Source: Popovič et al. (2012)

Popovič et al. (2012) used nine indicators to measure the 'use of information in business processes', which can be defined as business benefits. In order to develop these nine indicators, they used Berente & Vandenboschs's (2000) study to assess how the available information is used for managing business processes, Choo's (1996) study to assess how the information is used for decision making in organisations business processes, and Davenport & Beers (1995) study to assess which benefits organisations achieve by managing their information. Popovič et al. (2012) found that that all of the nine indicators were significant, see table 6 for the indicators.

Table 6: BI benefit measures

Elbashir et al. (2008) BI benefits	Hou (2012) BI benefits	Popovič et al. (2012) BI benefits
Organisational benefits Reduction of lost sales Increased geographic distribution of sales Increased return on investment (ROI) Improved competitive advantage **Business supplier/partner relation benefits** Improved coordination with business partners/suppliers Reduction in the cost of transactions with business partners/suppliers Improved responsiveness to/from suppliers Increased inventory turnover Reduced inventory levels **Internal processes efficiency benefits** Improved efficiency of internal processes Increase staff productivity Reduction in the cost of effective decision-making Reduced operational cost **Customer intelligence benefits** Reduced customer return handling costs Reduced marketing costs Reduced time-to-market products/services	**Job performance:** Using the BI system improves my job performance. **Individual productivity:** Using the BI system in my job increases my productivity. **Job effectiveness**: Using the BI system enhances my effectiveness in my job. **Decision-making quality:** Using the BI system improves my decision-making quality. **Problem identification speed:** Using the BI system helps me to identify potential problems faster. Using the BI system notices me potential problems before they become serious crises. Using the BI system helps me to sense key factors impacting my area of responsibility. **Decision-making speed:** Using the BI system helps me to make decisions quicker. Using the BI system helps me to shorten the time frame for making decisions. Using the BI system helps me to spend less time in meetings. **Extent of analysis in decision-making:** Using the BI system helps me to spend significantly more time analyzing data before making a decision. Using the BI system helps me to examine more alternatives in decision-making. Using the BI system helps me to use more sources of information in decision-making Using the BI system helps me to engage in more in-depth analysis.	…exposes the problematic aspects of current business processes and makes stakeholders aware of them. …provides a valuable input for assessing business processes against standards, for continuous process improvement programs, and for business process change projects. …stimulates innovation in internal business processes and external service delivery The information reduces uncertainty in the decision-making process, enhances confidence and improves operational effectiveness. The information enables us to rapidly react to business events and perform proactive business planning. We are using the information provided to make changes to corporate strategies and plans, modify existing KPIs and analyze newer KPIs. Through managing the organisation's information, we are … …adding value to the services delivered to customers. …reducing risks in the business. …reducing the costs of business processes and service delivery.

Table 6 contains only the measures that were found to be significant by Elbashir et al. (2008), Hou (2012) and Popovič et al. (2012). These measures can be translated to the benefits of BI. However, these benefits are dependent on variables, such as the use of BI and the sector of the BI user. Still, the table gives a clear overview of the benefits that can be realised with BI. Because BI is very closely related to mobile BI, we expect that the majority of these BI benefits are the same as the benefits of mobile BI.

4.2 USE

System usage has played a central role in IS research since the 1970s (Burton-Jones & Straub, 2006). Many researchers have studied antecedents to usage. DeLone and McLean (1992) found 27 empirical studies which used system use as at least one of their measures of success. They argue that use is probably the most objective and the easiest variable to quantify. However, they also argue that usage, either actual or perceived, is only pertinent when such use is voluntary. Petter & McLean (2009) examined whether the voluntariness of system use affected the relationship between use and user satisfaction. They did not find that voluntariness impacted the results; however, they also stated that it didn't provide conclusive evidence that it is irrelevant in the IS success model. Added to that, actual use can be easy to measure, however, Petter et al. (2008) argue that heavy users tend to underestimate use, while light users tended to overestimate it. Which would suggest that self-reported usage may be a poor surrogate for the actual use of a system. Also Dame & Study (2003) and Burton-Jones & Straub (2006) argue that inappropriate choices of usage measures can significantly reduce explanations of performance improvements. Burton-Jones & Straub (2006) concluded in their study concerning reconceptualising system usage, that the most common measures of system usage included the following items: task supported, extent of use, decision to use (use or non-use), frequency of use and duration of use. Their study was based on a sampling of 48 published articles in major IS journals of the period of 1977 – 2006. Furthermore, Hou (2012) used 'duration of use' and 'frequency of use' to measure system usage of a BI system, and found a significant relationship between system usage and individual performance.

DeLone and McLean (2003) state that use is a key variable in understanding IS success. They also argue that intention to use (an attitude) and use (behaviour) can differ, which resulted in an extension of the DeLone and McLean IS success model. Petter and McLean (2009) described use as 'consumption of an IS or its output described in terms of actual or self-reported usage' and intention to use as 'expected future consumption of an IS or its output'. They found that with the exception of service quality, every construct of DeLone and McLean's IS success model had a significant relationship with 'intention to use' and 'use' (see previous chapter), and that intention to use seems to have a stronger relationship with the constructs of the DeLone and McLean IS success model than use. However, Petter and McLean (2009) state that intention to use does not always result in an actual behaviour as a possible reason of the difference in the relationship strength of intention to use and use with the other constructs. Petter et al. (2008) considered both intention to use and other measures of system use as the same construct in their study. They found at the individual level of analysis a significant relationship between use and net benefits. However, they only found mixed results between information quality, system quality and use. A relationship between service quality and use was not found at all.

Use is an important construct to measure the effective success of an IS, however, measures of use have to be taken with care. We adapted the construct use in the conceptual model to avoid model complexity, hence by parsing 'system use' into two separate sub-constructs (i.e., intention to use and use) it extends the model with at least three pairwise relationships, we chose to consider both intention to use and use and other measures of system use as the same construct for this study.
Sabherwal et al. (2006), Petter et al. (2008) and Petter et al. (2009) found a significant relationship between use → net benefits. Based on that, and the discussion above, the first hypothesis is created as follows:

H1. Use will positively influence net benefits in the mobile BI context

4.3 USER SATISFACTION

According to DeLone and McLean (1992), user satisfaction is one of the most important dependent variables used in measuring the success of an IS. They argue that (1) satisfaction has a high degree of face validity. In other words, it is hard to deny the success of an IS when users say that they like it. (2) Development of the Bailey and Pearson (user satisfaction questionnaire) instrument and its derivatives has provided a reliable tool for measuring satisfaction and for making comparisons among studies. (3) Most of the other measures are poor, being either conceptually weak or empirically difficult to obtain. Furthermore, hundreds of scientific studies have been published on user satisfaction or closely related constructs (McHaney, Hightower, & Pearson, 2002). In fact, DeLone and McLean tabulate in 1992 39 studies that empirically measure user satisfaction. User satisfaction is a common measure of IS success and effectiveness, for which several standard instruments have been developed and tested (Delone & McLean, 2003). DeLone and McLean (2003) state that the use of an IS and user satisfaction with it leads to net benefits which can be attributed to that system. This relationship is proved to be significant by Petter et al. (2008) and Petter and McLean (2009). Petter et al. (2008) and Petter and McLean (2009) also found a significant relation between 'user satisfaction → 'use', see table 5. Therefore, the following hypotheses are created:

H2. User satisfaction will positively influence net benefits in the mobile BI context
H3. User satisfaction will positively influence use in the mobile BI context

4.4 ENGAGEMENT

Tapadinhas (2012) states that the engaging experience provided by mobile BI is considered globally to be more relevant, than the breadth and depth of the functionality of mobile BI. He states that various mobile BI solutions have engaging charts and table layouts, interactive and engaging dashboards, engaging information visualizations, and visual components etc. However, what does engaging mean? What is the definition of engagement? Webster & Ahuja (2006) described engagement as an intrinsically enjoyable experience that involves control, attention focus and curiosity. Novak (2000) described engagement as an optimal experience which is called flow. Jacques et al. (1995) refers to engagement as a positive interactive state, in which attention is willingly given and held. During engagement, people experienced feelings of curiosity, interest, confidence and surprise. Chou & Conley (2009) defined engaging experience as a specific kind of experience that a user acquires during and after using a product frequently, actively, vividly and completely etc. These are different kind of views on engagement; common amongst these views is that engagement is described as a form of pleasure that is experienced during activities driven by intrinsic interest and enjoyment. Engagement can e.g. make the interaction with a product more interesting and enjoyable it reinforces the experience of using it and attention is willingly given and held. Engagement is according to Webster & Ahuja (2006) similar to Csikszentmihalyi's (1975) flow theory, which is a state representing the extent of pleasure and involvement in an activity. More specifically, flow is as a multidimensional construct encompassing perceptions of user control, attention focus, user's curiosity and intrinsic interest in a computer interaction (Webster et al., 1993). Webster et al. (1993) argued that flow experience is associated with perceived characteristics of the computer software. They state that information systems that are designed to provide more user control, focus the user's attention, and incite their cognitive enjoyment may result in more positive attitudes, more system use and more positive work outcomes such as perceived communication effectiveness. This indicates that a mobile BI solution that is flexible, that is modifiable to the users individual needs, may contribute to flow. Therefore, increasing the use of mobile BI.

Csikszentmihalyi (1975) argues that the most important characteristic of an activity in his flow theory is the provision of clear challenges. Webster & Ho (1997) found that students will experience higher

engagement during multimedia presentations which are more challenging. Webster & Ahuja (2006) researched the influence of engagement effects on outcomes of web navigation systems, with the use of an experimental setting of 207 graduate and undergraduate students. They concluded that higher engagement in a website results in higher performance; performance in this context means: more effective web searches. Also, higher engagement in a website leads to higher intentions to use the web site in the future, and disorientation results in lower engagement with a website. Chou & Conley (2009, p. 31 – p. 40) argues that engagement is different from the study of functionality, usability, aesthetics, interaction and affection. They state that whilst these constructs are important in satisfying the user needs, an engaging experience is different. However, it is potentially as significant as these constructs. Chou & Conley (2009) state that every digital product including software, programs or even a small display can engage users. Rozendaal (2007) researched in his PhD study how the experience of engagement in interaction can be explained by examining the experiences of richness and control and how these experiences are influenced by the features of a digital product, the expertise of a person and the type of task. He described digital products as intelligent products that can collect, process and produce information such as mobile phones. Rozendaal (2007) states that users of digital products can experience engagement while they are interacting with it, because it looks good, is interesting to use, or because the product allows one to achieve goals that are personally relevant. He presented richness and control as two qualities that can positively influence the levels of engagement. Richness for digital products can be increased by the various ways in which a digital product can behave, respond to users actions and the variety of formal elements such as colour, and form within the visual design. Control can influence the level of engagement due to the sense of freedom that can arise when people use a product to fit their own purposes. Richness and control work via a multiplications rule, meaning that engagement is low when richness is high and control is low, and engagement is low when richness and control are low. However, engagement is high when richness and control are high.
Rozendaal et al., (2009) researched how distributing the controls of a video game among multiple players affect the sociality and engagement experienced in game play. They used an experimental setting in which eight groups of three players were asked to play a video game whilst the distribution of the game controls was increased in three steps. After each playing session, players' experiences were assessed. Their factor analyses show that engagement consist of the variables fun, enjoyment, excitement, complexity, possibilities, skill development, personal fit and motivation.

Based on the aforementioned studies, it can be stated that engagement has been researched in relation to video games, web applications and interactive training simulations, but not yet in relationship to information systems. Therefore, it is in the first instance doubtful whether engagement is important for mobile BI and whether control and richness are important factors to influence engagement of mobile BI. Next to that, business workers should use mobile BI to support and improve their decision making. Their motivation to use mobile BI should not be because it looks good, is intrinsically interesting, enjoyable to use etc. Business workers have other kinds of motives to use digital products than consumers. However, just like consumers, business workers are also emotional beings. Therefore, as Webster et al. (1993) argues, engagement could be important for information systems to increase the use and outcomes. DeLone and McLean's IS success model (2003) states that a higher user satisfaction and use leads to positive impacts on net benefits. A higher engagement reinforces the experience of using the product. Thus, higher engagement may have a positive impact on the use of an IS, and may therefore positively affect the net benefits and increase of the adoption rate of mobile BI. If mobile BI is engaging because of the characteristics that Tapadinhas (2012) describes, it could be an important variable of mobile BI.

DeLone and McLean (1992) state that it is hard to deny the success of a system when its users say that they like it. This raises the question, is engagement not the same as user satisfaction? This could be inferred as meaning that users are satisfied with the IS, and/or that they enjoy using the IS. In other words, what is the value of measuring engagement, when you are also measuring user satisfaction? Doll & Torkzadeh (1988) developed an end-user computer satisfaction model with 12 items to measure the end-user satisfaction with content, accuracy, format, ease of use and timeliness of the IS. DeLone and McLean (1992) compared several other studies to indentify user satisfaction measures. In general, user satisfaction was mostly measured by asking whether users were satisfied with the IS, and whether they were content with the characteristics of the underlying IS itself. However, DeLone and McLean (1992) also argued that user satisfaction is associated with attitude. In other words, users who find a specific IS to be efficient, effective and easy to use, will probably have a high attitude towards that system to use. However, Saks (2006) argues that engagement is not attitude, it is the degree to which an individual is attentive and absorbed in the performance of their roles, while engagement involves the active use of emotions and behaviours in addition to cognitions. Next to that, Sabherwal et al., (2006) argue that user satisfaction is the extent to which the user believes that the IS meets his or her information requirements.

As described at the beginning of this section, engagement is a form of pleasure that is experienced during activities, driven by intrinsic interest and enjoyment. During engagement, a range of positive emotions can be experienced such as feelings of excitement, freedom and enjoyment, whilst time and energy is willingly invested. Hence, engagement is driven by emotions, while IS user satisfaction is driven by the functional aspects of the IS. Based on the arguments made earlier in this section, engagement may be important for the success of mobile BI. Still, it was not possible to find scientific studies that measured engagement of IS in organisations. This could indicate that engagement is in the end considered not important or relevant enough for researchers to investigate its relationship with information systems in organisations. However, there is a big difference between the devices used by the traditional information systems and mobile BI. Mobile BI is specifically made for mobile devices, whereas traditional IS is made for laptops and desktop computers. Mobile devices are easy to carry, have an attractive design, are cool, glitzy, fun (Stodder, 2012) and have an inviting interface (Mashman, 2011). Aspects which are different from laptops and desktop computers. Next to that, mobile devices with touchscreen gestures that are powerful enough to run business information systems are also relatively new, which affects the amount of scientific publications written about this subject. Hence, we still assume, and Gartner (Tapadinhas, 2012) also states that an engaging experience is a success factor of mobile BI.

In order to measure if engagement is a success factor of mobile BI, we extended the original DeLone and McLean (2003) IS success model with a construct that we have named: 'engagement'. We assume that engagement is influenced by system and information quality factors. For example, information visualization (richness) is measured by sophistication, which is a system quality factor (DeLone & McLean, 1992). Furthermore, information can help a user to increase his task performance. Task performance is related to experienced control. However, information is constantly changing and therefore, information can also be indicated as a richness factor. Just as flexibility is a system quality variable that can be defined as a control variable, it enables users to fit the mobile BI solution to their information needs. It is therefore likely that information and system quality factors consist both of control and richness factors that may influence engagement. We assume that just as with user satisfaction, higher system and information quality will lead to higher engagement and use, in turn having to positive impacts on net benefits. This leads to the following hypotheses:

H4. Engagement will positively influence use in the mobile BI context
H5. Engagement will positively influence net benefits in the mobile BI context

4.5 SYSTEM QUALITY

System Quality is concerned with the overall performance of the information processing system (DeLone & McLean, 1992). Based on the academic literature, DeLone & McLean (1992) developed 21 system quality measures, see table 7. Other researchers developed system quality measures. Sedera & Gable (2004) adapted the DeLone and Mclean (1992) model through a review of the literature, identification survey and a series of expert workshops, and proposed an enterprise systems success measurement model, which included a comprehensive instrument for system quality with nine measures. Nelson, Todd, & Wixom (2005) defined through an assessment of 20 studies (that characterised constructs of system quality), five measures of system quality, which they also divided into system-related and task-related categories. Based on an extensive literature research, Sabherwal et al., (2006) defined system quality into three variables. Furthermore, Rivard, Poirier, Raymond, & Bergeron (1997) developed and tested a model that consists of 40 items that measured eight 'system' (software) quality factors. See table 7 for the system quality measures of these researchers.

Table 7: Empirical measures of system quality

System Quality Measures				
Delone & Mclean (1992)	Nelson et al. (2005)	Sedra & Gable (2004)	Sabherwal et al. (2006)	Rivard et al. (1997)
Ease of use		Ease of use	Ease of use	User-friendliness
Flexibility	Flexibility	Flexibility		
Integration	Integration	Integration		
Response time	Response time		Response time	
Reliability	Reliability		Reliability	Reliability
Convenience of access	Accessibility			
Ease of learning		Ease of learning		
User requirements		User requirements		
Usefulness of system features and functions		System features		
Accuracy		Accuracy		
Sophistication		Sophistication		
		Customization		
				Portability
				Verifiability
				Effectiveness
				Economy
				Maintainability
				Understandability
Data currency				
Database contents				
Human factors				
System efficiency				
Resource utilization				
Turnaround time				

In table 7, ease of use, flexibility, integration, response time and reliability are the most frequently mentioned system quality measures. In general the authors in table 7 based their system quality measures on an extensive literature review. This, this could therefore suggest that e.g. the four most mentioned measures are the ideal system quality measures. However, DeLone and McLean (2003) state that the used system quality measures should be the desired characteristics of the IS that is to be measured. For example, DeLone and McLean (2003) used adaptability, availability, reliability, response time and usability as the desired system quality characteristics of an e-commerce system. Lee & Chung (2009) used security, accessibility, ease of use and anytime, anywhere as system quality measures to understand which factors affect trust and satisfaction with mobile banking in Korea, and

Wang & Liao (2008) used only two system quality measures; user friendliness and ease of use, when measuring the success of an eGovernment system. Therefore, we haven't used all the system quality measures that are available, but have only selected the desired system quality characteristics that are significant in BI studies, characteristics that are desired for mobile BI and that can be measured from the users perspective, which we will define as mobile BI capabilities.

4.5.1 FLEXIBILITY

There is little literature available concerning the success factors of BI. However, Yeoh & Koronios (2010) developed a critical success framework for BI systems, which they based on an extensive literature review, 15 interviews with BI system experts and five case studies of large and complex organisations. They concluded for the system part, that flexibility and scalability are critical elements in order to meet the incremental needs of business. Isik et al. (2013) concluded in their study concerning the role of the decision environment in how well business intelligence (BI) capabilities are leveraged to achieve BI success, that flexibility positively affects BI success. They based this conclusion on a survey that was completed by 116 BI professionals. Olszak & Ziemba (2007) and Vandenbosch & Huff (1997) also argued that BI systems need to be scalable and flexible. Flexibility refers to the organisational capability of BI to provide decision support when variations exist in the business processes, technology or the business environment in general. Flexibility is dependent on the strictness of the business processes rules and the supported regulations. If strict sets of policies and rules are embedded in the applications, BI will have a relatively low flexibility; if regulations become stricter dealing with exceptions and urgencies becomes more difficult (Isik et al., 2013). Users should easily be able to modify their BI system to their needs, insufficient flexibility may withhold users in using the BI system. However, too much flexibility may increase complexity and reduce usability (Gebauer & Schober, 2006; Olszak & Ziemba, 2007). Next to that, technology does not always support exceptional situations, although organisations need flexibility and robust functionality to experience the optimal potential of BI (Isik et al. 2013). Scalability refers in this case to a (mobile) BI design that is able to grow to meet expectations, and that has a suitable selection of scalable hardware and software components (Yeoh & Koronios, 2010). A mobile BI user uses the mobile BI solution without insight of the technical architecture of the mobile BI solution. Hence, measuring scalability according to the user's perceptions is not feasible. A mobile BI user should be able to modify the mobile BI solution to his needs, and therefore, we define flexibility as an important capability of mobile BI.

4.5.2 ACCESSIBILITY

Business Intelligence provides information, however, in order to gain business value, users have to use that information. Based on an extensive literature review of studies of information quality, Jeong & Lambert (2001) concluded that perceived accessibility is an important attribute of the use of information. Hostmann et al. (2007) argued that the way in which users access and use BI is critical for BI success. Higher quality user access methods should increase decision making effectiveness, which is supported by Isik et al. (2013). Isik et al. (2013) concluded in their BI study that user access is an important BI capability in relation to BI success. It has a significant relationship with BI success. They define that user access should vary within an organisation. Users at the operational level need a different level of access than upper-level managers. User access needs may differ across sectors regardless of level. In the financial services sector, users may need to access information about the intraday profits or losses, while users in the manufacturing sectors may need access to manage operation efficiency and provide plant visibility. Isik et al. (2013) argue that it is critical that organisations achieve the necessary balance to allow the way in which BI users access information to fit the types of decisions they make using BI. How organisations provide access to the information with authorization/authentication controls should match the user's needs. Isik et al. (2013) even suggest that user access quality is the cornerstone of the overall user satisfaction with BI.

A recent study of Popovič et al. (2012) examined the relationships between maturity, information quality, analytical decision making culture, and the use of information for decision making as significant elements of the success of BI systems. They tested a model previously developed using a survey that was answered by 181 CIO's and senior managers from whom they assumed to have adequate knowledge of BI systems, and the quality of available information for decision making. This model also contains information access quality. They concluded that information access quality is not a relevant factor for the success of BI systems. Popovič et al. (2012) described information access quality as bandwidth, customization capabilities and interactivity. These are in fact three information quality criteria's of Eppler (2003, p. 84) information quality framework, namely; timeliness, convenience and traceability. When mobile BI is used outside the wireless business network it is dependent on the provided 3G/4G technologies (bandwidth). When accessed information is not processed and delivered as expected, due slow internet connection, this could frustrate the user, and decrease mobile BI usage in situations for which it was developed; that is to use mobile BI anytime and anywhere. Hence, bandwidth/timeliness could be an important accessibility quality for mobile BI.

According to Tapadinhas (2012) and Murphy (2012), anywhere and anytime is one of the success factors of mobile BI. Mobile devices are very portable, it is easy to carry a smartphone or tablet in a shop, factory, meeting, hospital etc. or even to use it as a presentation device in e.g. business meetings. Next to that, travelling with a smartphone/tablet is more comfortable than with a laptop. The portability of a mobile device makes it possible to access, with the use of mobile BI, information at anytime and anywhere. Anytime and anywhere are also one of the success factors of mobile banking in Korea (Lee & Chung, 2009). While mobile banking is different from mobile BI, anytime and anywhere could be a critical capability for both solutions.

It is critical that users can access the information that is required for their decision making quickly, and obtain it anytime and at anywhere. In this study, we define accessibility according to the users perceptions of the user access quality, bandwidth and anytime and anywhere usability.

4.5.3 EASE OF USE

Ease of use can be defined as the degree to which a system is user friendly (Doll & Torkzadeh, 1988). Doll & Torkzadeh (1988) used it as one of the five components in their widely used and empirically validated end-user computer satisfaction (EUCS) instrument (e.g. Abdinnour-Helm, Chaparro, & Farmer, 2005; McHaney, Hightower, & Pearson, 2002; McHaney, Hightower, & White, 1999). Doll & Torkzadeh (1988) measured ease of use with two questions: 'Is the system user friendly? And 'Is the system ease to use?'. Hou (2012) used the EUCS framework in order to examine the effect of user satisfaction on system usage and individual performance with BI systems. They used data from 330 questionnaires, and both items of 'ease of use' were found significant in this study. Howson (2010) conducted a research (which was sponsored by BI vendors) to gain a broader perspective on what users considered to be the key features which would enhance use and adoption of BI systems. 47% of the 255 respondents of their survey rated ease of use as very important in the use of BI, and 32% believed it to be essential. Tapadinhas (2012) states in a Gartner study about the critical capabilities for mobile BI, that ease of use is a key adoption driver for mobile BI. Chandras (2011) states in a blog article on Informationweek.com, that for users to benefit from mobile BI, they must be able to navigate dashboards and guided analytics comfortably, or as comfortably as the mobile device will allow.

Another big factor as to why ease of use is important, is because the constantly changing interfaces, software upgrades and increased requests to adopt new technologies etc. create large amounts of information that must be processed. According to Rutkowski & Saunders (2010), this can cause emotional (frustration, impatience) and cognitive (accepting lower performance levels, making poorer decisions) overload. Which in the long-term can mentally exhaust employees and cause semi-permanent or chronic stress, which is similar to a burnout (Rutkowski & Saunders, 2010). Obviously, a mobile BI solution shouldn't increase the emotional and cognitive overload of an employee.

4.5.4 ATTRACTIVE INTERFACE DESIGN

Mishra (2012, p. 181) states in his software engineering book that, users like software that has an attractive and appealing user interface. Software is not only judged by its functionality, it is also judged by its looks. The interface is the visual part of software which consists of opening screens, input screens, output screens etc. (Mishra, 2012, p. 182). Santosa, Wei, & Chan (2005) researched the user involvement and user satisfaction in the context of information seeking activity in websites. The researchers conducted a laboratory experiment with a total of 235 students and utilised http://www.amazon.com as the website in their experiment. They concluded that an attractive appearance and visually appealing interface has a significant positive effect on user satisfaction of information seeking activities on websites. Rozendaal (2007) argued that the richness of a digital product can be increased by elements such as colour and the form within the visual design. According to Rozendaal (2007) richness is a quality that can positively influence the level of engagement.

Howson (2010) states in a BeyeNETWORK research report that users who require access to data have a higher degree of tolerance for unappealing interfaces; their job requires data access and manipulation regardless of whether or not the interface is appealing. However, she also states that an appealing interface provides a powerful first impression, it can engage users, it can improve the adoption rate of BI, and it can also affect the degree in which someone enjoys continued use of a particular BI tool (Howson, 2010). Business users also prefer more attractive interfaces of business software to less attractive interfaces (Schrepp, Held, & Laugwitz, 2006). Furthermore, Imhoff & White (2011) researched the features that make BI attractive to business users in a TDWI research report. They used a survey to gather the data for their research and based their results on 1.960 responses from 557 respondents who were IT professionals, consultants and business sponsors. Imhoff & White (2011) concluded that appealing and attractive visualisations are one of the features that make BI attractive for business users.

The discussion points in this chapter suggest that a visually attractive interface design not only make the experience of using a BI tool more pleasant to work with, it can also affect the adoption rate, user satisfaction and engaging factor of mobile BI. The attractive interface design of mobile BI includes visualisations, graph, table, report dashboard layouts etc. Which could be one of the factors that explain the success of mobile BI.

4.5.5 CONCLUSION

Accessibility, attractive interface design, ease of use and flexibility are defined as four important (system quality) mobile BI capabilities. DeLone and McLean (2003) integrated the system quality characteristics into one construct. In this study, the four system quality mobile BI capabilities are divided into four separate constructs, making it possible to investigate which mobile BI capability is significant; this leads to the follow hypotheses:

Accessibility

H6. Accessibility will positively influence use in the mobile BI context
H7. Accessibility will positively influence user satisfaction in the mobile BI context
H8. Accessibility will positively influence engagement in the mobile BI context

Attractive interface design

- **H9.** Attractive interface design will positively influence use in the mobile BI context
- **H10.** Attractive interface design will positively influence user satisfaction in the mobile BI context
- **H11.** Attractive interface design will positively influence engagement in the mobile BI context

Ease of use

- **H12.** Ease of use will positively influence use in the mobile BI context
- **H13.** Ease of use will positively influence user satisfaction in the mobile BI context
- **H14.** Ease of use will positively influence engagement in the mobile BI context

Flexibility

- **H15.** Flexibility will positively influence use in the mobile BI context
- **H16.** Flexibility will positively influence user satisfaction in the mobile BI context
- **H17.** Flexibility will positively influence engagement in the mobile BI context

4.6 INFORMATION QUALITY

Information quality refers to the quality of the information the system produces (DeLone & McLean, 1992) and is the second quality construct in DeLone and McLean's (2003) IS success model. However, there are many definitions and descriptions of information. Therefore, we start in this section with a discussion of information and its importance for BI, which begins and ends with a discussion on information quality.

4.6.1 INFORMATION

There are many researchers that have made an attempt to define information in a conceptually informed way. Based on an extensive literature research on information, Gasser et al. (2007) defined data, information and knowledge. Gasser et al. (2007) defined information as '*data plus the context of its interpretation and/or use*'. To understand the meaning of data, they defined data as '*as a raw sequence of symbols*'. In other words, information has a meaning or interpretation which is dependent on the receiver. Therefore, information is more valuable to the receiver than data. The next level in the information hierarchy is knowledge. This is the part where information is turned into knowledge. Gasser et al. (2007) defined knowledge '*as a stock of information internally consistent and relatively stable for a given community*'. High quality makes it easier to transform information into knowledge, by helping to interpret and evaluate the information, by assisting the connection to prior knowledge, and by facilitating the application of the information to new contexts (Eppler 2003, p.35).

Information is critical in the core activities of an organisation and has added value for customers. It is one of the most significant bases for the current and future value of an organisation. Organisations need information to support decision making. High quality information enables organisations to make better decisions in order to protect themselves from business risks; managerial objectives can be set and existing options can be evaluated, prioritized and timed etc. Poor quality information can result in lost productivity or failed enterprises. Next to that, poor information quality is one of the many factors that can cause information overload (Eppler & Mengis, 2004). Information overload occurs when information received becomes a hindrance rather than a help even when the information is potentially useful (Bawden, Holtham, & Courtney, 1999). It is a situation where time pressure can decrease the decision quality when there is received too much information in the decision making process (Hahn, Lawson, & Gye Lee, 1992; Lurie, 2004; Schick, Gordon, & Haka, 1990). Hence, information of high quality is important for organisations, and in order to gain the business value of BI, the quality of information that is available through the BI system has to be used in business processes (Popovič et al., 2010). Popovič et al. (2012) recently conducted a research to examine the relationships between maturity, information quality, analytical decision-making culture, and the use of information for decision-making as significant elements of the success of BI systems. They concluded that information content quality is relevant for the use of information. Popovič et al. (2012) argue that the unsuitability of content quality affects future uses of information and can easily lead to a less suitable business decision. Which results in dissatisfaction of the BI system, and ultimately in the non-use of the BI system. Hence, it is a critical success factor for the success of BI systems (Popovič et al., 2012). But what makes information, quality information?

4.6.2 INFORMATION QUALITY

The information definition of Gasser et al. (2007) states that it is natural to expect that quality in general and information quality in particular counts as the degree of usefulness of information in a specific typified task/context, or more than one task/context. In the IQ field, many researchers have considered what can be qualified as 'good information'. To answer this question, there have been several proposed conceptual frameworks and information criteria lists (i.e., adjectives that describe information characteristics which make information useful for its users) in order to measure the quality of information (Bovee, Srivastava, & Mak, 2003; Gasser et al., 2007; Y. W. Lee, Strong, Kahn, & Wang, 2002). Also DeLone & McLean (1992) developed for their model, with the use of a literature review, a sizeable list of IQ measures, see table 8.

Table 8: DeLone and McLean information quality measures

Information Quality measures
Accuracy, Precision, Currency, Completeness, Comparability, Conciseness, Format, Freedom from bias, Perceived usefulness of specific report items, Perceived importance of each information item, Reliability, Report usefulness, Sufficiency, Timeliness, Relevance, Usefulness of information, Understandability

Source: Delone & McLean (1992)

However, Gasser et al. (2007) argue that some of these IQ frameworks and IQ lists are too specifically context based, meaning that they are focused on just a few variables determined by the local needs. Frameworks that are ad hoc, intuitive and incomplete which make them limited in their reuse.

Eppler (2003) wrote a book about managing information quality. His book contains a four year research project on information quality, which was conducted with the use of a survey, focus group results and an extensive scientific literature research about IQ. He identified 70 of the most widely used IQ criteria, of which some of them are synonyms or closely related terms. Eppler's (2003) review of 20 selected information quality frameworks showed that most of the frameworks are often domain-specific, and that they rarely analyze interdependencies between the information quality criteria. Based on his extensive research, Eppler (2003) developed an IQ framework with 16 criteria covering all aspects of IQ, see table 9 on the next page.

This framework can be categorized into relevant information (also called community view), sound information, optimized process and reliable infrastructure. Relevant and product criteria relate to actual (content) information itself, and process and infrastructure relate to whether the delivery process and infrastructure are of adequate quality. Eppler (2003, p. 68) labelled the upper two levels of the IQ framework as content quality and the lower two levels as 'media quality'. He argued that the upper two levels relate to the actual information itself, and therefore to the term content quality. The lower two levels to the management of that information, and whether the delivery process and infrastructure are of adequate quality. Thus, media quality stresses the channel by which information is transported (Eppler, 2003, p. 68). Popovič et al. (2012) used the information content items of Eppler's (2003) IQ framework to measure the information content quality of BI, and found a significant relationship between information content quality and the use of information in business processes.

Table 9: Eppler's information quality criteria framework

Information Quality level	Information Quality criteria	Description
Community Level (Relevance)	Comprehensiveness	Is the scope of information adequate? (not too much nor too little)
	Accuracy	Is the information precise enough and close enough to reality?
	Clarity	Is the information understandable or comprehensible to the target group?
	Applicability	Can the information be directly applied? Is it useful?
Product Level (Soundness)	Conciseness	Is the information to the point, void of unnecessary elements?
	Consistency	Is the information free of contradictions or convention breaks?
	Correctness	Is the information free of distortion, bias, or error?
	Currency	Is the information up- to-date and not obsolete?
Process Level	Convenience	Does the information provision correspond to the user's needs and habits?
	Timeliness	Is the information processed and delivered rapidly without delays?
	Traceability	Is the background of the information visible (author, date etc.)?
	Interactivity	Can the information process be adapted by the information consumer?
Infrastructure Level	Accessibility	Is there a continuous and unobstructed way to get to the information?
	Security	Is the information protected against loss or unauthorized access?
	Maintainability	Can all of the information be organized and updated on an on-going basis?
	Speed	Can the infrastructure match the user's working pace?

Source: Eppler (2003, p. 83)

4.6.3 CONCLUSION

Information quality is maybe the most important mobile BI capability. High quality information is important in the decision making process, and therefore mobile BI should be able to deliver high quality information. Information also has a richness quality (Rozendaal, 2007), Daft & Lengel (1984) define this richness as the potential information-carrying capacity of data. In this study, we define information quality as the fifth important mobile BI capability, which leads to the following hypotheses:

- **H18.** Information quality will positively influence use in the mobile BI context
- **H19.** Information quality will positively influence user satisfaction in the mobile BI context
- **H20.** Information quality will positively influence engagement in the mobile BI context

4.7 SERVICE QUALITY

The third quality construct of the DeLone and McLean (2003) IS success model is 'service quality'. DeLone and McLean (2003) state that to measure the success of a single IS, 'information quality' or 'system quality' may be the most important quality components. However, to measure the success of an IS department, 'service quality' may be the most important variable. Next to that, Petter et al. (2008) and Petter and McLean (2009) weren't able to find a significant relationship between 'service quality' → 'user satisfaction' and 'service quality' → 'use' at the individual level. This study is based on the individual level and on a single IS, therefore, we excluded the 'service quality' construct from the conceptual model.

4.8 CONTROL VARIABLES

The IS success model of DeLone & McLean (2003) doesn't include any control variables such as 'user involvement' and 'top management support'. DeLone & McLean (2003) argue that such variables may cause success rather than being part of success. However, we wanted to have a clear understanding of the effects of engagement, user satisfaction and use on net benefits and therefore, we searched in the BI literature for other variables that have the potential to influence the net benefits. Two control variables, *top management support and time since adoption* are included in the conceptual model.

1. Committed management support and sponsorship are one of the most important factors for BI implementation. Consistent support and sponsorship from business executives make it easier to secure the necessary operating resourcing such as funding, human skills etc. Next to that, dynamic business requirements necessitate a BI system to evolve. To overcome continual organisational issues such as political barriers, the commitment and involvement of senior management are important (Yeoh & Koronios, 2010). Watson & Wixom (2007) argue that top management support is significant because they insist on the use of information-based decision making, which is also supported by Sabherwal et al. (2006). They state that top management support motivates greater user participation and leads to pronounced IS success in terms such as user satisfaction and system use. Therefore, top management support is chosen as control variable one.

2. A longer period (of use) may enable organisations to develop expertise to use the system more effectively to generate business benefits (Purvis & Robert, 2001). This was proven significant in Hou's (2012) BI study. Hou (2012) concluded that it had an expected positive influence on individual performance. Therefore, time since adoption is adapted as control variable two.

There are two BI studies that also used firm size as a control variable. Larger firms may have more experience and expertise in information system use, which could result in higher benefits than those of smaller firms (Subramani, 2004). However, in both BI studies (Elbashir et al., 2008) and (Hou, 2012) firm size was not proven to be significant. Therefore, we chose not to include this variable. This leads to the last hypotheses of this study.

H21. Top management support will positively influence net benefits in the mobile BI context

H22. Time since adoption will positively influence net benefits in the mobile BI context

4.9 CONCEPTUAL MODEL AND HYPOTHESES

Based on the DeLone and McLean (2003) IS success model, and an extensive literature review, a conceptual model was developed for this study. We removed the service quality construct from the original DeLone and McLean (2003) IS success model, and extended it with the following constructs; engagement and two control variables; top management support and time since adoption. We divided the original system quality construct into four separated constructs; accessibility, ease of use, flexibility and attractive interface design. The conceptual model is provided in figure 11, and the developed hypotheses are summarized in table 10 (next page), which will be tested in this study.

In this model the constructs, accessibility, attractive interface design, ease of use, flexibility, and information quality are defined as the mobile BI capabilities. Engagement, use and user satisfaction are measures of effectiveness mobile BI success, which explain the relationship between the mobile BI capabilities and the closest variable of mobile BI success, net benefits. To have a clear understanding of the effects of use, engagement and user satisfaction on net benefits, two control variables are added to the model that have the potential to influence net benefits.

In addition, voluntariness of use is applied as a moderating variable, and is therefore not included as a construct in the conceptual model. Voluntariness of use will be used to examine if the mobile BI usage is voluntary and to examine if there is a difference when the mobile BI usage is voluntary or mandatory, as recommend by DeLone and McLean (2003).

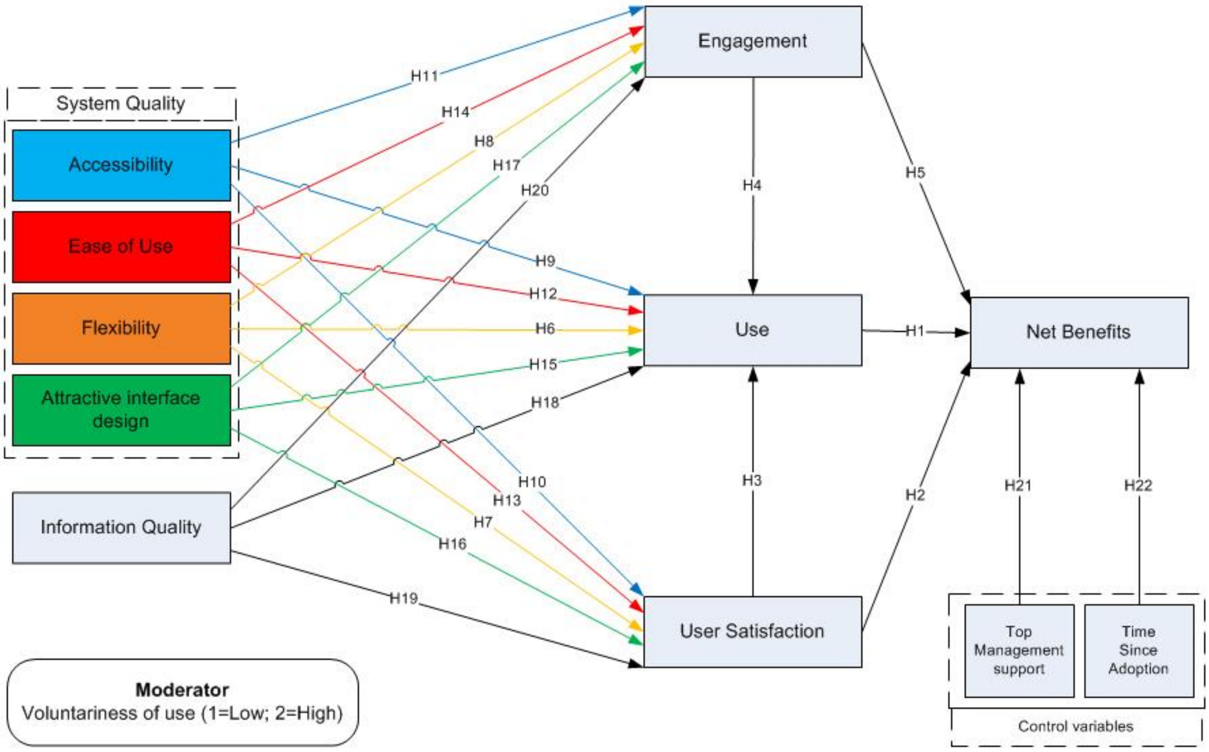

Figure 11: Conceptual/Research model

Table 10: Summarized Hypotheses

Summarised Hypotheses	
H1.	Use will positively influence net benefits in the mobile BI context
H2.	User satisfaction will positively influence net benefits in the mobile BI context
H3.	User satisfaction will positively influence use in the mobile BI context
H4.	Engagement will positively influence use in the mobile BI context
H5.	Engagement will positively influence net benefits in the mobile BI context
H6.	Flexibility will positively influence use in the mobile BI context
H7.	Flexibility will positively influence user satisfaction in the mobile BI context
H8.	Flexibility will positively influence engagement in the mobile BI context
H9.	Accessibility will positively influence use in the mobile BI context
H10.	Accessibility will positively influence user satisfaction in the mobile BI context
H11.	Accessibility will positively influence engagement in the mobile BI context
H12.	Ease of use will positively influence use in the mobile BI context
H13.	Ease of use will positively influence user satisfaction in the mobile BI context
H14.	Ease of use will positively influence engagement in the mobile BI context
H15.	Attractive interface design will positively influence use in the mobile BI context
H16.	Attractive interface design will positively influence user satisfaction in the mobile BI context
H17.	Attractive interface design will positively influence engagement in the mobile BI context
H18.	Information quality will positively influence use in the mobile BI context
H19.	Information quality will positively influence user satisfaction in the mobile BI context
H20.	Information quality will positively influence engagement in the mobile BI context
H21.	Top management support will positively influence net benefits in the mobile BI context
H22.	Time since adoption will positively influence net benefits in the mobile BI context

5 RESEARCH METHODOLOGY

This chapter describes the research methodology employed in this study. As discussed in section 1.5, this research contains a theoretical and an empirical section. Based on the literature review in chapter 2, 3 and 4 a conceptual model was built, (see figure 11), which theoretically explains the relationship between the mobile BI capabilities and mobile BI success from the users perspective. However, this model is not empirically tested, which needs to be done before it can be used to answer the main research question. This chapter is the first empirical part of the study to test the developed hypotheses in table 10, which will be tested by conducting a questionnaire-based data-gathering technique. This chapter describes the design of the empirical part. Section 5.1 discusses the research population. Section 5.2 discusses the research design, which includes the sample size and non-response bias. In section 5.3 the survey methodology will be discussed, including the wording and design of questions, structure of the questionnaire and which scales and scaling were used. Chapter 5.4 discusses the survey development, including the content validity and construct measurement. In the last chapter, 5.5, the data collection will be discussed.

5.1 RESEARCH POPULATION

According to Cooper and Schindler (2003, p. 179) a population is defined as 'the total collection of elements which we wish to make inference'. A population element is the subject on which the measurement is being undertaken. BI can be used at the strategic, tactical and operational level (Negash, 2004). Mobile BI can be used by executives, field employees, sales people (Watson & Leonard, 2011), store managers (Stodder, 2012), managers (Borg & White, 2012), etc. Indicating that mobile BI can be used at the same levels as BI, it enables employees to access the latest BI information at anytime and anywhere. Therefore, the research population of this study is composed of mobile BI users who use mobile BI for decision making at the strategic, tactical and operational level across a range of organisations and industries.

5.2 RESEARCH DESIGN

The research design used in this study is a questionnaire/survey. Using a survey helps the researcher gather information from a representative sample and generalize those findings back to a population, within the limits of random error (Bartlett, Kotrlik, & Higgins, 2001b). The advantages of a survey depends on what type of survey is being conducted. In this study the data was collected by means of an online survey. The advantages of an online survey include flexibility in reaching a wide range of respondents, elimination of paper, postage and sending mail. Online surveys are also easier to send remainders, follow-ups and importing collected data into data analysis programs (Fricker & Schonlau, 2002).

As with many other researchers we also didn't have access to the entire population of interest, which in this study are the mobile BI users. Furthermore, it is generally not necessary to study all possible cases to understand the phenomena under consideration (Chuan & Penyelidikan, 2006). The right sample size, therefore had to be measured for this study. Determining the sample size and dealing with non-response bias is essential for research that is based on a survey methodology (Bartlett et al., 2001b).

Sample size

If the sample size is too low, it lacks precision to provide reliable answers to the research questions investigated. If the sample size is too large, time and resources could be wasted often for minimal gain (Chuan & Penyelidikan, 2006).

The two most commonly used measures to estimate the sample size are Cohan Statistical Power Analysis and Krejcie and Morgan's formula (Chuan & Penyelidikan, 2006). Cohan's power analysis is commonly used in social behavioural research (Faul, Erdfelder, Lang, & Buchner, 2007). It is also intended for situations where the population consists of two or more groups (Cohen, 1988, p. 273). This study consist of one group, the mobile BI users. Moreover, the goal of this study is not to compare the differences between two or more groups, and therefore, this method is not feasible for this study. The sample size formula from Krejcie and Morgan can be used to determine the sample size that is representative of a given population (Krejcie & Morgan, 1970). This means that the formula of Krejcie and Morgan can be used to determine the sample size for this study and is the reason we chose to use this formula.

The formula of Krejcie and Morgan:
$$s = X^2 * N * P(1-P) \div d^2(N-1) + X^2 * P(1-P)$$

s = required sample size
X^2= Chi-square for the specified confidence level at 1 degree of freedom
N= Population size
P= Population proportion (assumed to be 0.5 since this would provide the maximum sample size)
d= degree of accuracy expressed as a proportion (0.05)
Source: Krejcie & Morgan (1970)

The specified confidence level is the amount of uncertainty that can be tolerated. It indicates how confident, for example a researcher can be in his results. The most common used confidence level is 95% (5% margin of error), this means that you can be 95% certain that the truth lies somewhere within the 95% confidence level (Gosling, 1995). The exact population size of all mobile BI users is at this point unknown and, therefore, we chose a population size of 100.000 mobile BI users, since a larger population size doesn't increase the sample size with the formula of Krejcie and Morgan. This results in a sample size of at least 384 mobile BI users.

Non-response bias

When non-responders are systematically different from respondents, non-response bias is present, and can severely limit the ability to generalise the survey findings. Non-responders can be different in crucial aspects from responders, such as the level of education, gender, age, job type, department etc. The best way to avoid possible problems that accompany response bias is to take proactive steps to maximize the percentage of survey returned (Edwards, 1997, p. 94). There are several factors that have been developed and studied by survey researchers to increase the survey response rate, see table 11 for a summarisation of factors that according to Edwards (1997, p. 94) can be used to increase the response rate on a survey.

Table 11: Factors to increase survey response rates

Factors to increase survey response rates
Repeated contact: the most important factor in increasing response rates
Survey follow-ups/remainders
Incentives
Prenotification: contact potential respondents before mailing the actual survey
Survey length: shorter survey length is associated with higher response rates

Based on: Edwards (2007, p. 95)

Armstrong (1975) is one of the first studies that researched the effect of monetary incentives on the response rate and concluded that a monetary incentive has a strong impact on the response rate of a survey. Monetary incentives work because accepting the money without responding would create dissonance since one is violating the norm reciprocity (the expectation that people will respond favourably to each other by returning benefits for benefits). Monetary incentives also work for members in a professional group and don't affect the data quality (Armstrong & Yokum, 1994; Armstrong, 1975; Shaw, Beebe, Jensen, & Adlis, 2001). Deutskens et al. (2004) researched the effects of follow-ups, lottery, donations, vouchers, length of questionnaires and visually enhanced questionnaires on the response rate to a survey. They concluded that a follow-up influences the response rate, but it didn't affect the response quality. Vouchers and a lottery had the same positive impact on the response rate, and donations also had a positive but lower impact on the response rate. Vouchers, lottery and donations didn't influence the response quality. Shorter questionnaires (nine product categories in the research setting) have a higher response rate than longer questionnaires (19 product categories), and respondents stopped relatively earlier in the long version than in the short version. Furthermore, visually enhanced questionnaires decrease response rates compared to text based questionnaires (Deutskens et al., 2004). Based on the discussion above, the following methods were used to increase the response rate on the survey for this study:

- Prenotification, contact potential respondents before mailing the mobile BI survey.
- Survey follow-up, sending remainders.
- Short survey.
- Text based survey.
- Incentives.

There are only a few Dutch organisations that use mobile BI. Therefore, to apply at the minimum sample size, the survey had to be widened to additional countries. This made it difficult to apply a monetary incentive as donating money to potential participants can hugely increase costs. Therefore, other kind of incentives were used:

- For every completed survey, one dollar will be donated to the World Wide Fund for Nature.
- Lottery, one participant can win 150 dollar.
- Each participant may choose if he/she wants to receive the results of this study.

It is still feasible that we are unable to send every participant a pre-notification; therefore, we investigate the non-response bias after the survey distribution is ended by comparing the average values for dependent, independent, moderate and demographic variables between respondents that were sent a pre-notification, and respondents that didn't receive a pre-notification, as recommended by Edwards (1997, p. 94).

5.3 SURVEY METHODOLOGY

A questionnaire or survey is a formalized set of questions in order to extract information from the target respondents. In order to design the questionnaire for this study, we followed Sharma's (2007, p. 17) general principles of a questionnaire design, which are based on numerous studies and experiences of survey researchers. See figure 12 for an overview of these principles.

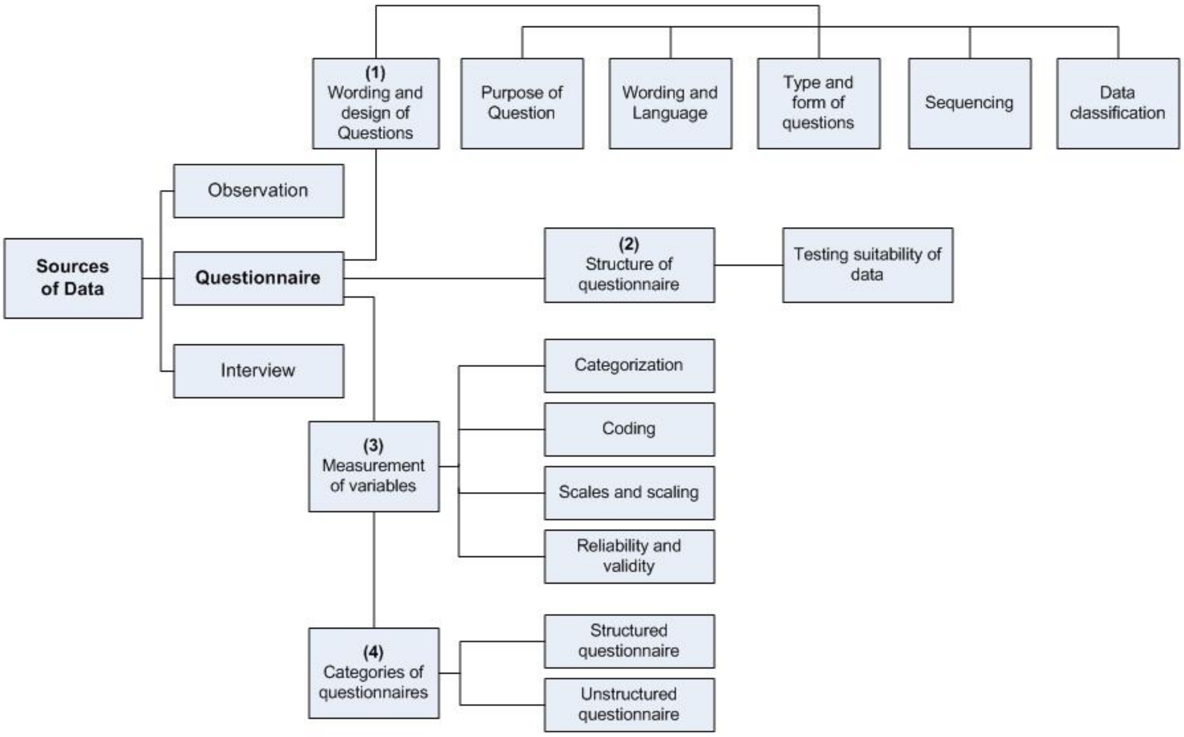

Figure 12: Principles of questionnaire design Source: Sharma (2007, p. 17)

5.3.1 WORDING AND DESIGN OF QUESTIONS

The content and wording of the questions in a survey are amongst those factors that impact on the effectiveness of surveys. When survey questions are too difficult to answer, for example because the wording is confusing to respondents or the questions are inappropriate, the outcome can be misleading and fail to reveal accurate data which could answer the main question. Therefore, the goals are for each respondent to interpret the question in the same way, answer accurately, and be open and willing to answer the question. To reach these goals, the word choice used in questions should be simple, easily understood, clear, and direct. Furthermore, questions should be short and simple (Niederhauser & Mattheus, 2010).

5.3.2 STRUCTURE OF THE QUESTIONNAIRE

There are two main types of survey questions, open-ended and closed-ended. Open-ended questions allow respondents to answer in any way they choose. A closed question would ask respondents to make choices from a set of alternatives. It helps the respondent to form quick decisions by making a choice from the several alternatives provided (Sharma, 2007, p. 18). The questionnaire for this study is built on closed-ended questions, because the responses of closed-ended questions can be compared across participants; they also take less time to complete than open-ended questions do, which should have a positive effect on the response rate.

Closed questions are used in a structured questionnaire. A structured questionnaire is a formal list of questions that is to be posed to the respondents in a predetermined order and the responses permitted are entirely predetermined. A structured questionnaire can be disguised or non-disguised. This classification is based on whether the objectives of the study are disclosed or not disclosed to the respondents. A disguised structured questionnaire is chosen when the objective of an research is not disclosed to the respondent. When, for example is suspected that the respondent may not remain objective or impartial, due to matters affecting goodwill or the reputation of an organisation. A non-disguised structured questionnaire is chosen when the objective of a research is disclosed to the respondent. Questions are presented with exactly the same wording, in the same order, to all respondents, which makes it easy to tabulate and analyse (Sharma, 2007, p. 20). The purpose of this study is disclosed to the respondent. Therefore, the questionnaire for this study is non-disguised and structured. There are various kinds of questions that have a structured question-answer format. Table 12 outlines which closed-end questions are commonly used.

Table 12: Closed-end question response types, description, and examples

Response type	Description	Question	Response examples
Dichotomous	The dichotomous question is generally a ''yes/no'' question	Have you had any surgeries in the past 12 months?	Yes/No
Multiple choice	The multiple-choice question consists of 3 or more exhaustive, mutually exclusive categories; multiple-choice questions can ask for single or multiple answers	What type of insurance does your child have?	Private; Medicaid; No insurance
Rank order	Rank order scaling questions allow a certain set of brands or products to be ranked based on a specific attribute or characteristic	Based on your experience with our hospital services, place a ''1'' next to the area where the best service was provided, a ''2'' where the second best service was provided, and so on	3 Radiology 1 Admission 2 Laboratory 4 Pharmacy
Rating scales	A rating scale question requires a person to rate a product or brand along a well-defined, evenly spaced continuum; rating scales often are used to measure the direction and intensity of attitudes	How would you rate the service that you received in the pharmacy department today?	Very good; good; fair; poor; very poor
Semantic Differential Scale	The Semantic Differential Scale asks a person to rate a product, brand, or company based on a 7-point rating scale that has 2 bi-polar adjectives at each end	How would you rate the taste of the new chewable vitamin?	1 Tastes great 2 3 4 5 6 7 Tastes terrible
Likert scale	The likert scale is a psychometric response scale, which is primarily used in questionnaires to obtain participant's preferences or degree of agreement with a statement or set of statements.	Please indicate how much you agree or disagree with the statement: The Elisabeth hospital is easy to find.	1 Strongly agree 2 Agree 3 Neither 4 Disagree 5 Strongly disagree

Based on: Niederhauser & Mattheus (2010) and Cooper & Schindler (2003, p. 253)

5.3.3 SCALES AND SCALING

Although the questionnaire response categories show a great variety, there are only four main types of data that can be used to measure the respondents answers:

- **Nominal scale:** a nominal scale is one in which numbers are used as labels and have no numerical sanctity. For example, to categorise male and female respondents, a nominal scale of 1 for male and 2 for female could be used. However, 1 and 2 do not represent any order or distance, they are simple used as labels (Nargundkar, 2003, p. 55).
- **Ordinal scale:** a variable is ordinal when the answers can be put into the correct sequence. For example 1= strongly agree and 5= strongly disagree (Nargundkar, 2003, p. 55).

- **Interval scale:** ordinal scale with the additional factor that the distance between observations is meaningful. For example: temperature; the difference between 30 degrees and 40 degrees represents the same temperature difference as the difference between 80 degrees and 90 degrees (Nargundkar, 2003, p. 55).
- **Ratio scale:** Ratio scale refers to the level of measurement in which the attributes composing variables are measured on specific numerical scores or values that have equal distances between attributes or points along the scale and are based on a 'true zero' point. There is an absolute zero that indicates an absence of the variable measured. Examples are length, weight and time. The variable, number of vehicles owned in the past five years is an example of a ratio-scale variable. A score of zero for this variable means the respondent owned no vehicles in the past 5 years (Nargundkar, 2003, p. 56).

In the next section we will discuss the survey development which also includes the measurement scale that is chosen for the survey in this study.

5.4 SURVEY DEVELOPMENT

Based on the research design in the previous subsections a survey was developed that consists of four parts. This survey was refined by suggestions of (mobile) BI experts. Several mobile BI experts of Capgemini and three BI professors of three different universities, namely; Tilburg University, Vlerick Business School and the University of Ljubljana reviewed the survey. Based on their suggestions, ambiguity, sequencing and flow of the questions were addressed.

The first part of the survey contains an introduction. This introduction states the identity of the researcher, the field of study and affiliation (Tilburg University). The introduction also contains a brief description of the purpose of the research stated, confidentially and anonymity were addressed, incentives were summarized and instructions were given to the participants. Contact details which participants could use to communicate with the researcher were also provided. The second part of the survey contains questions aimed at collecting demographic information from the respondents in order to provide a clear overview of their origins. The third part starts with a second very short introduction which explains that in cases where participants are using more than one mobile BI solution, they need to focus on only one of them, and to answer the questions based on that specific solution. Participants are also made aware of the favourable and unfavourable statements. A lengthy introduction could result in a situation where participants start the survey without carefully reading the full introduction and instructions. This introduction is followed with statements about the constructs of the conceptual model. The fourth and last part contains closing questions which participants can answer if they would like to receive the outcomes of the research, and comment, if desired, on the survey. Finally, the survey ends with a closing statement to thank the respondent for their participation. The survey can be found in appendix A. The survey consisted of four online pages and was kept as short as possible to decrease the possibility of errors due to fatigue ore boredom.

How the constructs are measured is discussed in the next section.

5.4.1 CONSTRUCT MEASUREMENT

Measurement scales

Most studies that were used to derive the statements for the survey used a 5- or 7-point Likert scale. According to Cooper & Schindler (2003, p. 253) the Likert scale is the most frequently used variation of the summated rating scale. A summated scale is made up of favourable and unfavourable statements to which the participant either agrees or disagrees. The wider the range of the scale, the greater the variance expected and the larger the sample size required (variance is a value, that represents the total amount of dispersion of values for a single variable about its mean (Hair et al. 209, p. 105). However, Dawes (2008) concluded in a study concerning 'to what extent does the number of response categories in a Likert-type scale influence the resultant data?', that five and seven-point scales can easily be re-scaled with the resultant data being quite comparable. In Dawes (2008) study, the five and seven-point scales produced the same mean score as each other, once they were re-scaled. There only appeared to be a little difference between the 5-point and 10-point format. Dawes couldn't find a clear advantage between a 5- or a 7- point scale. This conclusion is also stated by Goodwin (2009, p. 477). Goodwin states that a 5-point scale normally provides sufficient discrimination among levels of agreement. A 7-point scale still yields five points if people avoid the extremes, but adding the extra levels of discrimination can increase the time it takes to complete the survey. Goodwin (2009, p. 477) states that one general rule is to avoid mixing formats. In other words, don't mix a 5-point and a 7-point scales in the same survey. In order to increase the response rate, a 5-point Likert scale was selected for this study. The longer it takes to complete a survey the lower the response rate. The Likert scale ranges in this survey from 'strongly agree' to 'strongly disagree'. Next to the 5-point Likert scale, three statements are measured with a 5-point semantic differential scale, these are the ones from use and time since adoption.

In order to prevent participants rushing, the survey consists out of favourable and unfavourable statements. This forces respondents to read each statement carefully and make item-by-tem decisions. Participants are made aware of this method in the introduction of the survey. This also helps to avoid response bias: response acquiescence, which is a tendency to agree with statements. Statements of a similar general subject are clustered in the same place on the survey (Goodwin, 2009, p. 477). The next section will discuss how the constructs are measured.

Accessibility
Accessibility was measured using three statements, a statement to measure user access quality (Isik et al., 2011), another statement to measure if the information is processed and delivered without a delay (Eppler, 2003, p. 83; Popovič et al., 2012) and lastly a statement to measure if mobile BI users can access their mobile BI solution at anytime and anywhere they want to (Lee & Chung, 2009).

Ease of use
Ease of use was measured by two statements that were adapted from Doll & Torkzadeh's (1988) EUCS instrument, which is widely used in the literature (e.g. Abdinnour-Helm, Chaparro, & Farmer, 2005; McHaney, Hightower, & Pearson, 2002; McHaney, Hightower, & White, 1999). The two statements are also used in a BI study of Hou (2012) and in a DSS study of Moreau (2006).

Flexibility
Three statements were used to measure if mobile BI systems are flexible enough to align with the desired changing information needs of mobile BI users (Isik et al., 2011; Yeoh & Koronios, 2010).

Attractive interface design
Attractive interface design was measured by two statements which are adapted from Santosa, Wei, & Chan (2005).

Information Quality
To measure Information Quality, Popovič et al. (2012) used seven previously researched and validated indicators from Eppler's (2003, p. 83) IQ framework. Eppler's (2003) IQ framework is one of the broadest and most thorough analysis of IQ criteria. In this research we adapted the same seven IQ statements that are used by Popovič et al. (2012) of Eppler's (2003, p. 83) IQ framework, to measure the relevance and soundness of the information. In other words, to measure the

information content quality with the following elements, comprehensiveness, accuracy, clarity, conciseness, consistency, correctness and currency.

Engagement
Six statements were developed to measure engagement, which are all based on those that were used in engagement studies of Rozendaal et al. (2009), Webster & Ho (1997) and Webster & Ahuja (2006).

User Satisfaction
Several standard instruments have been developed and tested to measure user satisfaction of an IS (Delone & McLean, 2003). In this study, user satisfaction is measured by three statements. Two statements were adapted from Lee and Chung (2009) and the third statement is adapted from Wang & Liao (2008). Both studies used DeLone and McLean's (2003) IS success model.

Use
Frequency of use and duration of use by the individual are commonly used for measuring system use (Hou, 2012). In this study, mobile BI usage was measured by (1) Duration of use, which asked participants to indicate how much time was spent on the mobile BI solution per week, using a 5-point semantic differential scale ranging from '1' *(less than 10 minutes)* to '5' *(more than 2 hours)* and (2) frequency of use, which was measured on a five-point scale ranging from "1" *(less than once a week)* to "5" *(more than once a day)*. Both measures were adapted from Hou (2012) and Iivari (2005). To distinguish between mandatory or voluntary usage situations, the conceptual model posits voluntariness as a moderating variable. Two items are used to measure voluntariness of mobile BI and are adapted from Hou (2012), Heo & Han (2003) and Moore & Benbasat (1991).

Net Benefits
Net benefit was assessed using nine statements, which in this study are the elements of mobile BI net benefits. Eight of these statements were adapted from the net benefit measuring items in table 6, and from a DSS study of Moreau (2006). Moreau (2006) isn't included in table 6, however, she studied the decision quality of intelligence DSS. Not all the items are adapted from table 6 and Moreau (2006), because that would have resulted in a large survey, which could have decreased the response rate. Therefore a selection was made based on items that could be transformed into individual performance benefits, items that were highly validated, and items with a high significance level and feedback of mobile BI experts. Six of these statements measuring the perceived impact of mobile BI solutions on job performance, individual productivity, job effectiveness and decision-making were adapted from Hou (2012), Heo & Han (2003) and Moreau (2006). One statement measuring the problem identification speed is adapted from Hou (2012) and Popovič et al. (2012). Another statement, measuring the key performance indicators is adapted from Popovič et al. (2012), and the last statement, measuring the costs of business processes is adopted from Popovič et al. (2012) and Elbashir et al. (2008).

Control Variables
Top management support is measured with a statement that is adapted from Sabherwal (2006). Time since adoption is measured with an adapted statement from Sabramani (2004), used to indicate how many years the organisations of the mobile BI user has been using mobile BI, using a 5-point semantic differential scale ranging from '1' *(less than 6 months)* to '5' *(over 3 year)*.

5.4.2 CONTENT VALIDITY

For a measurement to be correct, it should be valid and reliable (Cooper & Schindler, 2003, p.231). The next section discusses the content validity and how the statements of the survey are derived.

Validity refers to 'the extent to which a test measures what we actually wish to measure' (Cooper & Schindler, 2003, p. 231). That is, the degree to which the measuring instrument actually measures what it is designed to measure. Validity can be divided into internal and external validity. External validity refers to the data's ability to generalise between an individual's settings, and times. Internal validity refers to the ability of a research instrument to measure what it is purported to measure. Before a survey is addressed, content validity (part of internal validity) should be covered (Cooper & Schindler, 2003, p. 231:236).

Content validity is 'the degree to which content of the items adequately represents the universe of all relevant items under study' (Cooper & Schindler, 2003, p. 232). In other words, whether the questions, called items in the instrument, cover all the factors they were intended to address. A measure has content validity when its items accurately represent the construct that is being measured. Content validity is judgemental and is generally to be established by adapting the constructs and items carefully from the literature, and by consulting experts in the topic area in determining the appropriateness of each survey question (Boudreau, Gefen, & Straub, 2001). The third part of the survey contains statements of the constructs of the conceptual model. Cooper and Schindler (2003, p. 232) suggested two approaches to determine the content validity of the survey instrument.

The first approach is to determine the content validity through a careful definition of the topic of concern, the items to be scaled, and the scales to be used. If the instrument adequately covers the topics that have been defined as relevant constructs, then the instrument can be said to have good content validity (Cooper & Schindler, 2003, p. 232). The conceptual model consist of twelve constructs which are all defined as relevant constructs in chapter four. The statements for all twelve constructs were derived from scientifically published articles. However, the combination of some of the statements used to measure a construct has previously been not used in research. Some statements were slightly rewritten to fit the mobile BI context.

The second approach to ensure content validity, is to engage a panel to judge how well the instrument meets the standards (Cooper & Schindler, 2003, p. 232). A global mobile BI team of Capgemini, acknowledged as the mobile BI experts of Capgemini, and three BI professors from three different universities; Tilburg University, Vlerick Business School and the University of Ljubljana, reviewed the survey on wording, clarity, sequence, questionnaire format, appropriateness of the questions and whether the items adequately cover the relevant constructs on the topic being examined. The survey was modified based on their feedback. Also Dr. M. Rozendaal (Rozendaal, 2007 and 2009) was contacted specifically for feedback on the engagement statements.

Using the two approaches of Cooper & Schindler (2003) it is assumed that the content validity of the survey is validated.

5.5 DATA COLLECTION

Mobile BI is an information system not used by many organisations, which makes it difficult to spread the survey to a sufficient number of organisations. Different data collection methods were therefore used to gather responses from (key) mobile BI users of various organisations.

Mobile BI vendors

Mobile BI vendors that are mentioned by Gartner in mobile BI reports of Tapadihas (2011) and Sood, Bitterer & Richardson (2011) were contacted for their cooperation in promoting this mobile BI survey (24 mobile BI vendors, see appendix A for an overview). In return, the mobile BI vendors were allowed to use the final results of this study in their marketing activities. Many mobile BI vendors declined cooperation for reasons such as they had their own internal studies on the subject, and therefore wanted to prevent survey fatigue. Mobile BI vendors that agreed to promote this mobile BI survey are: Andara, MicroStrategy Benelux, Qlikview Benelux, Tableau, SurfBI, PushBI (Extended Results) and Tibco. This resulted in 48 surveys being initiated and 23 completed, see table 14.

Mobile BI case studies
Some of the 24 mobile BI vendors have published one or more mobile BI success stories on their own website. Each organisation that was mentioned in those mobile BI success stories was contacted. More specifically, each case consisted of one or more persons interviewed by the organisation that deployed a mobile BI solution. We contacted those persons by Linkedin, and asked if they wished the mobile BI survey to be addressed to a key end mobile BI user, or to complete it themselves, if they were themselves a mobile BI user. Most contact persons were interested in this mobile BI study, but didn't forward or complete the survey after the initial contact. Therefore, between one and five reminders were sent to those potential participants who didn't complete the mobile BI survey. Eventually this resulted in almost success story individual who was contacted, completing the survey, and/or forwarding the survey to a key mobile BI user at that organisation. This resulted in 66 surveys being initiated, and 53 completed surveys.

BIScorecard
After contacting research organisations such as Gartner, BeyeNETWORK, TDWI, Aberdeen, Dresner, Forrester and BIScorecard to ask if they would be interested in promoting the mobile BI survey of this study, only BIScorecard responded positively. They included the mobile BI survey in a mailing to their subscribers which they emailed on Febuari 27, 2013. Unfortunately, that resulted only in four surveys getting off the ground, and none of them were completed.

Mobile BI vendor forums
We assumed that key end mobile BI users were active on mobile BI vendor forums, out of interest in their solution and to learn more, or when they have problems with their solution. Most of the mobile BI vendors that are listed in appendix A have a forum for (mobile) BI users and developers. However, not all the forums did have a mobile section, or were actively visited; on some the last post was written two or three months previously. Therefore, we posted the mobile BI survey only on active forums with a mobile section, which were Tableau, MicroStrategy, Qlikview and SAP, and also tried to make the mobile BI survey popular by answering questions of forum members. This resulted in 97 surveys being initiated, and 36 completed.

Capgemini
Capgemini tweeted the mobile BI survey three times on their twitter account, which resulted in 38 surveys being initiated, and six completed.

Qlikfix
Promoting the mobile BI survey using the described methods gained the attention of http://www.qlikfix.com, which is a blog with Qlikview tips, tricks and tutorials. The owner of Qlikfix was interested in the results of this mobile BI study, and therefore, we were allowed to write a blogpost to promote it, see http://www.qlikfix.com/2013/02/28/mobile-bi-survey. This blogpost was published on February 28, 2013 and resulted in 43 surveys being initiated, and 13 completed.

DMG Federal
Promoting the mobile BI survey also gained the attention of DMG Federal, a consulting practice in the USA that provides Information Technology services. DMG promoted the mobile BI survey with a tweet, which resulted in six surveys being initiated, and four completed.

Linkedin

The mobile BI survey was published on 25 Linkedin BI groups, see table 13, as we expected that key-end mobile BI users were active on Linkedin BI groups, and it could gain the attention of mobile BI vendors which may were interested to spread the survey in order to receive the results of the survey. The survey was published once in a specific group, and to gain more attention, comments were posted after one or two weeks to move the survey to the 'latest discussions' in that Linked BI group. This often resulted in comments of other members who were in the mobile BI survey and study. It wasn't possible to post the survey at the same moment in every Linkedin group, because some groups required a screening test of new Linkedin members. However, the first survey was posted on March 2 2013, and the last one on June 4 2013. This resulted in 164 surveys being initiated, and 70 completed.

Table 13: Linkedin BI Groups

Linkedin BI Groups
Australian Mobile Business Intelligence Group
Benelux Network of Business Intelligence Professionals
BI Leadership Forum
Business Intelligence
Business Objects
Business Intelligence, Big Data, Analytics, MIS Reporting & Database
Gartner Business Intelligence & Information Management (Xchange)
Microsoft Business Intelligence
MicroStrategy
MicroStrategy Busines Intelligence
MicroStrategy Benelux Networks of BI professionals
Mobile Intelligence
Mobile Business Intelligence
Mobile Business Intelligence Solutions
Mobile Business Intelligence Australia
Nederlandse Tableau Gebruikersgroep
Oracle Business Intelligence
Qlikview
Roambi Developers
Roambi Partners
SAP BI (Business Intelligence)
SAP BI and Business Objects
SAP Mobile BI
Tableau Software Fans and Friends
TDWI Business Intelligence and Data Warehousing Discussion Group

Table 14: Data collection methods

By	Method	Surveys started	Surveys completed
Organisations of mobile BI case studies	Contacted personally	66	53
Andara	Mailing	19	12
BIScorecard	Mailing to their subscribers	3	0
Capgemini	Twitter	38	6
DMG Federal	Twitter	6	4
Linkedin groups	Post + discussions	164	70
MicroStrategy Benelux	Twitter + Facebook +Linkedin	3	2
Mobile BI vendor forums	Forumpost	97	36
Qlikview Benelux	Twitter + Mailing	8	3
Qlikfix	Blogpost	43	13
PushBI	Twitter	6	4
SurfBI	Mailing	0	0
Tableau	Blogpost	5	1
Tibco	Twitter + Facebook +Linkedin	7	1
Total		**465**	**205**

5.6 CONCLUSION

A research population is defined, the necessary sample size is calculated, and a survey is developed and used to gather the data to test the conceptual model. However, the calculated sample size in section 5.2 is 384 respondents and the data collection only resulted in 205 responses. Due to time limits it was not possible to spread the survey for a longer period. This means that the results of this research cannot be generalised. The next step is to analyse the data.

6 DATA ANALYSIS

Chapter 5 discusses the design of the empirical part of this study; the research population, research design, the survey development and the data collection methods. This chapter is the second and final empirical part of this study. It explains how the collected data was analysed. This begins with a data analysis on missing values, outliers, normality, non-response bias and common bias in section 6.1. Next the demographics of the respondents are discussed in section 6.2. Section 6.3 discusses the importance of distinguishing between reflective and formative constructs. Based on that we used a cross-validation method to examine the reliability and validity of the reflective constructs in section 6.4 and 6.5. Reliability and validity of the formative constructs is discussed in section 6.6. Section 6.7 shows a summarised conclusion of the validation analyses of the reflective and formative constructs. Finally, in section 6.8 the developed hypotheses will be tested. A mediation effect of the model is tested in 6.9 and the chapter ends with a discussion of the voluntariness of use of mobile BI in section 6.10.

The data analyses in this chapter are conducted with SPSS version 18 and SmartPLS version 2.0 M3. SmartPLS is a component-based path modelling program based on partial least squares (PLS). PLS is a structured equation modelling estimation technique which generates estimation of item loadings and path coefficients simultaneously. Path coefficients indicates the strength of the relationships between the independent and dependent variables. We chose PLS because it performs a confirmatory factor analysis (Gefen & Straub, 2005), it is widely used and accepted, it handles both reflective and formative constructs (Esposito et al., 2010, p. 203; Hair et al., 2009, p. 760) it is an appropriate technique when sample sizes are small and the assumption of a normal distribution cannot be made (Hair et al. 2011), and Hair et al. (2011) even describe it as the 'silver bullet' for estimating causal models in many theoretical models and empirical data situations.

6.1 DATA SCREENING

Before starting with the data analysis , the answers of the unfavourable statements are reserved, so that they are in line with the favourable statements.

6.1.1 MISSING VALUES

Missing values are gaps in data sets, which occur when there is no response to a question or statement. Including cases that have not answered a particular question presents data analysis with several problems, such as, it can distort results, it confuses real responses with non responses, it can destroy the ordinal or interval character of any variable (a missing-value code cannot be ranked meaningful) and the inclusion of cases with missing values also inflates or deflates the scale scores. The logical assumption would be to exclude these cases, however, doing so may cause systematic differences in cases with valid values. Excluding these cases may lead to a biased sample and distorted patterns (Vaus, 2002, p. 66). In the mobile BI survey of this study, respondents may decline to answer any particular question that they are uncomfortable with or feel is not appropriate (see appendix A), which may result in some completed surveys that have missing values.

We used the Frequency feature in SPSS (version 18) and identified six cases with missing values. One respondent did not answer ten questions, another seven questions, a third four questions and three respondents declined to answer two questions. There are three main approaches to deal with those missing values:

1. Pairwise deletion: excludes a case that has a missing value on either a pair of variables for which a relationship is being examined. In other words, when we examine the relationship between IQ and Use, and a case has a missing value on either IQ or Use, that case would be excluded from the analysis. *Problems*: on which number of cases should the other cases be based on?, this can give problems in multiple regression, factor analysis and cluster analysis (Vaus, 2002, p. 67)
2. Listwise deletion: Simply deleting an entire case if it is missing any item used in the analysis. *Problems*: Listewise deletion can cause a very serious loss of cases that can compromise the analysis. This should not be used if it involves more than 10-15% of the cases (Vaus, 2002, p. 67)
3. The replacement-based techniques: substitute a valid value for the missing value. It involves calculating a best estimate of what the person's value would have been had they answered the question. *Problems*: Any short or simple correction may be more likely to generate biases. It is a risky method (Vaus, 2002, p. 68)

We have 205 cases, and six cases have missing values, which is only +/- 3% of the cases. Lynch (2003) suggest to use the Listwise delete approach when you have less than 5% of missing cases. Because only 3% of the cases have missing values, we chose to delete those six cases. This approach also avoids problems with the factor analysis in a later stadium, and avoids to probability to impute a bias value.

6.1.2 OUTLIERS

An outlier is a deviant case, it is an extreme numeric value in a distribution, and as such can have an undue influence on some statistics. Outliers can be a problem when variables are used to describe the distribution or a relationship between variables. Outliers and extreme scores may be an indication of an error in the data entry. It is therefore important to check the data on outliers (Vaus, 2002, p. 92). To screen for outliers, we used the SPSS Boxplot feature, which gives a graphical representation of the data (Weinberg & Abramowitz, 2008, p. 41) and used the standard deviation option of excel to check the variables on anomalies. If, respondents were paying attention while completing the mobile BI survey, this would indicate that in this study engaged responses is likely a better definition than outliers. We studied the responses to see if were just answered systematically, such as 3, 3, 3, 3, 3, 3, or 1, 2, 3, 1, 2, 3, and also carefully checked which answers those respondents gave on the unfavourable statements.

Based on these criteria we could identify three cases as outliers, in these cases respondents answered with 3333 etc. and 5555 etc. also doing the same on the unfavourable statements. This indicates that they were rushing through the survey, and it means their answers are irrelevant because there isn't any variance in the responses. Those three cases were therefore dropped from the dataset.

This means that the dataset used is now 196 cases instead of 205 cases as outlined in the previous chapter.

6.1.3 NORMALITY

Normality refers to the distribution of the data for a particular variable. It is used to describe a symmetrical, bell-shaped curve, which has the greatest frequency of scores in the middle, with smaller frequencies towards the extremes. The normal distribution is probably the most important distribution in statistics, mainly because it has a link with the Central Limit Theorem, which states that *regardless of the form of the original distribution, the distribution of means will approximately normal when N is large*. In other words, if we repeatedly take independent random samples of size N from any population, then when N is large, the distribution of the sample means will approach a normal distribution. Thus it indicates that the sampling distribution of a mean, will tend to follow a normal distribution even when the underlying population has a non-normal distribution. Having a normal distribution is important because statistics is based upon the fact that it is rarely feasible or practical to collect all the data from an entire population, it is the foundation for interval estimation and a variety of inferential statistics, including F and t statistics and analysis of variance. With the Central Limit Theorem we can estimate the parameters (mean and standard deviation/variance) of a normal distribution with a small number of samples. The mean indicates where the centre of that distribution is, and the standard deviation reveals the spread. The shape of the distribution can be assessed with two measures: kurtosis and skewness (Hair et al., 2009, p. 71; Huck, 2004, p. 29).

Kurtosis

Kurtosis refers to the 'peakedness' or 'flatness' of the distribution compared with the normal distribution. A normal distribution has a kurtosis value of zero. Data that exhibit positive kurtosis are more clustered around the mean ('peaked') and the tails of the distribution are longer. A negative kurtosis score occurs when the data are clustered less around the mean and have shorter tails (Hair et al., 2009, p. 71; Huck, 2004, p. 29).

Skewness

Skewness is used to describe the balance of the distribution. Hence, it is unbalanced and shifted to one side (right or left) or it is centred and symmetrical with the same shape on both sides. If a distribution is unbalanced it is skewed. A negative skew denotes that the mass of the distribution is concentrated to the right, it has relatively few low values. A positive skew denotes that the mass of the distribution is concentrated to the left, it has relatively few high values (Hair et al., 2009, p. 71; Huck, 2004, p. 29).

Table 15: Skewness and Kurtosis

Demographic variables	Skewness	Kurtosis
Education	1,708	3,164
Principal industry	-1,152	
Work position		-1,438
Mobile platform	1,013	
Construct		
SQEU_1 (Ease of use)	-1,474	3,551
SQEU_2 (Ease of use)	-1,155	
SQID_1 (Design)	-1,203	
SQID_2 (Design)	-1,278	2,512
SQA_3 (Anytime/Anywhere)	-1,194	
IQ_5 (Information consistent)	-1,109	3,133
US_2 (User satisfaction)	-1,222	2,111
UV1_1 (Voluntariness)	-1,019	
U2_1 (Use)		-1,082
MBB_1 (Net Benefits)	-1,016	
Top Management Support	-1,021	
Time Since Adoption		-1,015

Kurtosis and skewness results

Huck (2004, p. 29) states that there is no problem in terms of normal distribution if the skewness coefficient of distribution is between -1.0 and +1.0, and the coefficient of kurtosis is between -1.0 and +2.0. We used SPSS version 18 to examine the kurtosis and skewness of the independent, dependent, moderate and the demographic variables. Table 15 shows the variables that have some kurtosis and skewness issues, the full SPSS output can be found in appendix C.

For the demographic variables, education and mobile platform are positively skewed, which means that the majority of the respondents have a bachelor and or master degree, and that most answered that they completed the survey based on their tablet mobile BI usage. Principal industry is negatively skewed, in this case it means that the majority of the respondents work in a different principal industry than stated on the provided list. There are eight construct items that are negatively skewed. The majority of the respondents answered positively on the ease of use statements and design statements. Furthermore, most of those who affirmed that they are able to use their mobile BI solution at anytime and anywhere, found the information supplied to be consistent, recommend mobile BI solutions to others, can make higher quality decisions, use their mobile BI solution voluntary and have top management support.

Education has a positive kurtosis value, which means that there isn't a lot of variance in that item as answers were very similar. This also applies to four construct items in table 15. Work position, use and time since adoption have a negatively kurtosis value, which means that respondents answered very differently, and there wasn't a central tendency towards the median.

The analysis of kurtosis and skewness shows that there are problems with the normal distribution of some items. We haven't deleted these items, only examined them in the exploratory factor analysis to see if they cause problems, for example, that they might not load on a factor. Furthermore, we use PLS for the most data analysis; PLS does not presume that the data are normally distributed, it assumes that the sample distribution is a reasonable representation of the intended population distribution. Therefore, further statistical analyses are not invalid because of the non-normal data (Hair, Ringle, & Sarstedt, 2011).

6.1.4 NON-RESPONSE BIAS

There are different data collection method used for this study, which can result in a non-response bias. In general the respondents can be divided into four groups:

1. Participants of the mobile BI case stories. We contacted those respondents personally, and had to send up to a maximum of five remainders before they forwarded or completed the mobile BI survey.
2. Participants of the Linkedin Groups.
3. Participants of the mobile BI vendor forums; Tableau, Qlikview, SAP en MicroStrategy.
4. Respondents of mobile BI vendors and implementers; Andara, Capgemini, DMG Federal, MicroStrategy Benelux, Qlikview Benelux, Qlikfix, PushBI, Tableau and Tibco.

Group one consist of respondents who were stimulated by personal contact and personal reminders. We didn't combine group two, three and four because respondents in group two could have been prompted by the comments in the Linkedin discussions. Respondents in group three could have been stimulated by the answers we gave on the questions of forum members, and group four by multiple tweets.

To assess non-response bias, respondents from group one were compared against the other three groups. We compared the group to which we administered one or more personal pre-notifications with the three groups who didn't receive one, with respect to dependent, independent, moderate and demographic variables. This method is based on the assumption that subjects who respond less readily are similar to non-respondents. 'Less readily' is defined as answering later, or as requiring more stimulus to answer. The most common type of estimating 'less readily' is carried over 'success waves' of a survey (Armstrong & Overton, 1977a). Wave refers to the response generated by a stimulus, in this study, a personal reminder. Persons who respond in later waves are assumed to have done so because of the increased stimulus and are expected to be similar to non-respondents (Armstrong & Overton, 1977b; Kanuk & Berenson, 1975). This method to examine the possible presence of a non-response bias has shown to be an useful method, and has frequently been adopted by many IS researchers (Elbashir et al., 2008; Hou, 2012; Igbaria & Tan, 1997; Ramakrishnan et al., 2012; Seddon & Kiew, 1996).

The differences between the responses of the groups were examined with t-tests, more specifically, the 'independent samples t-test' was used. It is utilised both for primary statistical analysis to study variances, and as a supporting statistical test to validate the underlying assumptions associated with the statistical analysis of means (Gibbons, 2007, p. 1). This can be used to compare the mean of two independent groups of people or conditions. The term independent means that the two groups to be compared are not connected or related to each other (Rubin, 2010, p. 162). In other words, the ‘independent samples t-test’, tests whether there is a difference between two groups. For example, whether group A, on average scores better on a mathematics test than group B. In this study, we used this test to measure if there is a significant difference between the independent, dependent, moderate and demographic variables.

The independent samples t-test is a commonly used method to examine non-response bias and differences between two groups (Haringman et al., 2005; Niu, 2008, p. 132; Schoenmakers et al., 2007). The independent samples t-test consist of a ‘Levene’s test’ and a ‘t-test’. Levene’s test was developed by Howard Levene (Levene, 1960), improved by Brown & Forsythe (1974), and is also one of the most widely used test by statisticians (Schlotzhauer, 2007, p. 269). Levene's test whether the variance of scores for the two groups is the same. If the significance level of the Level’s tests is larger than 0.05 (e.g. 0.7) it concludes that equal variances are assumed. When the significance level of Levene’s test is 0.05 or less (e.g. 0.02) it assumes that there are no equal variances. To find out if there is a difference between the two groups (if the assumption made is correct), a t-test for ‘equality of means’ is conducted. When there are equal variances assumed, and the significance level (2-tailed) of the t-test is equal or less than 0.05, then there is a significant difference in the mean scores on the dependent variable for each of the two groups, and vice versa (Rubin, 2010, p. 163). In this study, SPSS version 18 is used to compute the independent samples t-test, full SPSS output can be found in appendix D.

Group 1 - Group 2

There were significant differences between group one and two for the geographic area, work position, functional area and time since adoption, see table 16. Because the participants of the mobile BI case stories were all at least middle-level managers, a significant difference in the work position is expected. The difference in the geographical area can be explained by the fact that most of the mobile BI cases are based on organisations of the United States, and it takes time to write a mobile BI case study which may explain the difference in time since adoption. One possible explanation for the difference between the functional area may be because mobile BI users that work in the information technology area, are more active in BI Linked groups, than mobile BI users that are working in other functional areas.

Table 16: Demographic and Construct comparison between Group 1 and Group 2

	Group 1 (n=50)		Group 2 (n=67)			95% CI of the difference	
Demographic	**Mean**	**SD**	**Mean**	**SD**	**P-Value**	**Lower**	**Upper**
Age	2,80	0,535	2,66	0,895	0,278	-0,117	0,404
Education	1,96	1,124	2,01	1,175	0,797	-0,476	0,366
Geographical area	7,40	1,841	6,12	2,538	0,003	0,441	2,120
Principal industry	8,04	2,204	8,61	2,239	0,186	-1,423	0,279
Work Position	2,90	1,147	2,03	1,113	0,000	0,448	1,292
Functional area	6,88	2.293	5,51	2,062	0,006	0,397	2,348
Mobile worker	3,06	1,058	3,10	0,983	0,818	-0,427	0,338
Tablet / Smartphone	1,34	0,688	1,52	0,682	0,157	-0,436	0,071
Construct							
Accessibility	3,95	0,590	3,99	0,644	0,719	-0,271	0,188
Ease of use	4,15	0,564	4,23	0,684	0,505	-0,323	0.160
Flexibility	3,51	0,667	3,60	0,873	0,559	-0,367	0.199
Interface design	4,29	0,631	4,27	0,595	0,856	-0,211	0.253
Information Quality	3,84	0,537	3,95	0,455	0,227	-0,297	0,071
Engagement	3,75	0,485	3,83	0,554	0,489	-0,260	0,125
Use	3,53	0.950	3,37	1,020	0,409	-0,218	0,531
Voluntariness of use	3,83	0,704	3,71	0,617	0.365	-0,134	0,361
User satisfaction	4,17	0,572	4,09	0,585	0,501	-0,149	0,303

table continues

Net benefits	3,92	0,531	3,85	0,598	0,528	-0,148	0,286
Top manag. support	4,26	0,664	4,13	0,766	0,351	-0,140	0,392
Time since adoption	3,18	1,132	2,67	1,146	0,029	0.053	0,964

Group 1 – Group 3

There were significant differences between group one and three regarding age, education, geographical area, work position and functional area, see table 17. This could be explained because mobile BI users that are active on BI forums are in general younger, have a lower education and work position than the interviewed participants of the mobile BI case stories, and are working in the information technology area. Higher level management is more educated and has more work experience, (which explains the difference in age), and directs its mobile BI questions to a service desk, instead of on a mobile BI forum. A possible explanation for the geographical area can be explained by the fact that most of the mobile BI cases are based on organisations of the United States.

Table 17: Demographic and Construct comparison between Group 1 and Group 3

	Group 1 (n=50)		Group 3 (n=47)			95% CI of the difference	
Demographic	**Mean**	**SD**	**Mean**	**SD**	**P-Value**	**Lower**	**Upper**
Age	2,80	0,535	2,24	0,766	0,000	0,291	0,831
Education	1,96	1,124	1,46	0,546	0.006	0,148	0,859
Geographical area	7,40	1,841	6,30	2,457	0,015	0,220	1,971
Principal industry	8,04	2,204	8,41	2,315	0,421	-1,289	0,543
Work Position	2,90	1,147	1,70	0,891	0,000	0,790	1,619
Functional area	6,88	2.293	5,70	2,493	0,035	0,084	2,285
Mobile worker	3,06	1,058	2,72	1,109	0,125	-0,097	0,783
Tablet / Smartphone	1,34	0,688	1,52	0,752	0,220	-0,474	0,110
Construct							
Accessibility	3,95	0,590	4,07	0,591	0,356	-0,351	0,128
Ease of use	4,15	0,564	4,39	0,665	0,058	-0,491	0,010
Flexibility	3,51	0,667	3,87	0,576	0,005	-0,617	0,111
Interface design	4,29	0,631	4,31	0,652	0,848	-0,286	0,024
Information Quality	3,84	0,537	3,97	0,568	0,268	-0,350	0,098
Engagement	3,75	0,485	3,95	0,589	0,072	-0,417	0,018
Use	3,53	0.950	3,69	1,185	0,450	-0,599	0,268
Voluntariness of use	3,83	0,704	3,71	0,841	0,477	-0,200	0,426
User satisfaction	4,17	0,572	4,20	0,638	0,770	-0,281	0,209
Net benefits	3,92	0,531	4,00	0,627	0,475	-0,319	0,150
Top manag. support	4,26	0,664	4,39	0,649	0,330	-0,398	0,135
Time since adoption	3,18	1,132	3,07	1,357	0,675	-0,428	0,657

Group 1 – Group 4

There were no significant differences observed between group one and four for dependent, independent and demographic variables at the 0.5 significance level, see table 18.

Table 18: Demographic and Construct comparison between Group 1 and Group 4

	Group 1 (n=50)		Group 4 (n=33)			95% CI of the difference	
Demographic	**Mean**	**SD**	**Mean**	**SD**	**P-Value**	**Lower**	**Upper**
Age	2,80	0,535	2,88	0,545	0,516	-0,319	0,162
Education	1,96	1,124	1,94	1,299	0,939	-0,513	0,554
Geographical area	7,40	1,841	6,55	2,386	0,070	-0,071	1,780
Principal industry	8,04	2,204	8,39	2,680	0,513	-1,426	0,718
Work Position	2,90	1,147	2,79	1,268	0,677	-0,422	0,646
Functional area	6,88	2.293	6,33	3,058	0,416	-0,784	1,878
Mobile worker	3,06	1,058	3,33	1,080	0,257	-0,749	0.206
Tablet / Smartphone	1,34	0,688	1,33	0,595	0,964	-0,285	0,298
Construct							
Accessibility	3,95	0,590	4,13	0,881	0,313	-0,499	0,143
Ease of use	4,15	0,564	4,17	1,094	0,936	-0,380	0,348
Flexibility	3,51	0,667	3,89	1,019	0,068	-0,779	0,282
Interface design	4,29	0,631	4,11	0,798	0,246	-0,129	0,497
Information Quality	3,84	0,537	4,03	0,771	0,199	-0,472	0,100
Engagement	3,75	0,485	3,81	0,742	0,710	-0,348	0,239
Use	3,53	0.950	3,49	1,093	0,842	-0,405	0,495
Voluntariness of use	3,83	0,704	3,81	0,693	0,940	-0,301	0,324
User satisfaction	4,17	0,572	4,01	1,018	0,426	-0,236	0,549
Net benefits	3,92	0,531	3,93	0,961	0,974	-0,375	0,363
Top manag. support	4,26	0,664	4,15	0,870	0,108	-0,227	0,444
Time since adoption	3,18	1,132	2,64	1,342	0,544	-0,049	1,137

Although there are some demographic differences, these are not problematic as they do not result in differences in the construct items.

6.1.5 COMMON METHOD BIAS

Common method bias refers to a bias in the dataset due to an external influence. Podsakoff, MacKenzie, Lee, & Podsakoff (2003) describe it as 'the variance that is attributable to the measurement method rather than the constructs the measures represents'. The underlying issue is that responses could be influenced by external factors, and as a result, fail to represent the respondent's true opinions. For example, collecting data using a single method, such as the used online mobile BI survey for the data collection of this study, may introduce systematic response bias, that will either inflate or deflate responses. It also can occur because of the way the questions are constructed, the scale length etc. A study that is affected by common method bias, suffers from false correlations and run the risk of reporting incorrect research results. A study that has significant common method bias is one in which a majority of the variance can be explained by a single factor (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003b; Podsakoff & Organ, 1986a). To test for such common method bias, this research follows Podsakoff and Organ (1986) who argue that a common method bias in a sample can be examined using Harman's one factor test. This test evaluates whether a significant amount of common bias exists in the data by examining whether or not most of the variance is observed by a single factor. In this study, we used SPSS version 18 to conduct a factor analysis on all the measured construct items. The testing single factor accounted for less than 50 percent of the variance (42%), indicating that common bias is not an issue with the collected data (Podsakoff et al., 2003b; Podsakoff & Organ, 1986b). See appendix E for a full SPSS output.

6.2 RESPONDENTS

The majority of the respondents were between the ages of 26 and 54 years old. 44,9% of the respondents had at least a bachelor's degree and most of the respondents live in Europe and the United States, see table 19, 20 and 21.

Table 19: Descriptive statistics on Age

Age	Number of responses	Percentage
Under 25	12	6,1
26 – 34	65	33,2
35-54	105	53,6
55 – 64	12	6,1
65 or over	2	1
Total	**196**	**100**

Table 20: Descriptive statistics on Education

Education	Number of responses	Percentage
Senior high school	11	5,6
Vocational/technical school	14	7,1
Bachelor's degree	88	44,9
Master's degree	76	38,8
Doctoral degree	4	2,0
Other	3	1,5
Total	**196**	**100**

Table 21: Descriptive statistics on Geographic Area

Geographic Area	Number of responses	Percentage
Africa	7	3,6
Asia/Pacific Islands	13	6,6
Australia/New Zealand	6	3,1
Canada	3	1,5
Central/South America	11	5,6
Europe	79	40,3
India	3	1,5
Middle East	1	0,5
South Asia	6	3,1
United States	67	34,2
Total	**196**	**100**

Almost 40% of the respondents didn't indicate the principal industry of their organisation in the list provided, while 46,9% indicated information technology as their functional area in the organisation. 34,7% of the respondents classified themselves as non-management/professional staff, and 27% as top-level management. 169 respondents gave their organisations name, and of these, 141 were different. This means that respondents of at least 142 different organisations participated in this research. The descriptive statistics for principal areas of organisation, functional area, the organisational level of the respondents and number of organisations is summarised on the next page in table 22, 23, 24 and 25.

Table 22: Descriptive statistics on Principal Industry Organisation

Principal Industry Organisation	Number of responses	Percentage
Agriculture, hunting and forestry	1	0,5
Construction	1	0,5
Education	3	1,5
Electricity, gas and water supply	3	1,5
Financial intermediation	21	10,7
Healthcare	14	7,1
Hotels and restaurants	6	3,1
Insurance	2	1,0
Manufacturing	27	13,8
Marketing, Advertising	7	3,6
Real estate, renting and business activities	3	1,5
Transport, storage and communication	6	3,1
Wholesale and retail trade	25	12,8
Other	77	39,3
Total	**196**	**100**

Table 23: Descriptive statistics on Functional Area

Functional Area	Number of responses	Percentage
Corporate communications	0	0
Finance / Accounting / Planning	19	9,7
General management	16	8,2
Human resources / Personnel	1	0,5
Information technology	92	46,9
Legal	0	0
Manufacturing / Operations	2	1,0
Marketing	12	6,1
Sales	33	16,8
Supply chain	8	4,1
Other	13	6,6
Total	**196**	**100**

Table 24: Descriptive statistics on Work Position

Work Position	Number of responses	Percentage
Non-management/professional staff	68	34,7
Middle-level management	54	27,6
First level supervisor	21	10,7
Top-level management/executives	53	27
Total	**196**	**100**

Table 25: Descriptive statistics on Organisations

Organisations	Number of responses	Percentage
Gave their organisations name	169	86,2
Different organisation names	141	71,1
Didn't gave their organisations name	27	13,7

The majority of the respondents are mobile workers, 72,4% of the respondents based their answers on mobile BI usage on a tablet and most of the respondents used a mobile BI solution of MicroStrategy, Qlikview, Roambi or SAP, see table 26, 27 and 28.

Table 26: Descriptive statistics on Mobile Worker

*Mobile worker	Number of responses	Percentage
Never	14	7,1
Rarely (0-25% a week)	47	24
Sometimes (25-50% a week)	71	36,2
Most of the Time (50-75% a week)	45	23
Always (75-100% a week)	19	9,7
Total	**196**	**100**

**Definition: A mobile worker is a worker who performs his/her works in numerous locations. The place of work may be locations such as customer sites, company offices, homes, vendor offices, planes and hotels amongst others.*

Table 27: Descriptive statistics on Mobile Device

Mobile device	Number of responses	Percentage
Tablet	142	72,4
Smartphone	54	27,6
Total	**196**	**100**

Table 28: Descriptive statistics on Mobile BI Solutions

Mobile BI solution	Number of responses	Percentage
Actuate	0	0
Andara	7	3,6
Arcplan	0	0
Birst	1	0,5
CompentArt	0	0
Enterprise Signal (SurfBI)	0	0
Exxova	0	0
Extended Results (PushBI)	10	5,1
IBM Cognos	3	1,5
Information Builders	2	1,0
Jaspersoft	0	0
LogiXML	2	1,0
MicroStrategy	52	26,5
Oracle	2	1,0
Qlikview	33	16,8
RoamBI	20	10,2
SAP Business Objects explorer	38	19,6
Strategy Companion	0	0
Tableau	8	4,1
Tibco Spotfire	1	0,5
Transpara	0	0
Yellowfin	2	1,0
In-house Development	4	2,0
I don't know	4	2,0
Other	7	3,6
Total	**196**	**100**

6.3 FORMATIVE & REFLECTIVE CONSTRUCTS

According to Edwards (2010), perhaps the most basic consideration of developing auxiliary theories involves the direction of the relationships between constructs and measures. Petter et al. (2007) conclude that the relationship between measurement items and constructs is often ignored. Researchers can choose between two options; treat constructs as causes of measures, which is also named as reflective constructs, or specify measures as causes of constructs, which is also named as formative constructs. In general, and by default researchers assume that the relationship between construct and item is reflective, meaning that the measurement items are a reflection of the construct.

While, many times the nature of the construct is formative (Petter et al., 2007). Petter et al. (2007) concluded after examining the complete volumes of MIS Quarterly and Information Systems Research between 2003 and 2005, that 30% of the published IS studies specified their constructs as reflective, while they are in fact formative. Also, in marketing and consumer research approximately the same percentage of studies have improperly specified formative and reflective constructs (Jarvis et al., 2003). To indentify formative constructs, Jarvis et al. (2003) developed four criteria:

1. Do indicators predict the construct?
2. Does dropping a measure change what the construct is measuring?
3. Does a change in one measure of the construct not require a change in all other measures of the construct?
4. Do the measures have different antecedents and consequences?

If all of these criteria are true, then a researcher should specify a construct as a formative construct. If the majority of these criteria are true, then it is necessary to consider if the theory base typically views it as a formative construct (Jarvis et al., 2003).

In the research model of this study, we used three formative constructs; accessibility, information quality and net benefits, that match the four criteria. To make the four criteria more practical to understand, we used the accessibility and flexibility construct in an example, see figure 13, and modelled the constructs based on the specifications of Jarvis et al. (2003).

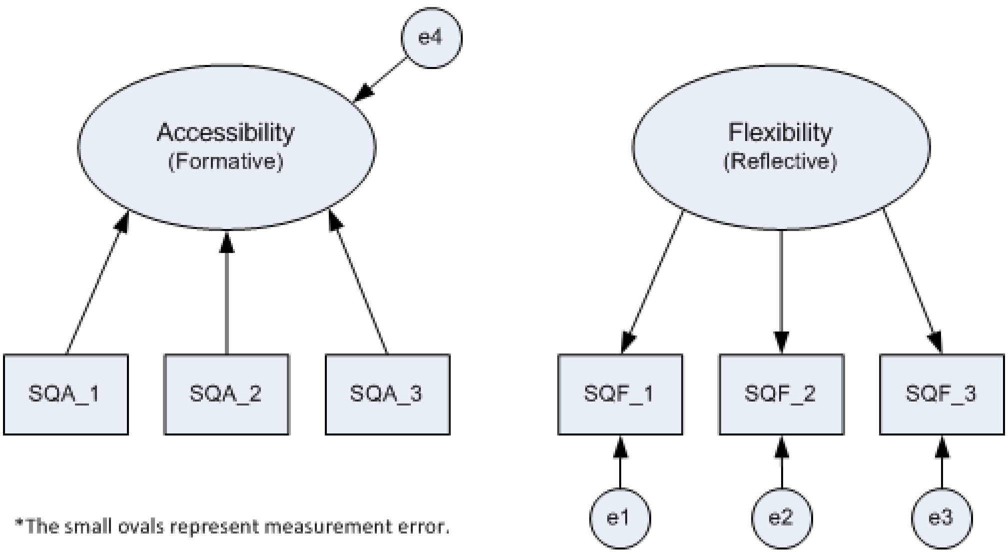

Figure 13: Formative and Reflective research constructs.

SQA1: The way I access my mobile BI fits well to the types of decisions I make using my mobile BI solution.
SQA2: The accessed information is processed and delivered rapidly without delay.
SQA3: I can use my mobile BI solution at anytime, anywhere I want.

SQF1: I can modify my mobile BI solution to my desired information needs.
SQF2: My mobile BI solution can accommodate changes in business requirements quickly.
SQF3: My mobile BI solution makes it easier to deal with exceptional situations.

Each of the flexibility items measures the same concept and, we expect therefore, that these items will be highly correlated. Removing one item wouldn't really change the nature of what we are asking. However, each of the accessibility items asks something different. Just because mobile BI can be used anywhere, anytime, doesn't mean the accessed information is processed rapidly. Even if that were the case, it doesn't mean that mobile BI fits the types of decisions the user makes using mobile BI. Perhaps the information is processed rapidly, but the user access is limited due to authorization/authentication. There is not an unobstructed way to get to the information. This is unlike the reflective measures of flexibility. If a mobile BI solution makes it easier to deal with exceptional situations, than it probably is able to accommodate changes in the business requirement. However, when we remove one item of accessibility, we change the nature of what we are asking. For example, only including SQA_1 and SQA_3 gives a different meaning to accessibility than when we include SQA_2 as well; together the items from the latent construct. While reflective measures are simple a reflective of the latent construct (Edwards, 2010; MacKenzie et al., 2005; Petter et al., 2007).

There is no reason to expect that the measures of the formative construct are correlated, that is, have a high internal consistency. Reliability and validity for reflective construct shouldn't be conducted in the same manner as for formative measures (Petter et al., 2007). However, that doesn't mean that formative indicators are not correlated, formative items can show positive, negative, or no correlation at all. And although there are a variety of reflective validity and reliability measures that are widely accepted by researchers and journals, that is not the case for formative measures. Authors are forced into overreliance on reflective measurement models specifications by journal reviewers who demand high internal consistency between measures and unidimensionality as a condition for acceptance and publication of latent variable (construct) research. Which is according to Jarvis et al. (2003), one of the most likely reasons that researchers do not know how to correctly specify formative constructs. Using formative constructs in the research model of this study, therefore, makes it a very complex data analysis process. In fact, using only reflective measures is the easiest way to measure reliability and validity. So, why did we use formative constructs?:

According to Fornell & Bookstein (1981, p. 5), '*constructs such as 'personality' or 'attitude' are typically viewed as underlying factors that give rise to something that is observed. Their indicators tend to be realized then as reflective. On the other hand, when constructs are conceived as explanatory combinations of indicators (such as population change, or marketing mix) that are determined by a combination of variables, their indicators should be formative*'.

Working out this definition, accessibility, net benefits and information quality can be specified as formative constructs in the research model of this study. After an extensive research Eppler (2003) defined information quality into several information characteristics that together define information quality. Thus, information quality is determined by a combination of variables, and therefore, we decided to use formative measures to measure information quality (chapter 4.6). In order to increase the response rate on the mobile BI survey, we decided to keep the mobile BI survey as short as possible. We therefore combined the three accessibility items into one construct, instead of three separate constructs with reflective measures (chapter 4.5.2). Net benefits is defined as composites that explain exactly what the net benefits are. Some of these items would not necessarily co-vary, which suggest that they are formative measures. For example, improved quality decisions does not necessarily mean that the decision-maker will be more productive, since it may take more time to make those decisions.

Even when formative constructs show evidence of acceptable reflective reliability and validity measures, there can still be a problem with model misspecification. Jarvis et al. (2003) researched model specification in marketing and consumer research, and concluded that their results provided strong evidence that misspecification of even one construct can have serious consequences for the theoretical conclusions drawn from that research model. More specifically, their results indicate that paths emanating from a construct in a misspecified research model are likely to be substantially inflated. Which means that they lead to type 1 errors. A type 1 error is the correct rejection of a true null hypothesis. A type 1 error leads to a conclusion that a relationships exists when this is not really so. Furthermore, Jarvis et al. (2003) argued that paths leading into a construct with a misspecified research model are likely to be deflated. Thus, leading to type II errors. A type II error is the failure to reject a false null hypothesis. With the result that misspecification can lead to inappropriate conclusions about hypothesized relationships between constructs. Jarvis et al. (2003) therefore argued that it is important that measurement relationships are appropriately modelled.

After discussing the differences between formative and reflective constructs, and why it is important to avoid misspecification, in the next subsection we begin the validation process of the formative and reflective constructs.

6.4 EXPLORATORY FACTOR ANALYSIS

6.4.1 FACTOR ANALYSIS

An exploratory factor analysis (EFA) is a technique to explore the number of latent constructs and the underlying factor structure of a set of variables (Hair et al., 2009, p. 94). A researcher employs an EFA as an exploratory or descriptive technique to determine the appropriate number of common factors and to uncover which measures variables are reasonable indicators of the various latent dimensions, e.g. by the size and differential magnitude of factor loadings. A factor loading represent the correlation between the original variable and its factor. In other words, it is a technique to explore and discover if the observed variables 'hang together' as a group. It proves a factor structure; a grouping of variables based on strong correlations, and is a good method for detecting ‘misfit’ variables. In general, an EFA prepares the variables to be used for cleaner structural equation modelling. It is suggested that an EFA should always be conducted for new datasets, and it is quite useful in the early stages of research (Brown, 2006, p. 13; Child, 2006, p. 6).

This research is built on prior information, we carefully selected items from prior research. Which assumes that an EFA is not necessary for this study. However, we used items of known and of unknown compositions. For example, the engagement construct consist mainly of new and adapted statements that aren’t used in the mobile BI context. Also, we weren’t able to find studies that measured user satisfaction as well as engagement in the same study. Meaning that perhaps there is no difference at all for information systems. We also used a new dataset, and therefore, we used an exploratory factor analysis technique to examine if the used items form a construct as we specified in chapters 4 and 5. To conduct a factor analysis there must be an adequate sample size, a factor extraction method and the number of factors to extract and the rotation method have to be chosen:

Sample size
There are many articles written about the adequate sample size to conduct an EFA. In general the minimal number of cases of reliable results are more than 100 observations and five times the

number of items (Suhr, 2003; Hair et al., 2009, p. 102). However, according to Fabrigar et al., (1999) it mostly depend on the nature of the data, and the majority of the studies had a variable-to-factor ratio of at least 4:1, although they also suggest using a minimal sample of 100. We had 41 items and 196 observations, that is a ratio of: 4.78:1. Hence, 196 respondents is an adequate sample size to conduct an EFA.

Factor extraction method

Factor extraction involves determining the smallest number of factors that can be used to represent the interrelations amongst the set of variables. There are a variety of approaches that can be used to identify/extract the number of underlying factors or dimensions, SPSS version 18 even has six extraction methods. Each extraction method has certain advantages and disadvantages. Fabrigar et al. (1999) and Costello & Osborne (2005) both prefer the maximum likelihood extraction method. The advantage of maximum likelihood is that it permits statistical significance testing of factor loadings and correlations among factors and the computation of confidence intervals for these parameters (Fabrigar et al., 1999). Conway & Huffcutt (2003) argues that maximum likelihood is preferred when the purpose is to understand the latent structure of a set of variables, and not the reduction of variables without interpreting the resulting variables in terms of latent constructs. Because the goal is to understand the latent structure of the used variables (items) we used the maximum likelihood extracted method as preferred by Conway & Huffcutt (2003), Costello & Osborne (2005) and Fabrigar et al. (1999).

Number of factors

After extraction, it must be determined how many factors to retain for the rotation. This criterion means keeping the factors that account for the most variance in the data. This is an important decision because when too few factors are used, the correct structure is not revealed, and if too many factors are retained, it becomes increasingly difficult to make an interpretation. In deciding how many factors to extract, a researcher should combine a conceptual foundation, with some empirical evidence. In other words, how many factors should be in the structure, and how many factors can be reasonably supported. In general there are four criteria which are commonly used, and the most common is to retain factors with eigenvalues greater than one. The eigenvalue of a factor represents the amount of total variance explained by that factor. It indicates the relative importance of each factor in accounting for the variance associated with the set of variables. Another criteria is to use a fixed number of factors before running the factor analysis. This is useful when the goal is to test a theory about the number of factors to be extracted, or to replicate another's researchers work. Next, there is the scee test criterion, The scree test is derived by plotting the latent roots against the number of factors in their order of extraction, and the shape of the resulting curve is used to evaluate the cutoff point. The point at which the curve first begins to straighten out is considered to indicate the maximum number of factors to extract. The last criterion is to extract enough factors to meet a specified percentage of variance explained, which is usually 60% or higher. However, an exact quantitative basis for deciding the number of factors to extract has not been developed (Hair et al. 2009 p. 99:148). Hair et al. (2009, p. 149) states that the four criteria must be balanced against any theoretical basis for establishing the number of factors.

Rotation method

The goal of the rotation method is to simplify and clarify the data structure; it causes factor loadings to be more clearly differentiated, which is often necessary to facilitate interpretation. As with the extraction method, there are a variety of choices, and in general there are two main categories; orthogonal rotations that produce factors that are correlated, and oblique methods, that allow factors to correlate (Fabrigar et al., 1999; Hair et al. 2009, p. 106). Varimax, an orthogonal rotation is by far the most common choice (Hair et al., 2009, p. 106), however, Costello & Osborne (2005) and Fabrigar et al. (1999) recommend the oblique rotation, because an oblique rotation will reproduce an orthogonal solution, but not vice versa. Also, according to Hair et al. (2009, p. 106), instead of oblique rotations, orthogonal rotations are preferred when the research goal is data reduction, which is not the goal in this study. We therefore chose an oblique rotation method, to be precise, we chose the 'Promax' oblique method (default kappa value of four) as advised by Costello & Osborne (2005).

Assessing statistical significance

Factor loadings can be interpreted as equivalent to correlation coefficients, ranging between -1.0 and + 1.0. The closer the value to 1.0, positive or negative, the stronger the relationship between the factor and the item. Hair (1988 p. 112) argued that factor loadings over 0.3 meet the minimal level, over 0.4 are considered more important, and 0.5 and greater are practically significant. Hair et al. (2009, p. 107) recommended using a stricter level to evaluate the factor loadings. They computed with a power level of 80%, .05 significance level and standard errors assumed to be twice those of conventional correlation coefficients, which are the sample sizes necessary for each factor loading to be considered significant, see table 29. In comparison with prior research by Hair et al. (1988), which denoted all loadings of 0.30 as having practical significance, this approach would consider loadings of 0.30 only significant for sample sizes of 350 or greater. We had a sample size of 196 respondents, and therefore, a factor loading would be considered significant at 0.40 or higher.

Table 29: Guidelines for identifying significant factor loadings based on sample size

Significant factor loadings based on sample size	
Sample size	**Sufficient factor loading**
50	0.75
60	0.70
70	0.65
85	0.60
100	0.55
120	0.50
150	0.45
200	0.40
250	0.35
350	0.30

Source: Hair et al. (2009, p. 107)

For the exploratory factor analysis of this study, we used the 'maximal likelihood' extraction method, 'promax' rotation method, which considers factor loadings of >0.40 significant and we selected the number of factors based on eigenvalues greater than one, scree plot criteria and a total variance explained of >0.60%.

6.4.2 FACTOR LOADINGS

Table 30 shows the first factor analyses with ease of use, attractive interface design, flexibility, engagement, user satisfaction, use and voluntariness of use items. In order to make the table readable, in this, and in the other factor analyses tables, factor loadings of <0.3 are omitted. Results as presented in table 30 show results other than were expected. The results are quite problematic; there are cross-loadings, negative low loadings, five, instead of seven factors as originally defined in the conceptual model and the total variance explained is only 54.7%. Costello & Osborne (2005) suggest dropping an item which is problematic, such as low loadings, cross-loadings or free-standing items. There are many problematic variables and deleting all (problematic) items is not a good idea, as deleting one item can impact other problematic items. Because the engagement items were largely developed in this study, there is no validation previous research and a factor analysis with only engagement items was carried out to see if the items loaded as posited for the construct, see table 31.

Table 30: Factor analysis - I

Items	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
SQEU_1	1.083				
SQEU_2	.810				
SQID_1	.602				
SQID_2	.340			.324	
SQF_1		.608			
SQF_2		.887			
SQF_3		.863		-.339	
EG_1	.364				.317
EG_2					.583
EG_3					1.024
EG_4		.395			.317
EG_5				.337	.331
EG_6				-.380	.528
US_1				.790	
US_2				.540	
US_3				.900	
U1_1			1.123		
U2_2			.605		
UV_1					
UV_2				.363	
Eigenvalues	8.448	1.462	1.356	1.186	1.039
Total variance explained	54.7%				

Factor analysing the engagement items resulted in two factors. Factor two consists of one item: EG_6, and seems problematic because it is a free-standing item, see table 31. Engagement is measured with six items and removing EG_6 doesn't compromise the integrity of the data. Therefore, EG_6 is removed, as it is a free-standing item. After re-running the factor analyses with the remaining five items, all items loaded onto one factor, see table 33. EG_6 ('Using my mobile BI solution is challenging') was deemed to be a poor indicator of engagement .

Table 31: Factor analyses engagement – I

Items	Factor 1	Factor 2
EG_1	.769	
EG_2	.791	
EG_3	.749	
EG_4	.669	
EG_5	.790	
EG_6		.999

Table 32: Factor analyses engagement – II

Items	Factor 1
EG_1	.763
EG_2	.792
EG_3	.746
EG_4	.671
EG_5	.793

Re-running the total factor analysis without EG_6 resulted in a slightly improved factor analysis, in that the total variance explained increased, and the cross-loading of EG_5 disappeared, see table 33. However, the factor analysis still resulted in five, instead of seven factors, SQF_3 has a negative cross-loading, EG_4 has a cross-loading and U1_1 and SQID_2 have even loadings below the 0.30. This factor analysis is not sufficient, because it has a low total variance explained, five factors, and problems with some items. The scee plot (appendix F) does not show a clear 'elbow' in the eigenvalues to identify seven factors. However, to further understand the relationship amongst these items, a further factor analysis was conducted which was forced to produce seven factors, as theoretically defined.

Table 33: Factor analysis - II

Items	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
SQEU_1		1.059			
SQEU_2		.703			
SQID_1		.501			
SQID_2					
SQF_1			.604		
SQF_2			.890		
SQF_3			.852		-.332
EG_1	.506				
EG_2	.762				
EG_3	1.142				
EG_4	.468		.373		
EG_5	.495				
US_1					.694
US_2					.488
US_3					.816
U1_1					
U2_2					.362
UV_1				1.078	
UV_2				.593	
Eigenvalues	8.443	1.420	1.272	1.044	1.019
Total variance explained	56.9%				

Results as presented in table 34 (next page) show clear loadings for seven factors, with a total variance explained of 63,4%. Although the eigenvalues of factor six and seven do not fit the criterion eigenvalues of one, these factors are deemed sufficient in terms of total variance explained (>0.60%), significant loadings (>.0.40) and fit the underlying theoretical basis. We therefore, chose to continue using these items in the further data analysis. The communalities presented in table 34 show how much variance in a particular variable is accounted for by the factor solution, it is the extent to which an item correlates with all other items. Higher communality values indicate that a large amount of variance is accounted for by the factor solution. If a variable has a low communality it will struggle to load significantly on any factor (Hair et al. 2009, p. 136). Costello & Osborne (2005) argue that if an item has a communality of less than 0.40, it may either not be related to other items or suggest that an additional factor should be explored. This indicates that for UV_2 a substantial portion of the variance is not accounted for by factor seven.

Table 34: Factor analysis - III

Items	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Communality
EG_3	1.039							.675
EG_2	.716							.626
EG_5	.508							.695
EG_1	.477							.664
EG_4	.461							.505
SQF_2		.828						.645
SQF_3		.796						.507
SQF_1		.552						.473
SQEU_1			.992					.999
SQEU_2			.635					.714
SQID_2				.779				.444
SQID_1				.681				.732
U1_1					.798			.714
U2_2					.575			.475
US_3						.912		.921
US_2						.573		.723
US_1						.552		.736
UV_1							.765	.557
UV_2							.499	.232
Eigenvalues	8,443	1.420	1.272	1.044	1.019	.786	.756	
Total variance explained	63.4%							

Factor loadings of less than .40 have not been printed and variables have been sorted by loadings on each factor

Following the results of the exploratory factor analyses, all the original items of the survey remain to conduct the next data analyses, except for one item of engagement, which was removed as discussed. Furthermore, Conway & Huffcut (2003) and Tinsley & Tinsley (1987) argued that researchers who conduct an EFA should include the communalities, percentage of variance accounted for, the full factor loading matrix, and inter-factor correlations if an oblique solution is used. We have included these SPSS outputs in appendix F.

6.5 CONFIRMATORY FACTOR ANALYSIS

An EFA is a data-drive exploratory approach to determine the appropriate number of common factors and to uncover which measured variables are reasonable indicators to the various latent dimensions, by e.g. factor loadings as explained in the previous chapter. An EFA is the counterpart of confirmatory factor analysis (CFA). In a CFA the researcher specifies the number of factors and the pattern of indicator-factor loadings in advance (Brown, 2006, p. 1). Unlike an EFA, therefore, a CFA requires a strong empirical or conceptual foundation to guide the specification and evaluation of the factor model. A CFA deals specifically with measurement models, in other words, the relationships between the observed measures. A CFA is the next step after the EFA to determine the factor structure of the dataset. The factor structure is explored in the EFA, and the CFA confirms the factor structure that is extracted in the EFA. A CFA enables the researcher to test how well the items represent the constructs. Therefore, a CFA is typically used in the later phases of scale development or construct validity after the underlying structure has been established by an EFA analysis, as well as on theoretical grounds (Brown, 2006, p. 41; Hair et al., 2009, p. 668). In this study we use the CFA to verify the number of underlying dimensions of the factors, the pattern of item-factor relationships (factor loadings) and to estimate the scale reliability of the survey.

The reliability and the validity of the research model are tested by using a CFA approach (Brown, 2006, p. 2). These are the two most important and fundamental characteristics of any measurement procedure. Reliability and validity are two different things. Reliability is concerns whether the measure, measures with accuracy and precision. A measure is reliable to the degree in which it supplies consistent results that are free from random error (Cooper & Schindler, 2003, p. 236; Brown, 2006, p. 320). Validity refers to 'the extent to which a test measures what we actually wish to measure' (Cooper & Schindler, 2003, p. 231; Brown, 2006, p. 2). We follow the recommendations of Cooper & Schindler (2003, p. 231-236), Hair et al. (2011) and Henseler et al. (2009) to assess the reliability and validity of the reflective constructs by testing the internal consistency (Cronbach Alpha), composite reliability, convergent and discriminant validity (construct validity) with a PLS path modelling. Chapter 6.6 discusses the reliability and validity of the formative constructs.

6.5.1 RELIABILITY

There are three aspects of reliability, namely: equivalence, stability and internal consistency (homogeneity). Equivalence shows the degree to which alternative forms of the same measures are used to produce the same or similar results. It is a matter of whether an instrument produces consistent measurements, for a given entity, in the hand of two or more researchers, or when utilised in two different forms (Brockopp & Hastings-Tolsma, 2003; Cooper & Schindler, 2003). Equivalence is not tested in this study. This study is a result of a graduating process at Tilburg University, and is therefore conducted by one researcher, in one form.

Stability is the extent to which an instrument performs consistently when used to measure the same entity on repeated occasions. It refers to the degree to which participants change over time. A common method for this test is named: test-retest (Brockopp & Hastings-Tolsma, 2003; Cooper & Schindler, 2003). Stability is not tested in this study. Conducting a test-retest takes a lot of time, and the first measure may sensitise the participants and could influence the results a second time with participants not answering questions carefully.

Internal consistency is the extent to which items on a scale or measurement instrument are homogeneous and reflect the same underlying construct. It concerns the extent to which items on the test or instrument are measuring the same thing. Internal consistency can be estimated via the split-half technique, Cronbach's coefficient alpha, the Kuder-Richardson formula (Brockopp & Hastings-Tolsma, 2003, p. 217) or composite reliability (Esposito et al., 2010, p. 433). Cronbach's alpha is widely used as a criterion to assess the internal consistency of a multi-item instrument (Hou, 2012; Isık et al., 2013; Popovič et al., 2012; Brown, 2006, p. 320).

Cronbach's alpha
In this study the Cronbach's alpha and composite reliability used to assess the reliability of the multi-item measurement scales of the survey. A Cronbach's coefficient alpha ranges from 0 to 1, the higher the score, the more reliable the generated scale is (Cronbach, 1951). According to Cooper and Schindler (2003, p. 417), an alpha score of 0.7 indicates that the measures are internally consistent. However, Nunnally (1978, p. 245-246) suggests that an alpha score of 0.6 can be accepted for new scales. Cronbach's coefficient alpha was computed for each construct and a brief summary of the analysis is shown in table 35 (listed on page 65). Of the six constructs, five had values that exceeded the recommend level of 0.7, and ranged from 0.7165 to. 0.9016. The Cronbach's alpha for attractive interface design is 0.6857. Although this is lower than the suggested level, this is according to Nunnally (1987, p. 245-246) acceptable for new instruments. Which would suggest the instrument to be reliable and internally consistent as recommend by Cooper and Schindler (2003, p. 417) and Hair et al. (2009, p. 125).

Composite reliability
Composite reliability is similar to the Cronbach's alpha, they both measure the internal consistency. However, whereas the Cronbach alpha uses equal weighting, the composite reliability includes the actual factor loadings (Esposito et al., 2010, p. 433, p. 695). The composite reliability can vary between 0 and 1. According to Nunnally (1978, p. 245) a value of 0.7 is applicable in the early stages of research, and 0.8 is a stricter value for basic research. However, values greater than 0.6 are frequently judged as acceptable (Esposito, 2010, p. 695). Of the six constructs, all values exceeded 0.7, and ranged from 0.8858 to 0.9530, table 35. See appendix G for the SmartPLS output of the cronbach and composite reliability.

6.5.1 CONSTRUCT VALIDITY

Construct validity is the extent to which items of a specific construct actually presents the theoretical latent construct which those variables were designed to measure; it deals with the accuracy of the measurement (Hair et al., 2009, p. 669). It provides confidence that a scale measures the construct as it was intended to measure it (Cooper & Schindler, 2003, p. 234). Construct validity is typically assessed with convergent and discriminant criteria (Cooper & Schindler, 2003, p. 234; Hair et al., 2009, p. 686).

Convergent validity
Convergent validity is shown when items of a particular construct converge or share a high proportion of variance in common. Items purporting to measure the same construct should be highly correlated. It means that each item that is measuring a particular construct, also loads on that particular construct (Hair et al., 2009, p. 686). According to Hair et al. (2009, p. 686), there are several ways to estimate the amount of convergent validity among the items. To asses convergent validity, they advise measuring the factor loadings, average variance extracted (AVE) and the construct reliability. Construct reliability is also known as composite reliability, which was measured in the previous sub section. A high composite reliability doesn't mean that there is an adequate convergence, it is simply an indicator of convergent validity. Factor loadings are important, because in the case of high convergent validity, high loadings on a factor indicate that they converge on a common point; that is, the construct (explained in the previous EFA section). Factor loadings were already examined in the EFA analysis, and we do not therefore expect problems with low factor loadings. The AVE is calculated as the mean variance extracted for the items loading on a construct. It is the average percentage of variance explained among the items of a construct. A low AVE indicates that, on average, more error remains in the items than variance explained by the latent factor structure. The error is variance that cannot be accounted for by correlations with other variables but is due to unreliability in the data-gathering process, measurement error or a random component in the measured phenomenon (Hair et al., 2009, p. 687). Hair et al. (2009, p. 686:687) recommends factor loadings that exceed absolute values of 0.7, and recommends an AVE of 0.5 or higher as a good rule of thumb suggesting adequate convergence. The resulting factor loadings with t-values, and AVE are presented in table 35 (next page). These results show as expected (because of the EFA) an adequate convergent validity. See appendix G for the SmartPLS output.

Table 35: Reliability and validity measures of the research model

Constructs	Items	Construct reliability and validity				
		Factor loadings	t-value	Cronbach's alpha	Composite reliability	Average variance extracted
Ease of use	SQEU1	0.9557	29.0343	0.9016	0.9531	0.9104
	SQEU2	0.9525	35.6703			
Flexibility	SQF1	0.7959	12.6989	0.7560	0.8600	0.6724
	SQF2	0.8693	17.0262			
	SQF3	0.7924	11.3882			
Attractive interface design	SQID1	0.9272	11.4260	0.6857	0.8581	0.7525
	SQID2	0.8032	8.8870			
Engagement	EG1	0.8196	20.0980	0.8672	0.904	0.6535
	EG2	0.8313	20.0254			
	EG3	0.7879	17.4592			
	EG4	0.7507	16.2754			
	EG5	0.8487	21.7451			
Use	U1	0.8831	17.2857	0.7165	0.8759	0.7791
	U2	0.8823	16.8476			
User satisfaction	US1	0.8915	33.0149	0.8944	0.9344	0.8261
	US2	0.8920	29.9016			
	US3	0.9422	38.1705			

Note: All factor loadings are significant at the 0.1% significance level (p = 0.001, N=196, t-value 2-tailed 3.291)

Discriminant validity

Hair et al. (2009, p. 669) describe discriminant validity as the extent to which a construct is truly distinct from other constructs, both in terms of how much it correlates with other constructs, and how distinctly measured variables represent only this single construct. It evaluates whether the items load onto the theorized construct, and not on others. Hence, high discriminant validity provides evidence that a construct is unique, that it is truly distinct from other constructs. Hair et al. (2009, p. 688) suggest assessing the discriminant validity by comparing the AVE for any two constructs with the square of the correlation estimate between two constructs. Thus, comparing the square root of AVE associated with each construct, with the correlations among the constructs and ascertaining if the square root of AVE has a greater value. When this value is greater, a latent construct explains more of the variance in its item measures than it shares with another construct. Table 36 presents the square root of AVE and the correlations between the reflective constructs. The values on the diagonal are all larger than the off-diagonal values. Hence, evidence of discriminant validity exists. See appendix G for the SmartPLS output.

Table 36: Correlations between the latent variables and square roots of the average variance extracted

	Attractive Interface design	Ease of use	Engagement	Flexibility	Use	User satisfaction
Attractive Interface design	**0,8675**					
Ease of use	0,6471	**0,9541**				
Engagement	0,5575	0,6673	**0,8084**			
Flexibility	0,4004	0,5245	0,5900	**0,8200**		
Use	0,3464	0,3757	0,4774	0,4607	**0,8827**	
User satisfaction	0,5899	0,7056	0,7909	0,5931	0,4949	**0,9089**

The shaded numbers on the diagonal are the square root of the variance shared between the constructs and their measures. Off-diagonal elements are correlations among constructs. For discriminant validity, diagonal elements should be larger than off-diagonal elements.

6.6 VALIDATION OF THE FORMATIVE CONSTRUCTS

Formative constructs require a different validation process. As discussed earlier, formative indicators can reveal positive, negative or no correlations at all. Therefore, the reliability and validity methods we used for the reflective constructs are not appropriate for the formative constructs. At the present moment, there are no formative measures that are widely accepted by scientific researchers and journals, however, there is a growing trend towards formative measurement (Edwards, 2010). Various researchers have developed methods to assess and analyse formative constructs. Petter, Straub and Rai (2007) have developed a framework which consists of methods already developed to assess the validity and reliability of the formative constructs. These series of methods are also recommended by Hair et al. (2011) and Henseler (2009). These methods are used to assess the accessibility, information quality and net benefits (formative) constructs.

6.6.1 CONSTRUCT VALIDITY

To assess the construct validity, Petter et al. (2007) recommends examining the weightings for the items, to assess if the items in the construct are significant. Weights must not be interpreted as factor loadings. According to Esposito et al. (2010, p. 698) they should be compared to determine the relative contribution to the relevant construct. Formative weights are relatively smaller than reflective item loadings, however, the PLS approach optimizes the indicators' weights to maximize the explained variance of the independent variable in the model. There are two options when the formative construct consist of items that are non-significant: 1. May choose to eliminate non-significant items (Diamantopoulos & Winklhofer, 2001). 2. May choose to keep the non-significant items to preserve content validity (Bollen & Lennox, 1991).

A PLS algorithm was performed with SmartPLS 2.0 M3 to evaluate the item weight, and the boot strapping procedure with 5000 bootstrap samples and 196 cases (which is equal to the number of observations in the original sample of this study) was performed to evaluate the t-statistics as recommend by Chin (1998) and Hair et al. (2011). Without discussing bootstrapping in detail, it allows for the estimation of statistics through the repeated re-sampling of data. It runs simulations with the sample data set. Table 37 shows the results of the validity test.

Table 37: Construct validity test for the formative constructs.

Construct	Item	Weight	t-values	
Accessibility	SQA1	0.7011	8.8719	****
	SQA2	0.3020	3.1370	***
	SQA3	0.2168	2.4640	**
Information Quality	IQ1	0.2974	2.8352	***
	IQ2	0.1145	1,5320	-
	IQ3	0.4105	3,5794	****
	IQ4	0.0567	0,5493	-
	IQ5	0.0537	0,4213	-
	IQ6	0.0314	0,3055	-
	IQ7	0.3481	3,3322	****
Net benefits	MBB1	0.1725	2,0196	**
	MBB2	0.2468	3,6061	****
	MBB3	0.1575	1,8494	*
	MBB4	0.1032	1,5159	-
	MBB5	0.0306	0,4191	-
	MBB6	0.1342	1,5712	-
	MBB7	0.1679	2,2078	**
	MBB8	0.0818	1,0945	-
	MBB9	0.1181	1,8306	*

* Significant at the p = 0.1 level (t-value 2-tailed 1.645) / ** Significant at the p = 0.05 level (t-value 2-tailed 1.96)
*** Significant at the p = 0.01 level (t-value 2-tailed 2.576) / **** Significant at the p = 0.01 level (t-value 2-tailed 3.291)

All the accessibility items are significant at P < 0.05, and therefore construct validity is accepted for accessibility, however, only three IQ items are significant at P < 0.05. According to Diamantopoulos & Winklhofer (2001), this suggests that perhaps not all the seven IQ items should be included in the IQ construct. It signifies that IQ1, IQ3 and IQ7 contribute most substantially to the IQ construct (Esposito et al., 2010, p. 698). However, inspection of the three significant items revealed that they are not able to cover the content of the whole IQ construct. When that is the case, Diamantopoulos & Winklhofer (2001) recommend keeping the non significant items, because elimination of these would carry the risk of changing the construct itself. When the information quality construct was a reflective construct, and the weights were factor loadings, then construct validity was accepted by eliminating the items with low factor loadings. However, in this situation, it is not possible to eliminate the IQ items that are non-significant without changing the nature of the construct, according to Eppler's (2003, p. 86) IQ criteria. Still, it is arguable that the non-significant items cannot be considered as valid measures of the construct. One suggestion could be to use the significant IQ items, and change the nature of the construct into: *Easily understandable information*. However, we choose to follow the original definition of the IQ construct in the research model of this study, and have kept the non-significant IQ items.

The same applies to net benefits, only five net benefits items, MBB1, MBB2, MBB3, MBB6 and MBB9 are significant at P <=0.1. Removing the other items impacts the nature of the net benefits construct in this study, and therefore, have not removed those items either. Still, it must be noted that it could be possible that there are other kind of net benefits perceived by the user, which aren't included in the net benefits construct of this study. Therefore, the net benefits as defined in this study, may be different in reality. However, the items are carefully adapted from scientific BI and DSS studies, and therefore, we expect that this construct covers the nature of the perceived mobile BI net benefits. See appendix G for the SmartPLS output.

6.6.2 RELIABILITY

While the elimination of a non-significant item is not always recommended, it is advised if substantial multicollinearity occurs. Multicollinearity indicates the indicators degree of linear dependency. In other words a high multicollinearity indicates that the items are highly correlated, and may suggest that multiple indicators are tapping into the same aspect of the construct. This is undesirable for formative constructs, as it can lead to highly biased parameter estimations, and can destabilize the model. In other words, it can provide redundant information or create effects that are difficult to separate. Therefore, low correlations are desirable, because formative measures imply that each measure represents an unique facet of the construct (Edwards, 2010; Jarvis et al., 2003; Petter et al., 2007).

There are various methods that can be applied to reveal multicollinearity within a construct, one of them is variance inflation factor (VIF). This is a statistical method to determine when formative measures are too highly correlated. Hair et al. (2011) argue that when the VIF value is greater than five, the item has multicollinearity problems and recommends removing that item. Furthermore, O'brien (2007) notes that the tolerance value of an item of less than 0.20 also indicates a multicollinearity problem. SPSS version 18 (regression-linear) is used to measure the VIF and Tolerance, see table 38. All VIF values ranges from 1.381 to 4.050, which is below the generally accepted cut-off value of five, and all the tolerance values are above 0.2. This indicates that there is little or no multicollinearity among the formative constructs. Therefore, all items were retained for initial inclusion in the index. See appendix G for the SPSS output.

Table 38: Reliability test of Accessibility en Information Quality formative items

Construct	Item	Tolerance	VIF
Accessibility	SQA1	.479	2.089
	SQA2	.528	1.894
	SQA3	.724	1.381
Information Quality	IQ1	.474	2.111
	IQ2	.769	1.301
	IQ3	.423	2.364
	IQ4	.490	2.403
	IQ5	.453	2.207
	IQ6	.589	1.697
	IQ7	.442	2.264
Net Benefits	MBB1	.269	3.724
	MBB2	.372	2.689
	MBB3	.247	4.050
	MBB4	.456	2.192
	MBB5	.262	3.818
	MBB6	.281	3.555
	MBB7	.248	4.036
	MBB8	.368	2.715
	MBB9	.518	1.930

6.7 VALIDATION CONCLUSION

The ultimate goal of a CFA is to ascertain whether a given measurement model is valid. The CFA is a way of testing how well measured variables represent a smaller number of constructs (Hair et al., 2009, p. 668). We have conducted various reliability and validity methods to test the reflective constructs, and can state that we met the conditions of these methods. Therefore, the reflective constructs of the research model can be considered as valid.

The CFA cannot be applied for formative constructs, and we used, therefore, the summarised validation and reliability analysis methods of Petter, Straub and Rai (2007) for the formative constructs. The construct validation method revealed that the IQ construct consists of indicators that do not all have a significant weight on the IQ construct. However, removing those indicators changes the nature of the IQ content. Therefore it was decided to keep the non-significant weights. This situation also applies to the net benefits construct. The rest of the reliability and validity measures show an acceptable validity and reliability, and therefore, in the next section the hypothesized relationships between the constructs can be tested.

6.8 HYPOTHESES TESTING

SmartPLS version 2.0 M3 (PLS path modelling) is used for the hypotheses testing, it is capable of handling both reflective and formative constructs. For hypothesis testing and to obtain reliable results, we used the bootstrapping procedure, with 5000 bootstrap samples and 196 cases, which is equal to the number of observations in the original sample of this study (Chin, 1998; Hair, Ringle, & Sarstedt, 2011). The research model is then assessed by examining the determination coefficients (R^2), the path coefficients and their significance levels, using t-tests.

6.8.1 DETERMINATION COEFFICIENT

R^2 and path coefficients show how well the model is performing. Path coefficients should be significant and directionally consistent with expectations, whose values from range between -1 to +1. The standardized path coefficient indicates the strengths of the relationships between the independent and dependent variables (Chin, 1988).

R^2 is the coefficient of determination, it describes the proportion of the variance in the dependent variable that is explained by all the independent variables taken together. R^2 helps to interpret and analyse how many differences in one variable can be explained by a difference in a second variable. For example, a R^2 of 0.50 means that the independent variables together explain 50% of the variance in the dependent variable. It is a goodness of fit measure. The higher percentage variability is explained, the better the fit, and because it is the proportion of variability explained, the R^2 ranges between 0 and 1. Chin (1998) describes R^2 values of 0.67, 0.33 and 0.19 in PLS path models as substantial, moderate and weak respectively. However, Hair et al. (2011) argues that the judgement of the R^2 depends on the specific research discipline. For example, a R^2 of 0.20 is considered high in consumer behaviour studies, while it is low in success driver studies, and a R^2 of 0.75 would be perceived as high in success driver studies. We followed the R^2 definitions of Chin (1988), and consider a R^2 of 0.75 as high.

Engagement, use, user satisfaction and the control variables together explain 75.75% of the variance in net benefits, which can be considered as high. The mobile BI capabilities explain 64.8% of the variance in engagement, 30.48% in use, and 66,86% in user satisfaction. Only the variance explained in use is respectively moderate, which suggests that factors that are not included in the research model are more important in explaining the variance for use. Overall, the model has a good explanatory relevance. See appendix G for the SmartPLS output.

6.8.2 HYPOTHESES 1 TO 5

Hypotheses H1, H2 and H5 posit that user satisfaction, use and engagement positively influence net benefits. All three hypotheses are supported, they have a positive path coefficient and are statistically significant at $p<0.01$ (table 39, next page). Note that the effect of engagement was found to be larger on net benefits than the effects of use and user satisfaction. Hypotheses H3 and H4 are concerned with the relationship between engagement and use, and user satisfaction and use. Hypotheses H3 is also supported, which indicates that user satisfaction has a direct impact on mobile BI usage. Hypothesis H4 is supported but has the least strongest relationship with use, as it is significant at $p<0.1$. This suggest that user satisfaction has a greater influence on use, than on engagement.

6.8.3 HYPOTHESES 6 TO 20

Hypotheses 6 to 20 are concerned with the relationships between the mobile BI capabilities and engagement, use and user satisfaction. Nine hypotheses have a positive path coefficient and are statistically significant at $p<0.05$. One hypothesis has a positive path coefficient and is statistically significant at $p<0.1$, and five relationships are not statistically significant. Another interesting finding is that the path coefficients of hypotheses H9 (β= -0,0828), H12 (β= -0,0291) and H18 (β=-0,0728) are negative. Which means that the relationships are the opposite of those hypothesised. Cohen et al. (2003, p. 77-78) suggest that the reason for negative path coefficients may be because of multicollinearity between two or more constructs. However, the negative path coefficients are not statistically significant, and we cannot, therefore, prove that they actually exist.

6.8.4 HYPOTHESES 21 AND 22

Hypotheses 21 and 22 are concerned with the relationships between top management support and time since adoption with net benefits. Of these two control variables, only the relationship between top management support and net benefits has a positive path coefficient that statistically is significant at $p<0.05$. This suggest that top management support has a direct impact on the perceived net benefits of mobile BI.

Table 39 presents the hypotheses, path coefficients and t-values, figure 14 shows the R^2, path coefficients and t-values of every hypothesised relationship in the conceptual model, see appendix H for the full SmartPLS output.

Table 39: Path coefficients and t-values for the hypotheses

Hypotheses	Path: from → to	Path Coefficient (β)	t-value	
H1	Use → Net benefits	0.1218	2.5213	***
H2	User satisfaction → Net benefits	0.3929	4.4789	****
H3	User satisfaction → Use	0.2726	2.5201	***
H4	Engagement → Use	0.1982	1.7574	*
H5	Engagement → Net benefits	0.3848	4.9287	****
H6	Flexibility → Use	0.2596	2.9534	***
H7	Flexibility → User satisfaction	0.1357	2.3013	**
H8	Flexibility → Engagement	0.1339	2.1042	**
H9	Accessibility → Use	-0.0828	0.8704	-
H10	Accessibility → User satisfaction	0.2104	2.5827	***
H11	Accessibility → Engagement	0.3164	4.1833	****
H12	Ease of use → Use	-0.0291	0.2598	-
H13	Ease of use → User satisfaction	0.2249	3.1048	***
H14	Ease of use → Engagement	0.1564	1.7303	*
H15	Attractive interface design → Use	0.0744	0.8708	-
H16	Attractive interface design → User satisfaction	0.1155	1.9728	**
H17	Attractive interface design → Engagement	0.0967	1.5592	-
H18	Information quality → Use	-0.0728	0.6736	-
H19	Information quality → User satisfaction	0.2906	4.3826	****
H20	Information quality → Engagement	0.2489	3.3344	****
H21	Top management support → Net benefits	0.1006	2.0945	**
H22	Time since adoption → Net benefits	0.0273	0.6571	-

* Significant at the p = 0.1 level (t-value 2-tailed 1.645)
** Significant at the p = 0.05 level (t-value 2-tailed 1.96)
*** Significant at the p = 0.01 level (t-value 2-tailed 2.576)
**** Significant at the p = 0.01 level (t-value 2-tailed 3.291)

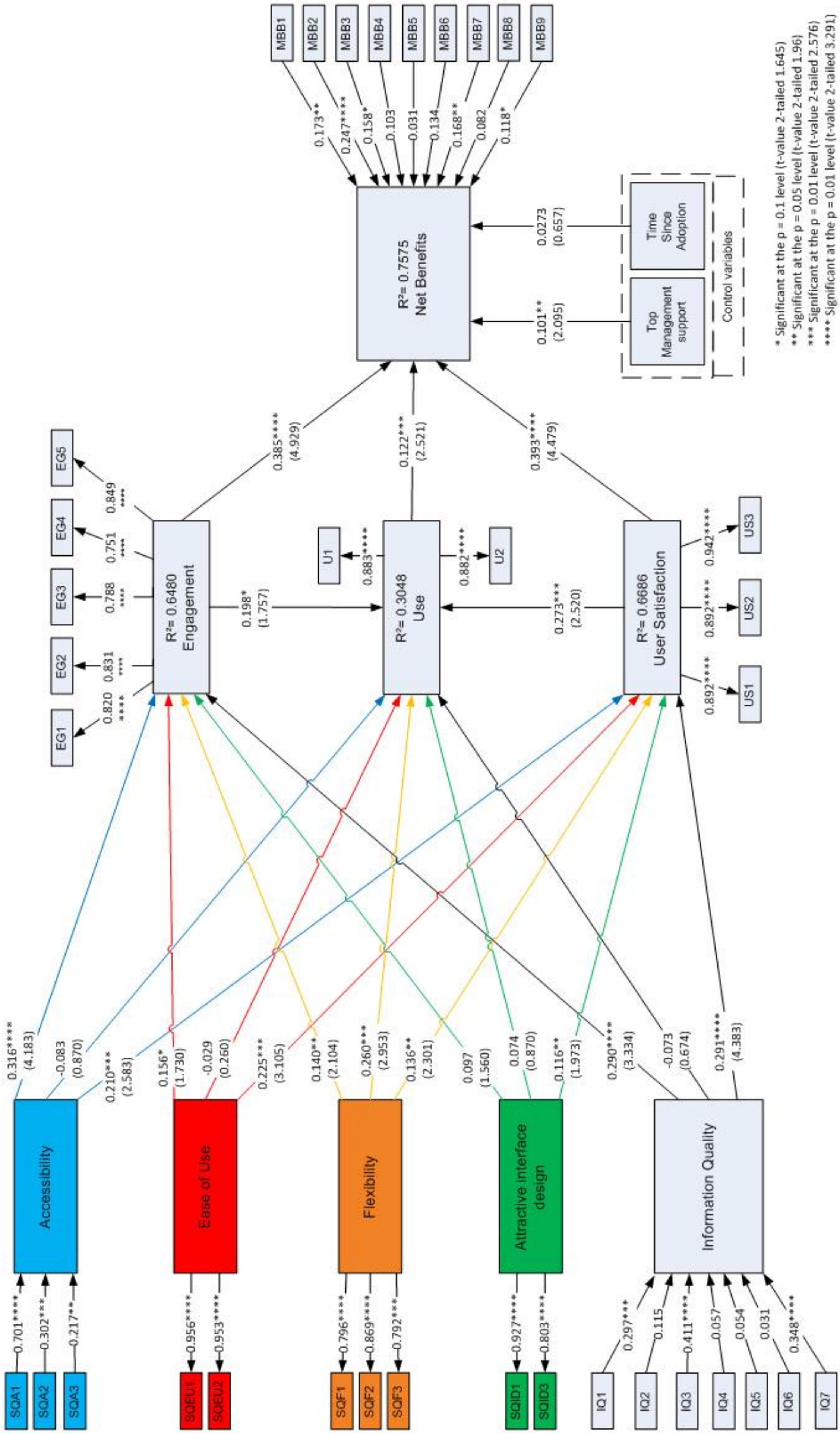

Figure 14: Final measurement model

6.9 MEDIATION

Mediation involves the comparison of a direct effect between two constructs while also including an indirect effect through a third construct. Direct effects are the relationships linking two constructs with a single row. Indirect effects are those relationships that involve a sequence of relationships with at least one intervening construct involved. An indirect effect is a sequence of two or more direct effects and is represented visually by multiple arrows. For example, figure 15 shows an indirect effect of the independent variable on the outcome variable in the form of independent variable →mediator → outcome variable (Hair et al., 2009, p. 751). A mediation variable can explain or clarify the relationship between two constructs, and can therefore, also influence the relationship between the independent and outcome variable. A complete mediation effect facilitates the relationships between the other two constructs, and a partial mediation effect is situated when some of the relationships between two constructs are not explained by the third construct. Testing for mediation requires significant correlations amongst all three constructs (Hair et al., 2009, p. 752). There are two relationships in the conceptual model that can have a mediating impact:

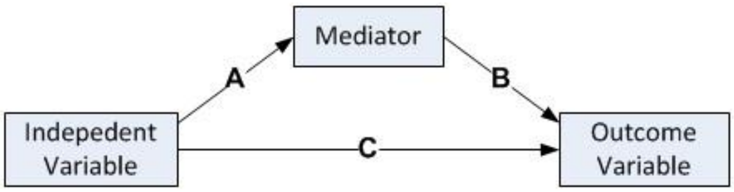

Figure 15: Mediation effect

- Use on the relationship between engagement and net benefits
- Use on the relationship between user satisfaction and net benefits.

We therefore, examined if use is a mediating variable. To evaluate if use is a mediating variable the extent of the mediation variable is according to Hair et al. (2009, p. 752) assessed. Two models are estimated with only the direct effect between engagement → net benefits, and user satisfaction → net benefits. Next, two models are estimated including use as a mediating variable, see figure 16 and 17. The figures show only the constructs which have been examined, however, they include all the other relationships and constructs in the model, which are left out of the figure to make it easier to read. As shown in the models, the relationship between engagement → net benefits, and user satisfaction → net benefits remains significant and unchanged when use is included in the model. Hence, mediation is not supported in the research model of this study.

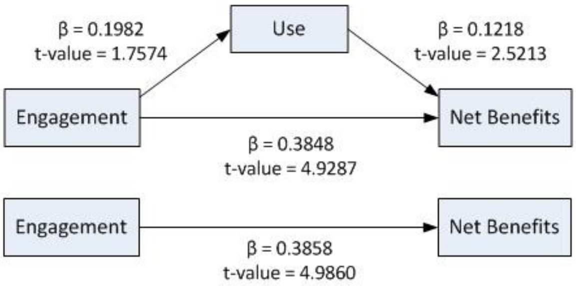

Figure 16: Mediation use – engagement

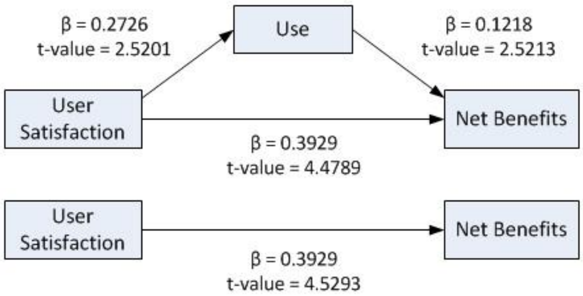

Figure 17: Mediation use – user satisfaction

6.10 VOLUNTARINESS OF USE

DeLone and McLean (1992) argues that use is only pertinent in measuring information systems success when such use is voluntary. In other words, it only makes sense to measure actual use when it is voluntary, open to choice or optional. Devaraj & Kohli (2003) argues that performance improvements from the use of IS might be affected by whether the use was voluntary or mandatory, and concluded in their study that greater actual voluntary usage of technology leads to better financial and quality performance of hospitals. However, they didn't compare it against mandatory usage. Hou (2012) measured the voluntary usage in a BI environment, and concluded that system usage impacted individual performance noticeable more in mandatory contexts than in voluntary contexts. However, the split-sample approach that Hou (2012) used was not appropriately applied. Hou (2012) used a seven point Likert scale, and divided the mean results into two groups. Group one; mean score 1 to 4, and group two mean score 4 to 7. Mean score 4 is the exact middle point, which relates to group one and group two. However, Hou (2012) chose to put the respondents with a mean score of 4 into group two. Next to that, group one was n=129 while group two = 201. Hence, the groups were not equally divided, which makes the conclusion of Hou (2012) doubtful.

To measure if voluntariness of use has an effect on the perceived mobile BI net benefits, the model used in this study posits voluntariness as a moderating variable. The voluntariness of use is defined as the extent to which users perceive the mobile BI adoption or use decision as mandatory or non-mandatory (Agarwal & Prasad, 1997; Hartwick & Barki, 1994). To investigate if a difference exist in the net benefits when mobile BI usage is voluntary or mandatory, we first examined the mean scores of the two statements of voluntariness of use. The results in table 40 indicate that in this case we use a split-sample approach to divide the total sample group into two sub samples as recommend by Kleinbaum et al. (2007, p. 398) and Esposito et al. (2010, p. 554), and define mean score of 3 as inconclusive, or as a third group. It was not possible to draw conclusions out of it, because the number of respondents in the mandatory group was too low. This suggests that the majority of the respondents in the sample size of this study uses mobile BI voluntarily. This is recommend by DeLone and McLean (1992) when use is used as a construct in measuring information systems success.

Table 40: Voluntariness of use mean scores

Mean scores	Number of responses	Percentage	Groups
1	1	0.5	
1.5	4	2	9
2	5	2.6	
2.5	0	0	
3	26	13.3	26
3.5	43	21.9	
4	84	42.9	160
4.5	18	9.2	
5	15	7.7	
Total	**196**	**100**	

7 DISCUSSION AND CONCLUSION

This research studies the relationships between various mobile BI capabilities and mobile BI success from the user's perspective. This chapter begins with a discussion of the findings, then proceeds with limitations and future research directions, and ends with a conclusion and practitioner's relevance.

7.1 DISCUSSION

This study proposes a framework for examining mobile BI capabilities and how they impact mobile BI success from the user's perspective. In this model, ease of use, attractiveness interface design, accessibility, flexibility and information quality are defined as the mobile BI capabilities. Use, user satisfaction, and engagement are measures of the effectiveness of mobile BI success, which explain the relationship between the mobile BI capabilities and net benefits. Net benefits is the closest variable to mobile BI success, and has one control variable, top management support, which significantly influences the perceived net benefits from the user's perspective.

In this study, net benefits is defined as a formative construct. The results of this study suggest that faster and higher quality decision making, improved job effectiveness, reduction in the costs of business processes and being able to present arguments more convincingly, are more of a determinant of mobile BI net benefits than any other defined mobile BI benefits, such as for example, improved job performance and proactive business planning. The perceived net benefits are consistent with prior research. Borg & White (2012) concluded that mangers in organisations were able to make faster decisions with the use of mobile BI. Hou (2012) concluded that BI adoption in organisations helped individuals to improve the quality of their decision-making and job effectiveness. Popovič et al. (2012) and Elbashir et al. (2008) both concluded that BI usage decreased the cost of business processes, and Moreau (2006) concluded that the use of intelligent DSS enabled it system's users to present their arguments more convincingly.

Of the direct relations with net benefits, engagement was found to have the strongest direct and positive relation with net benefits. This finding is consistent with the statement of Tapadinhas (2012), who states that an engaging experience is a key adoption driver for mobile BI. This is also one of most interesting findings because it suggests that engagement is not only important for consumer products such as videogames, but may also be important for the newer generation information systems on mobile devices. Engaged mobile BI users enjoy their mobile BI solution, they find it intrinsically interesting. The significant relationship engagement and use suggests that engagement to mobile BI reinforces the experience of using mobile BI again. The finding suggests that engagement results in more use, added positive attitudes and increased perceived net benefits.

Also user satisfaction had a strong significant and positive relationship with net benefits. This is consistent with a prior BI study of Hou (2012). Literature suggests that measuring user satisfaction is a reliable method to measure IS success and effectiveness (McHaney et al., 2002), and this study supports this argument. Furthermore, it indicates the importance of user satisfaction in promoting the mobile BI benefits from the user's perspective.

Use was found to have the least robust positive relationship with net benefits. However, the relationship was strong, and as expected, consistent with prior research (Hou, 2012; Igbaria & Tan, 1997; Leidner & Elam, 1993; Petter et al., 2008; Petter & McLean, 2009). The results show that higher levels of mobile BI usage lead to higher levels of perceived net benefits. However, simply stating that an increased use will yield more net benefits is insufficient. Use depends on the nature of the use, extent of use, and quality and appropriateness of use. There is also a point at which more use results in information overload, and as a result, the decision-making quality decreases. This is influenced by many factors such as time pressure, IQ (Hahn, Lawson, & Gye Lee, 1992; Lurie, 2004; Schick, Gordon, & Haka, 1990; Eppler & Mengis, 2004), and is different per individual user (Rutkowski & Saunders, 2010). We were not able to research this effect, but Rutkowski & Saunders argued that psychometric tests can be used to identify how much an individual can handle before he/she is emotionally and cognitively overloaded with too much information.

All the mobile BI capabilities which were researched, accessibility, attractive interface design, ease of use, flexibility, and information quality, have one or more significant relationships with use, engagement or user satisfaction. What is surprising, is that flexibility is the only mobile BI capability that has a significant relation with use, user satisfaction and engagement. It is also the only mobile BI capability that has a significant relationship with use. The significance of flexibility as a mobile BI capability suggests that in order to be successful, a mobile BI initiative should be able to accommodate a certain amount of variation in the business processes, environment or technology (Gebauer & Schober, 2006). This finding is also consistent with the Isik et al. (2013) study that suggested that flexibility is one of the most important factors of BI success. Change is inevitable in the current business environment, it should be able to modify the mobile BI solution easily and quickly adapt to the changing business situation (Isık et al., 2013; Wixom, Watson, & Werner, 2011). The significant relationship with engagement confirms the argument of Webster et al. (1993) who suggest that the user perceptions of IS flexibility may contribute to engagement.

Accessibility has positive significant relationships with user satisfaction and engagement. The significance of accessibility indicates that organisations should pay attention to providing appropriate user access to the required information resources, heed information access speed, and enable mobile BI to be used at anytime and anywhere. The user access results are in line with the research of Isik et al. (2013), who suggest that user access quality is the cornerstone of the overall user satisfaction with BI. Also Popovič et al. (2012), argued that information access quality is important as perceived by the user, however, Popovič et al. (2012 argue that lower access quality is less likely to be used for excluding criterion when information is needed. This indicates why IQ has the strongest relationship with user satisfaction.

Mobile BI supports and improves decision making. High quality information is important in the decision making process, it reduces the uncertainty of the decision (Hostmann et al., 2007). BI users value the BI capabilities that allow them to deal with uncertainty (Isik et al., 2013). Information is a richness quality of engagement, and the unsuitability of certain information quality affects future uses of information and can easily lead to a less suitable business decision. Such approaches therefore, result in dissatisfaction of the mobile BI solutions, and ultimately, in the non-use of these solutions, yielding a lower success rate for mobile BI projects (Popovič et al., 2012). This explains why information quality has a strong significant relationship with user satisfaction and engagement. Information quality is a formative construct in this study, and our findings suggest that the scope of the information, easily understandable and error free information are more of a determinant of information quality than the other information quality characteristics.

Ease of use has just as accessibility and information quality, a positive significant relationship with user satisfaction and engagement. Ease of use is one of the five components of the EUCS model of Doll & Torkzadeh (1988). This research confirms that ease of use is important for the user satisfaction level of mobile BI. This finding is also in line with the argument of Tapadinhas (2012), who argues that ease of use is a key adoption driver of mobile BI. For this reason, when mobile BI is not experienced as easy to use, it may result in dissatisfaction with the mobile BI solution, effecting its non-use. Furthermore, the significant relationship with engagement is in line with the statement of

Blythe, Overbeek, Monk, & Wright (2005, p. XI), who suggest that a product or service can only be engaging when the product's functionality is easy to use.

Attractive interface design is the only mobile BI capability that has just one direct significant relationship, and this is with user satisfaction. This finding is particularly interesting, because mobile BI solutions use in general, many colours and graphics in their interface, and these are according to Rozendaal (2007) elements that can increase the richness of a digital product. Richness can positively influence the levels of engagement (Rozendaal, 2007). However, Rozendaal (2007) also states that as user experience increases in time, levels of experienced richness decrease. Which may be the reason why attractive interface design has not a direct signification relationship with engagement.
Harvey & Bolger (1996), Umanath & Vessey (1994) and Umanath (1994) state that graphs are particularly useful for the identification of trends and relationships among data and can result in higher quality decisions. This study did not research the effect of graphs on decision quality; however, the attractive visualizations, graph and table layouts for example, may improve the decision-making satisfaction of a user. Which consequently leads to a higher user satisfaction. Furthermore, the finding confirms the suggestion of Mishra (2012, p. 181) who suggested that information systems are not only judged by their functionality, but also judged on looks. Mobile BI users are more satisfied with an attractive user interface.

In addition, we investigated the effect of two control variables. One control variable, top management support, shows a direct and significant impact on net benefits. This finding confirms the statements of Watson & Wixom (2007) and Sabherwal et al. (2006) who argue that top management is important because their support motivates greater user participation and they insist on the use of information-based decision making. However, the second control variable, time since adoption, did not significantly affect net benefits. This result may appear surprising, because it is significant in Hou's (2012) BI study. One plausible explanation is that organisations that are using mobile BI, also use BI, and therefore, have already developed expertise to utilise the mobile BI solution effectively to generate benefits.

7.2 LIMITATIONS AND FUTURE RESEARCH

Although this study resulted in some interesting findings, there were several limitations. Firstly, the list of measured mobile BI capabilities is not exhaustive. The mobile BI capabilities investigated were identified with the use of an extensive literature research. This literature research consisted of BI studies and mobile BI reports. However, the BI academic literature lacks studies about mobile BI capabilities, and because it is a relatively new innovation, it is possible that there are important capabilities that have not yet revealed in the mobile BI reports. Next to that, only those mobile BI capabilities were researched that we theoretically could link to the success of mobile BI. Future research is needed to determine if there are other mobile BI capabilities which are important for mobile BI success.

A second limitation is that this study is based on user perceptions. Studies have found that self-reported measures are not consistent with actual measures. Subjective measures are therefore not always a very reliable substitute for objective measures of success (Petter et al. 2008). Dale (1995) states that the connection between user evaluations and actual performance is dependent on the user's ability to recognize improvements in performance and attribute it to the used IS. This explains the difficulty in measuring mobile BI benefits with user evaluations, in other words, a mobile BI solution enhances performance or it does not, and users recognize this or not. That leads according to Althuizen, Reichel, & Wierenga (2012) to four possible situations; 1. Harmful Neglect: the IS enhances performance, but users do not recognize this. 2. Seductive Illusion: the IS does not enhance performance, but users think it does. 3. Wise Abstention: the IS does not enhance performance and users recognize this. 4. Rightful Conviction: the IS enhances performance and users recognize this. Althuizen et al. (2012) conducted two empirical studies in which the researchers failed to find significant positive correlations between user evaluations of the DSSs and actual performance in either of the two studies. In actual fact, the researchers did find significantly negative correlations, meaning that improvements in actual performance were associated with less favourable evaluations of the DSS in question. It suggests that there is a possibility that there are mobile BI users who fail to recognize the benefits already experienced from their mobile BI solution.

A third limitation is that the sample size didn't meet the 384 users as calculated, and therefore the generalisation of this study may be questionable. Next to that, the sample group consists of mobile BI users from all over the world and because of cultural differences, it is possible that mobile BI users differ per country. This of course may also influence the results of this research. Future research is needed to determine the applicability of the results to all countries.

The fourth limitation is that the sample group consists of mobile BI users from four different work positions, namely: non-management, mid-level management, first level supervisor and top-level management. As discussed in chapter 2.3, the kind of decision-making differs per work position level. Therefore, it is possible that there exist a difference in the way how these four kind of decision-makers have experienced their mobile BI solution. We did not make a comparison between these work positions, because that was not the purpose of this research. However, it is a limitation of this research, and future research is needed to determine if there exist or not exist a difference.

The fifth limitation were some items used to measure the reflective constructs of this study. Some were deemed problematic when a criteria of eigenvalues of one was used. It is possible that the wording of the statements used for items such as, the ones of the construct 'attractive interface design' were ambiguous. Hair et al. (2009) recommends using more than two items per reflective construct in order to obtain a stable reflective construct. We did not used more than two items for every reflective construct, which may also have caused the problems with the EFA.

The final limitation is that this study measures users perceptions at a precise point in time. It is logical to assume that users perceptions may change as they gain more experience using mobile BI (Hou, 2012). For example, Rozendaal (2007) argues that engagement levels may decrease due to increased familiarity. Hence, a longitudinal approach should be considered in future research.

7.3 CONCLUSION

The purpose of this study was to investigate the relationship between mobile BI capabilities and mobile BI success from a user's perspective. The DeLone and McLean (2003) IS success model was adapted and extended for use in investigating this relationship. Data was collected from 196 mobile BI users to perform an empirical analysis. Findings pointed out several implications for developing better mobile BI solutions. Improving the mobile BI capabilities, accessibility (user access quality, bandwidth and use at anytime and anywhere), flexibility, attractive interface design, ease of use and information quality may be a key to mobile BI success. They influence the engagement, use and user satisfaction levels which explains the variance in the perceived net benefits. Results also suggest that organisations should provide top management support on mobile BI projects. Mobile BI adoption in organisations enabled individuals particularly to present their arguments more convincingly, make higher quality decisions and faster decisions, increase their job effectiveness and to reduce the costs of business processes.

From the practitioner's point of view, this study suggests that utilising the mobile BI capabilities we have researched are important to enable an organisation to improve the derived benefits from its mobile BI investment. Many organisations have begun implementing mobile BI or are considering deploying a mobile BI solution. This study provides a list and description of mobile BI capabilities that are important for a successful mobile BI implementation. It helps organisations to deploy mobile BI, and to improve their mobile BI solution. Furthermore, this study could also be useful for mobile BI vendors to promote mobile BI, and to explain why it could be successful for their customers and may help to increase the slow adoption rate of mobile BI.

8 REFERENCES

Abdinnour-Helm, S. F., Chaparro, B. S., & Farmer, S. M. (2005). Using the End-User Computing Satisfaction (EUCS) Instrument to Measure Satisfaction with a Web Site. *Decision Sciences*, *36*(2), 341–364. doi:10.1111/j.1540-5414.2005.00076.x

Agarwal, R., & Prasad, J. (1997). The Role of Innovation Characteristics and Perceived Voluntariness in the Acceptance of Information Technologies. *Decision Sciences*, *28*(3), 557–582.

Alter, S. (2004). A work system view of DSS in its fourth decade. *Decision Support Systems*, *38*(3), 319–327. doi:10.1016/j.dss.2003.04.001

Althuizen, N., Reichel, A., & Wierenga, B. (2012). Help that is not recognized: Harmful neglect of decision support systems. *Decision Support Systems*, *54*(1), 719–728. doi:10.1016/j.dss.2012.08.016

Anderson-lehman, R., Watson, H. J., Wixom, B. H., & Hoffer, J. A. (2004). Continental Airlines flies high with real-time business intelligence. *MIS Quarterly Executive*, *3*(4), 163–176.

Armstrong, J. S. (1975). Monetary incentives. *The Public Opinion Quarterly*, *39*(1), 111–116.

Armstrong, J. S., & Overton, T. S. (1977a). Estimating Nonresponse Bias in Mail Surveys. *Journal of Marketing Research*, *14*(3), 396. doi:10.2307/3150783

Armstrong, J. S., & Overton, T. S. (1977b). Estimating Nonresponse Bias in Mail Surveys. *Journal of Marketing Research*, *14*(3), 396. doi:10.2307/3150783

Armstrong, J. S., & Yokum, J. T. (1994). Effectiveness of Monetary Incentives : Mail Surveys to Members of Multinational Professional Groups. *Industrial Marketing Management*, *23*(2), 133–136.

Bartlett, J. E., Kotrlik, J. W., & Higgins, C. C. (2001a). Organizational Research : Determining Appropriate Sample Size in Survey Research. *Information Technology, Learning, and Performance Journal*, *19*(1), 43–50.

Bartlett, J. E., Kotrlik, J. W., & Higgins, C. C. (2001b). Organizational Research : Determining Appropriate Sample Size in Survey Research. *Information Technology, Learning, and Performance Journal*, *19*(1), 43–50.

Bawden, D., Holtham, C., & Courtney, N. (1999). Perspectives on information overload. *Library And Information Sciences*, *51*(8), 249–256.

Berente, N., & Vandenbosch, B. (2009). Information flows and business process integration. *Business Process Management*, *15*(1), 119–141.

Blanco, S., & Lesca, H. (1998). Business Intelligence: integrating knowledge into the selection of early warning signals. *ECIS' Workshop on Knowledge Management, Edité par CEA/DIST, Saclay, France*. Retrieved October 17, 2012, from http://www.veille-strategique.org/docs/1998-Blanco-Lesca-Articlewksp.pdf

Blythe, M. A., Overbeek, K., Monk, A. F., & Wright, P. C. (2005). *Funology From Usability to Enjoyment* (p. 293). Kluwer Academic Publishers.

Bollen, K., & Lennox, R. (1991). Conventional Wisdom on Measurement : *Pschological Association*, *110*(2), 305–314.

Borg, A., & White, D. (2012). Mobile BI 2012 : Accelerating Business on the Move. *Aberdeen*. Retrieved November 12, 2012, from http://www.aberdeen.com/Aberdeen-Library/7775/AI-mobile-business-intelligence.aspx

Boudreau, M.-C., Gefen, D., & Straub, D. W. (2001). Validation in Information Systems Research: A state-of-the-Art Assessment. *MIS Quarterly*, *25*(1), 1–16.

Bovee, M., Srivastava, R. P., & Mak, B. (2003). A conceptual framework and belief-function approach to assessing overall information quality. *International Journal of Intelligent Systems*, *18*(1), 51–74. doi:10.1002/int.10074

Brockopp, D. Y., & Hastings-Tolsma, M. T. (2003). *Fundamentals of Nursing Research* (3rd editio., p. 536). Jones & Bartlett Learning.

Brown, M. B., & Forsythe, A. B. (1974). Robust Tests for the Equality of Variances. *Journal of the American Statistical Association*, *69*(346), 364–367.

Brown, T. A. (2006). *Confirmatory Factor Analysis for Applied Research* (1 edition., p. 475). The Guilford Press.

Burton-Jones, A., & Straub, D. W. (2006). Reconceptualizing System Usage: An Approach and Empirical Test. *Information Systems Research*, *17*(3), 228–246. doi:10.1287/isre.1060.0096

Chandras, R. (2011). Is Mobile BI Worth the Hype? *Informationweek*. Retrieved December 11, 2012, from http://www.informationweek.com/software/business-intelligence/is-mobile-bi-worth-the-hype/229300446

Chau, P. Y. K., Kuan, K. K. Y., & Liang, T.-P. (2007). Research on IT value: what we have done in Asia and Europe. *European Journal of Information Systems*, *16*(3), 196–201. doi:10.1057/palgrave.ejis.3000666

Child, D. (2006). *The Essentials of Factor Analysis* (3rd editio., p. 192). Continuum International Publishing Group.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.). *Modern methods for business research*, 295–336.

Choo, C. (1996). The Knowing Organization How Organizations Use Information to Construct Meaning, Create Knowledge and Make Decisions. *International Journal of Information Managemen*, *16*(5), 329–340.

Chuan, L. C., & Penyelidikan, J. (2006). Sample size estimation using Krejcie adn Morgan and Cohen statistical power analysis: a comparison. *Jurnal Penyelidikan IPBL*, *7*, 78–86.

Chung, W., Zhang, Y., Huang, Z., Wang, G., Ong, T.-H., & Chen, H. (2004). Internet searching and browsing in a multilingual world: An experiment on the Chinese Business Intelligence Portal (CBizPort). *Journal of the American Society for Information Science and Technology*, *55*(9), 818–831. doi:10.1002/asi.20025

Citroen, C. L. (2011). The role of information in strategic decision-making. *International Journal of Information Management*, *31*(6), 493–501. doi:10.1016/j.ijinfomgt.2011.02.005

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2 edition., p. 590). Routledge Academic.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd editio., p. 736). Routledge Academic.

Conway, J. M., & Huffcutt, a. I. (2003). A Review and Evaluation of Exploratory Factor Analysis Practices in Organizational Research. *Organizational Research Methods*, *6*(2), 147–168. doi:10.1177/1094428103251541

Cooper, D. R., & Schindler, P. S. (2003). *Business Research Methods* (8th editio., p. 857). McGraw-Hill/Irwin.

Costello, A. B., & Osborne, J. W. (2005). Best Practices in Exploratory Factor Analysis : Four Recommendations for Getting the Most From Your Analysis. *Practial Assessment Research & Evaluation*, *10*(7), 1–9.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*(3).

Csikszentmihalyi, M. (1975a). *Beyond Boredom and Anxiety : Experiencing Flow in Work and Play* (1 edition., p. 231). Jossey-Bass Publishers.

Csikszentmihalyi, M. (1975b). *Beyond Boredom and Anxiety : Experiencing Flow in Work and Play* (1 edition., p. 231). Jossey-Bass Publishers.

Daft, R. L., & Lengel, R. H. (1984). Information Richness – a New Approach to Managerial Behavior and Organizational Design. *Research in Orgnaizational Behavior*, *6*, 191–233.

Daft, Richard L, & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science*, *32*(5), 554–571.

Daft, Richard L, & Macintosh, N. B. (1981). A Tentative Exploration into the Amount and Equivocality of Information Processing in Organizational Work Units A Tentative Exploration into the Amount and Equivocality of Informa- tion Processing in Or- ganizational Work Units Richard L . Daft and. *ASQ*, *26*(2), 207–224.

Davenport, T. H., & Beers, M. C. (1995). Managing information about processes. *Journal of Management Information Systems*, *12*(1), 57.

Dawes, J. (2008). Do data characteristics change according to the number of scale points used ? An experiment using 5 point, 7 point and 10 point scales. *International Journal of Market Research*, *50*(1).

Dedrick, J., Gurbaxani, V., & Kraemer, K. L. (2003). Information Technology and Economic Performance : A Critical Review of the Empirical Evidence. *ACM Computing Surveys*, *35*(1), 1–28.

DeLone, W. H. (1988). Computer Usage Business. *Determinants of Success for Computer Usage in Small Business*, *12*(1), 51–61.

DeLone, W. H., & McLean, E. R. (1992). Information Systems Success: The Quest for the Dependent Variable. *Information Systems Research*, *3*(1), 60–95. doi:10.1287/isre.3.1.60

Delone, W., & McLean, E. (2003). The DeLone and McLean Model of Information Systems Success : A Ten-Year Update. *Journal of Management Information Systems*, *19*(4), 9–30.

Deutskens, E., De Ruyter, K., Wetzels, M., & Oosterveld, P. (2004). Response Rate and Response Quality of Internet-Based Surveys: An Experimental Study. *Marketing Letters*, *15*(1), 21–36. doi:10.1023/B:MARK.0000021968.86465.00

Devaraj, S., & Kohli, R. (2003). Performance Impacts of Information Technology : Is Actual Usage the Missing Link ? *Management Science*, *49*(3), 273–289.

Diamantopoulos, A., & Winklhofer, H. M. (2001). Index Construction with Formative Indicators : An Alternative to Scale Development. *Journal of Marketing Research*, *XXXVIII (M*, 269–277.

Dimensional Research. (2012). The impact of mobile devices on information security: A survey of IT professionals. *Dimensional Research*. Retrieved October 10, 2012, from http://www.checkpoint.com/downloads/products/check-point-mobile-security-survey-report.pdf

Doll, W. J., & Torkzadeh, G. (1988). The Measurement of End-User Computing Satisfaction. *MIS Quarterly*, *12*(2), 259–274.

Dresner, H. (2011). DAS Mobile Business Intelligence Market Study – October 2011. *Dresner Advisory Services*. Retrieved July 27, 2012, from http://www.yellowfinbi.com/Document.i4?DocumentId=144743

Edwards, J. E., Thomas, M. D., Rosenfeld, P., & Booth-Kewley, S. (1997). *How To Conduct Organizational Surveys: A Step-by-Step Guide* (1 edition., p. 176). Sage Publications, Inc.

Edwards, J. R. (2010). The Fallacy of Formative Measurement. *Organizational Research Methods*, *14*(2), 370–388. doi:10.1177/1094428110378369

Elbashir, M. Z., Collier, P. a., & Davern, M. J. (2008). Measuring the effects of business intelligence systems: The relationship between business process and organizational performance. *International Journal of Accounting Information Systems*, *9*(3), 135–153. doi:10.1016/j.accinf.2008.03.001

Eppler, M. J., & Mengis, J. (2004). The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS, and Related Disciplines. *The Information Society*, *20*(5), 325–344. doi:10.1080/01972240490507974

Esposito, V. E., Chin, W. W., Henseler, J., & Wang, H. (2010). *Handbook of Partial Least Squares* (2010 editi., p. 860). Springer.

Evelson, B. (2011). Trends 2011 And Beyond: Business Intelligence | Forrester Blogs. *Forrester Research*. Retrieved August 2, 2012, from http://blogs.forrester.com/boris_evelson/11-03-31-trends_2011_and_beyond_business_intelligence

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, *4*(3), 272–299. doi:10.1037//1082-989X.4.3.272

Farrokhi, V., & Pokorádi, L. (2012). The necessities for building a model to evaluate Business Intelligence projects- Literature Review. *International Journal of Computer Science & Engineering Survey*, *3*(2).

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior research methods*, *39*(2), 175–91.

Fornell, C., & Bookstein, F. (1981). A comparative analysis of two structural equation models: LISREL and PLS applied to market data. *The University of Michigan*. Retrieved October 4, 2013, from http://deepblue.lib.umich.edu/bitstream/handle/2027.42/35611/b1378958.0001.001.pdf

Fricker, R. D., & Schonlau, M. (2002). Advantages and Disadvantages of Internet Research Surveys: Evidence from the Literature. *Field Methods*, *14*(4), 347–367. doi:10.1177/152582202237725

Frolick, M. N., & Ariyachandra, T. R. (2006). Business Performance Management: One Truth. *Information Systems Management*, *23*(1), 41–48. doi:10.1201/1078.10580530/45769.23.1.20061201/91771.5

Galbraith, J. R. (1974). Organization Design: An Information Processing View. *Interfaces*, *4*(3), 28–36. doi:10.1287/inte.4.3.28

Gasser, L., Twidale, M. B., & Smith, L. C. (2007). A Framework for Information Quality Assessment. *Journal of the American Society for Information Science and Technology*, *58*(12), 1720–1733. doi:10.1002/asi

Gebauer, J., & Schober, F. (2006). Information System Flexibility and the Cost Efficiency of Business Processes. *Journal of the Association for Information Systems*, *7*(3), 122–147.

Gefen, D., & Straub, D. (2005). PLS-GRAPH : TUTORIAL AND ANNOTATED EXAMPLE. *Communications of the Association for Information Systems*, *16*, 91–109.

Ghazanfari, M., Jafari, M., & Rouhani, S. (2011). A tool to evaluate the business intelligence of enterprise systems. *Scientia Iranica*, *18*(6), 1579–1590.

Gibbons, C. (2007). *Determination of Power and Sample Size for Levene's Test* (p. 69). ProQuest.

Goodwin, C. J. (2009). *Research In Psychology: Methods and Design* (6th editio., Vol. 2009, p. 624). John Wiley & Sons.

Gordon, B. (1999). A Research Perspective for Information Systems and Example of Emerging Area of Research. *Information Systems Frontiers*, *1*(3), 195–203.

Gosling, J. (1995). *Introductory Statistics* (1 edition., p. 342). Pascal Press.

Grover, V., Ryul, S., & Segars, A. H. (1996). Information systems effectiveness : The construct space and patterns of application, *31*, 177–191.

Hahn, M., Lawson, R., & Gye Lee, Y. (1992). The Effects of Time Pressure and Information Load on Decision Quality. *Psychology & Marketing*, *9*(5), 365–380.

Hair, J., Black, W., Babin, B., & Anderson, R. (2009). *Multivariate Data Analysis* (7th editio., p. 816). Prentice Hall.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. *The Journal of Marketing Theory and Practice*, *19*(2), 139–152. doi:10.2753/MTP1069-6679190202

Hair, J., Tatham, R., Anderson, R., & Black, W. (1988). *Multivariate data analysis* (5th editio., p. 730). Prentice-Hall International.

Hannula, M., & Pirttimaki, V. (2003). Business intelligence empirical study on the top 50 Finnish companies. *The Journal of American Academy of Business*, *2*(2), 593 – 600.

Haringman, J. J., Gerlag, D. M., Zwinderman, a H., Smeets, T. J. M., Kraan, M. C., Baeten, D., McInnes, I. B., et al. (2005). Synovial tissue macrophages: a sensitive biomarker for response to treatment in patients with rheumatoid arthritis. *Annals of the rheumatic diseases*, *64*(6), 834–8. doi:10.1136/ard.2004.029751

Hartwick, J., & Barki, H. (1994). Explaining in the Role of User Participation in Information System Use. *Management Science*, *40*(4), 440–465.

Harvey, N., & Bolger, F. (1996). Graphs versus tables: Effects of data presentation format on judgemental forecasting, *12*, 119–137.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. (J. Henseler, C. M. Ringle, & R. R. Sinkovics, Eds.)*International Marketing*, *20*, 277–319. doi:10.1108/S1474-7979(2009)0000020014

Heo, J., & Han, I. (2003). Performance measure of information systems (IS) in evolving computing environments: An empirical investigation. *Information and Management*, *40*(4), 243–256.

Hostmann, B., Herschel, G., & Rayner, N. (2007). The evolution of business intelligence: the four worlds. *Gartner*. Retrieved October 18, 2012, from http://www.gartner.com/DisplayDocument?id=509002

Hou, C.-K. (2012). Examining the effect of user satisfaction on system usage and individual performance with business intelligence systems: An empirical study of Taiwan's electronics industry. *International Journal of Information Management*, *32*(6), 560–573.

Howson, C. (2010). Ease of Use and Interface Appeal in Business Intelligence Tools. *BeyeNetwork*. Retrieved November 11, 2012, from http://www.beyeresearch.com/executive/13006

Huck, S. W. (2004). *Reading statistics and research* (4 edition., p. 592). Pearson Education.

Igbaria, M., & Tan, M. (1997). The consequences of information technology acceptance on subsequent individual performance. *Information & Management*, *32*(3), 113–121. doi:10.1016/S0378-7206(97)00006-2

Iivari, J. (2005). An Empirical Test of the Model of Information System Success. *The DATA BASE for Advances in Information Systems*, *36*(2), 8–27.

Imhoff, C., & White, C. (2011). TDWI Research Self-Service Business Intelligence. Empowering Users to Generate Insights. *TDWI Research*. Retrieved November 11, 2012, from http://tdwi.org/webcasts/2011/07/self-service-bi-empowering-users-to-generate-insights.aspx

Isik, O., Jones, M. C., & Sidorova, A. (2011). BUSINESS INTELLIGENCE (BI) SUCCESS AND THE ROLE OF BI CAPABILITIES. *Intelligent Systems in Accounting, Finance and Management*, *18*(January), 161–176. doi:10.1002/isaf

Isık, Ö., Jones, M. C., & Sidorova, A. (2013). Business intelligence success: The roles of BI capabilities and decision environments. *Information & Management*, *50*(1), 13–23. doi:10.1016/j.im.2012.12.001

Jacques, R., Preece, J., & Carey, T. (1995). Engagement as a design concept for multimedia. *Canadian Journal of Educational Communications*, *24*(1), 49–59.

Jarvis, B., Mackenzie, S. B., & Podsakoff, P. M. (2003). A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research. *Journal of Consumer Research*, *30*(2), 199–218.

Jeong, M., & Lambert, C. U. (2001). Adaptation of an information quality framework to measure customers' behavioral intentions to use lodging Web sites. *International Journal of Hospitality Management*, *20*(2), 129–146. doi:10.1016/S0278-4319(00)00041-4

Kanuk, L., & Berenson, C. (1975). Mail Surveys and Response Rates : A Literature Review, (November), 440–454.

Khan, R. A. (2012). BUSINESS INTELLIGENCE : AN INTEGRATED APPROACH. *Business Intelligence Journal*, *5*(1), 64–70.

Kleinbaum, D. G., Kupper, Lawrence, L., Nizam, A., & Muller, K. E. (2007). *Applied Regression Analysis and Multivariable Methods* (4 edition., p. 906). Cengage Learning.

Krejcie, R. V, & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and psychological measurement*, *30*, 607–610.

Lee, K. C., & Chung, N. (2009). Understanding factors affecting trust in and satisfaction with mobile banking in Korea: A modified DeLone and McLean's model perspective. *Interacting with Computers*, *21*, 385–392.

Lee, Y. W., Strong, D. M., Kahn, B. K., & Wang, R. Y. (2002). AIMQ: a methodology for information quality assessment. *Information & Management*, *40*(2), 133–146. doi:10.1016/S0378-7206(02)00043-5

Leidner, D. E., & Elam, J. J. (1993). Executive information systems : their impact on executive decision making. *Journal of Management Information Systems*, *10*(3), 139–155.

Levene, H. (1960). Robust tests for equality of variances, in: I. Olkin, S.G. Ghurye, W. Hoeffding, W.G. Madow and H.B. Mann (Eds.). *Stanford Univ. Press, Stanford*, 278–292.

Lilien, G. L., Rangaswamy, a., Van Bruggen, G. H., & Starke, K. (2004). DSS Effectiveness in Marketing Resource Allocation Decisions: Reality vs. Perception. *Information Systems Research*, *15*(3), 216–235. doi:10.1287/isre.1040.0026

Lock, M. (2012). Operational Intelligence - Part 2 : The Path to Best-in-Class Performance. *Aberdeen*. Retrieved November 11, 2012, from http://www.aberdeen.com/aberdeen-library/7657/RB-business-intelligence-analytics.aspx

Luftman, J., & Zadeh, H. S. (2011). Key information technology and management issues 2010–11: an international study. *Journal of Information Technology*, *26*(3), 193–204.

Luftman, J., Zadeh, H. S., Derksen, B., Santana, M., Rigoni, E. H., & Huang, Z. (David). (2012). Key information technology and management issues 2011–2012: an international study. *Journal of Information Technology*. Nature Publishing Group. Retrieved October 30, 2012, from http://www.palgrave-journals.com/jit/journal/vaop/ncurrent/full/jit201214a.html

Luhn, H. P. (1958). A Business Intelligence System. *IBM Journal of Research and Development*, *2*(4), 314–319. doi:10.1147/rd.24.0314

Lurie, N. H. (2004). Decision Making in Information-Rich Environments : The Role of Information Structure. *JOURNAL OF CONSUMER RESEARCH*, *30*(4), 473–486.

Lynch, S. M. (2003). Missing Data. *http://www.princeton.edu*. Retrieved April 16, 2013, from http://www.princeton.edu/~slynch/soc504/missingdata.pdf

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

MacKenzie, S. B., Podsakoff, P. M., & Jarvis, C. B. (2005). The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions. *The Journal of applied psychology*, *90*(4), 710–30. doi:10.1037/0021-9010.90.4.710

Maimbo, H., & Pervan, G. (2005). Designing a Case Study Protocol for Application in IS research. *The Ninth Pacific Conference on Information Systems*. Retrieved August 27, 2012, from http://www.pacis-net.org/file/2005/113.pdf

Malhotra, M. K., & Grover, V. (1998). An assessment of survey research in POM : from constructs to theory. *Journal of Operations Management*, *16*, 407–425.

Mashman, W. (2011). The iPad in cardiology: tool or toy? *JACC. Cardiovascular interventions*, *4*(2), 258–9. doi:10.1016/j.jcin.2011.01.001

McGill, T., & Hobbs, V. (2003). User-Developed Applications and Information Systems Success : A Test of DeLone and McLean ' s Model. *Information Resources Management Journal*, *16*(1), 24–45.

McHaney, R., Hightower, R., & Pearson, J. (2002). A validation of the end-user computing satisfaction instrument in Taiwan. *Information & Management*, *39*(6), 503–511. doi:10.1016/S0378-7206(01)00119-7

McHaney, R., Hightower, R., & White, D. (1999). EUCS test–retest reliability in representational model decision support systems. *Information & Management*, *36*(2), 109–119. doi:10.1016/S0378-7206(99)00010-5

Mishra, J. (2012). *Software Engineering* (1e edition., p. 387). Pearson Education India.

Moody, D., & Walsh, P. (1999). Measuring The Value Of Information : An Asset Valuation Approach 1. *ECIS 1999: Copenhagen, Denmark*. Retrieved September 22, 2012, from http://wwwinfo.deis.unical.it/~zumpano/2004-2005/PSI/lezione2/ValueOfInformation.pdf

Moore, G. C., & Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research*, *2*(3), 192–222.

Moreau, É. M.-F. (2006). The impact of intelligent decision support systems on intellectual task success: An empirical investigation. *Decision Support Systems*, *42*(2), 593–607. doi:10.1016/j.dss.2005.02.008

Murphy, I. B. (2012). How Touch Screens Create New Mobile BI and Analytics Interactions | Data Informed. *DataInformed*. Retrieved November 22, 2012, from http://data-informed.com/blog/2012/09/10/how-touch-screens-create-new-mobile-bi-and-analytics-interactions/

Nargundkar, R. (2003). *Marketing Research-Text & Cases 2E* (2nd editio., p. 494). Tata McGraw-Hill Education.

Negash, S. (2004). Business Intelligence. *Communications of the Association for Information Systems*, *13*, 177–195.

Nelson, R. R., Todd, P. A., & Wixom, B. H. (2005). Antecedents of Information and System Quality : An Empirical Examination Within the Context of Data Warehousing. *Journal of Management Information Systems*, *21*(4), 199–235.

Niederhauser, V. P., & Mattheus, D. (2010). The anatomy of survey questions. *Journal of pediatric health care : official publication of National Association of Pediatric Nurse Associates & Practitioners*, *24*(5), 351–354. doi:10.1016/j.pedhc.2010.04.013

Niu, K.-H. (2008). *Understanding Knowledge Management and Organizational Adaptation and the Influencing Effects of Trust and Industrial Cluster* (p. 252). ProQuest.

Novak, T. P., Hoffman, D. L., & Yung, Y. (2000). Measuring Online the Customer Experience in A Structural Environments : Modeling Approach. *Marketing Science*, *19*(1), 22–42.

Nunnally, J. (1978). *Construction methods and management* (2nd editio., p. 462). New York: McGraw–Hill.

Olszak, C. M., & Ziemba, E. (2007). Approach to Building and Implementing Business Intelligence Systems. *Interdisciplinary Journal of Information*, *2*, 135–148.

O'brien, R. M. (2007). A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity*, *41*(5), 673–690. doi:10.1007/s11135-006-9018-6

Petter, S., DeLone, W., & McLean, E. (2008). Measuring information systems success: models, dimensions, measures, and interrelationships. *European Journal of Information Systems*, *17*(3), 236–263. doi:10.1057/ejis.2008.15

Petter, S., & McLean, E. R. (2009). A meta-analytic assessment of the DeLone and McLean IS success model: An examination of IS success at the individual level. *Information & Management*, *46*(3), 159–166. doi:10.1016/j.im.2008.12.006

Petter, S., Straub, D., & Rai, A. (2007). Specifying Formative Constructs in Information Systems Research. *MIS Quarterly*, *31*(4), 623–656.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003a). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *The Journal of applied psychology*, *88*(5), 879–903. doi:10.1037/0021-9010.88.5.879

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003b). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *The Journal of applied psychology*, *88*(5), 879–903. doi:10.1037/0021-9010.88.5.879

Podsakoff, P. M., & Organ, D. W. (1986a). Self-Reports in Organizational Reserach: Problems and Prospects. *Journal of Management*, *12*(4), 531–544.

Podsakoff, P. M., & Organ, D. W. (1986b). Self-Reports in Organizational Reserach: Problems and Prospects. *Journal of Management*, *12*(4), 531–544.

Popovič, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2012). Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. *Decision Support Systems*, *54*(1), 729–739. doi:10.1016/j.dss.2012.08.017

Popovič, A., Turk, T., & Jaklic, J. (2010). Conceptual model of business value of business intelligence systems. *Management: Journal of Contemporary Management Issues*, *15*(1), 5–30.

Porter, M. E., & Millar, V. E. (1985). How information gives you competitive advantage. *Harvard Business Review*, *63*(4), 149–160.

Premkumar, G., & Ramamurthy, K. (2005). Information Processing View of Organizations : An Exploratory Examination of Fit in the Context of. *Journal of Management Information Systems*, *22*(1), 257–294.

Purvis, R. L., & Robert, V. S. (2001). The Assimilation of Knowledge Platforms in Organizations : An Empirical Investigation. *Organization Science*, *12*(2), 117–135.

Pérez-Mira, B. (2010). Validity of DeLone and McLean's model of information systems success at the website level of analysis. Retrieved November 5, 2012, from http://etd.lsu.edu/docs/available/etd-04162010-001906/unrestricted/Perez-Mira_diss.pdf

Raduan, C. R., Jegak, U., Haslinda, A., & Alimin, I. I. (2009). Management , Strategic Management Theories and the Linkage with Organizational Competitive Advantage from the Resource-Based View. *European Journal of Social Sciences*, *11*(3), 402–418.

Rai, A., Lang, S. S., & Welker, R. B. (2002). Assessing the Validity of IS Success Models : An Empirical Test and Theoretical Analysis. *Information Systems Research*, *13*(1), 50–69.

Ramakrishnan, T., Jones, M. C., & Sidorova, A. (2012). Factors influencing business intelligence (BI) data collection strategies: An empirical investigation. *Decision Support Systems*, *52*, 486–496.

Rivard, S., Poirier, G., Raymond, L., & Bergeron, F. (1997). Development of a Measure to Assess the Quality of User- Developed Applications.pdf. *The DATA BASE for Advances in Information Systems*, *28*(3), 44–58.

Rozendaal, M. C., Braat, B. a. L., & Wensveen, S. a. G. (2009). Exploring sociality and engagement in play through game-control distribution. *Ai & Society*, *25*(2), 193–201. doi:10.1007/s00146-009-0245-y

Rozendaal, Marius Cornelis. (2007). Designing engaging interactions with digital products. *TU Delft*. Retrieved January 22, 2013, from http://repository.tudelft.nl/assets/uuid:1c8d8933-8e19-407d-9238-54d87a9a75a0/dep_rozendaal_20071008.pdf

Rubin, A. (2010). *Statistics for Evidence-based Practice and Evaluation* (2nd editio., p. 332). Cengage Learning.

Rutkowski, A., & Saunders, C. S. (2010). Growing Pains with information overload. *Computer*, *June*, 94–96.

Sabherwal, R., Jeyaraj, A., & Chowa, C. (2006). Information System Success: Individual and Organizational Determinants. *Management Science*, *52*(12), 1849–1864. doi:10.1287/mnsc.1060.0583

Saks, A. M. (2006). Antecedents and consequences of employee engagement. *Journal of Managerial Psychology*, *21*(7), 600–619. doi:10.1108/02683940610690169

Santosa, P. I., Wei, K. K., & Chan, H. C. (2005). User involvement and user satisfaction with information-seeking activity. *European Journal of Information Systems*, *14*(4), 361–370. doi:10.1057/palgrave.ejis.3000545

Schick, A. G., Gordon, L. a., & Haka, S. (1990). Information overload: A temporal approach. *Accounting, Organizations and Society*, *15*(3), 199–220. doi:10.1016/0361-3682(90)90005-F

Schlotzhauer, S. D. (2007). *Elementary Statistics Using JMP (Google eBook)* (1e edition., p. 480). SAS Institute.

Schoenmakers, T., Wiers, R. W., Jones, B. T., Bruce, G., & Jansen, A. T. M. (2007). Attentional re-training decreases attentional bias in heavy drinkers without generalization. *Addiction (Abingdon, England)*, *102*(3), 399–405. doi:10.1111/j.1360-0443.2006.01718.x

Schrepp, M., Held, T., & Laugwitz, B. (2006). The influence of hedonic quality on the attractiveness of user interfaces of business management software. *Interacting with Computers*, *18*(5), 1055–1069. doi:10.1016/j.intcom.2006.01.002

Seddon, P. B., Staples, S., & Patnayakuni, R. (1999). Dimensions of information systems success. *Communications of the Association for Information Systems*, *2*(20).

Seddon, P., & Kiew, M.-Y. (1996). A partial test and development of DeLone and McLean’s model of IS success. *Australasian Journal of Information Systems*, *4*(1), 90–109.

Sedera, D., & Gable, G. (2004). A factor and structural equation analysis of the enterprise systems success measurement model. *Twenty-Fifth International Conference on Information Systems*. Retrieved November 9, 2012, from http://eprints.qut.edu.au/4733/1/SederaGable2004ICIS.pdf

Sharma, J. K. (2007). *Business Statistics* (2nd editio., p. 732). Pearson Education India.

Shaw, M., Beebe, T., Jensen, H. L., & Adlis, S. A. (2001). Methods The Use of Monetary Incentives in a Community Survey : Impact on Response Rates , Data Quality , and Cost. *Health Services Research*, *35*(6), 1339–1346.

Sood, B., Bitterer, A., & Richardson, J. (2011). Emerging Technology Analysis : Mobile Business Intelligence. *Gartner*. Retrieved January 2, 2013, from http://www.gartner.com/id=1744217

Stodder, D. (2012). Mobile business intelligence and analytics. *TDWI Research*. Retrieved July 23, 2012, from http://tdwi.org/webcasts/2012/01/mobile-business-intelligence-and-analytics-extending-insight-to-a-mobile-workforce.aspx

Subramani, M. (2004). How Do Suppliers Benefit from Information Technology Use in Supply Chain Relationships? *MIS Quarterly*, *28*(1), 45–73.

Suhr, D. D. (2003). Exploratory or Confirmatory Factor Analysis ? *Univeristy of Northern Colorado*. Retrieved April 17, 2013, from http://www2.sas.com/proceedings/sugi31/200-31.pdf

Tapadinhas, J. (2011). Who ’ s Who in Mobile BI. *Gartner*. Retrieved November 10, 2012, from http://www.gartner.com/id=1811015

Tapadinhas, J. (2012). Critical Capabilities for Mobile BI What You Need to Know. *Gartner*. Retrieved November 11, 2012, from http://www.gartner.com/id=1980218

Tinsley, H. E., & Tinsley, D. J. (1987). Uses of factor analysis in counseling psychology research. *Journal of Counseling Psychology*, *34*(4), 414–424. doi:10.1037//0022-0167.34.4.414

Umanath, N. S. (1994). Effect of IS variables on information acquisition modes: An experimental investigation. *Information & Management*, *27*(5), 287–301. doi:10.1016/0378-7206(94)90023-X

Umanath, N. S., & Vessey, I. (1994). Multiattribute data presentation and human judgment : A cognitive fit perspective. *Decision Sciences*, *25*(5,6), 795–824.

Vandenbosch, B., & Huff, S. L. (1997). Searching and Scanning: How Executives Obtain Information from Executive Information Systems. *MIS Quarterly*, *21*(1), 81–107.

Vaus, D. de. (2002). *Analyzing Social Science Data: 50 Key Problems in Data Analysis* (1 edition., p. 402). SAGE Publications Ltd.

Viaene, S., Hertogh, S. D. E., Lutin, L. U. C., Maandag, A., Hengst, S. D. E. N., & Doeleman, R. (2009). Intelligence-led policing at the amsterdam-amstelland police department: operationalized business intelligence with an enterprise ambition. *Intelligent Systems in Accounting, Finance and Management*, *18*(September), 279–292.

Wang, Y.-S., & Liao, Y.-W. (2008). Assessing eGovernment systems success: A validation of the DeLone and McLean model of information systems success. *Government Information Quarterly*, *25*(4), 717–733. doi:10.1016/j.giq.2007.06.002

Watson, H. J., & Leonard, T. (2011). U.S. Xpress: Where Trucks and BI Hit the Road. *Business Intelligence Journal*, *16*(2), 4–7.

Watson, H. J., & Wixom, B. H. (2007). The current statement of business intelligence. *Computer*, *40*(9), 96–99.

Watson, H. J., Wixom, B. H., & Bruce, Y. (2013). Delivering Value through Mobile BI. *Business Intelligence Journal*, *18*(1).

Webster, J., & Ahuja, J. S. (2006). Enhancing the Design of Web Navigation Systems: The Influence of User Disorientation on Engagement and Performance. *MIS Quarterly*, *30*(3), 661–678.

Webster, J., & Ho, H. (1997). Audience engagement in multimedia presentations. *The DATA BASE for Advances in Information Systems*, *28*(2), 63–77. doi:10.1145/264701.264706

Weinberg, S. L., & Abramowitz, S. K. (2008). *Statistics Using SPSS: An Integrative Approach* (p. 764). Cambridge University Press.

Williams, M. L., Dennis, A. R., Stam, A., & Aronson, J. E. (2007). The impact of DSS use and information load on errors and decision quality. *European Journal of Operational Research*, *176*(1), 468–481. doi:10.1016/j.ejor.2005.06.064

Williams, S. (2004). Assessing BI Readiness : A Key to BI ROI. *Business Intelligence Journal*, *9*(3), 15–23.

Wixom, B. H., Watson, H. J., & Werner, T. (2011). Developing an Enterprise Business Intelligence Capability: The Norfolk Southern Journey. *MIS Quarterly Executive*, *10*(2), 19–29.

Yamakami, T. (2008). Business Model Engineering Analysis on Mobile Client-side Software Platform Strategies. *7th International Conference Mobile Business (ICMB)*, (7-8 July).

Yeoh, W., & Koronios, A. (2010). Critical success factors for business intelligence systems. *Journal of Computer Information Systems*, *50*(3), 23–32.

APPENDIX A: MOBILE BI SURVEY

TILBURG UNIVERSITY

Are you an user of Mobile Business Intelligence (BI)? Then I would really appreciate it if I could have 5-8 minutes of your time.

To complete my study Information Management at Tilburg University (The Netherlands), I am writing a thesis about the success factors of mobile BI. With your help I can successfully complete my thesis.

For the purpose of this study, mobile BI refers to a system comprised of both technical and organizational elements that presents business information to its users for analysis on mobile devices such as smartphones and tablets.

This survey wil focus specifically on the benefits, accessibility, flexibility, ease of use, usage, information quality and user satisfaction of mobile BI.

The results of this survey will be processed anonymously.

With completing this survey, you are not only helping my research, but you are also supporting the World Wide Fund for Nature.
I will donate 1 dollar for every completed survey.
By leaving your email address, you also get the opportunity to win $ 150,-
And you get the option to receive the end results of this study.

In addition, your participation is voluntary. You may decline to answer any particular question that you are uncomfortable with or feel is not appropriate.

Thank you for you consideration.
Sincerely,

Twan Peters
t.j.a.c.peters@tilburguniversity.edu

<< >>

1/23. How old are you?

- Under 25
- 26-34
- 35-54
- 55-64
- 65 or over

2/23. What is the highest level of education you have completed?

- Bachelor's degree
- Master's degree
- Vocational/technical school
- Senior high school
- Doctoral degree
- Other

3/23. What is the principal industry of your organization?

- Agriculture, hunting and forestry
- Construction
- Electricity, gas and water supply
- Financial intermediation
- Hotels and restaurants
- Manufacturing
- Real estate, renting and business activities
- Transport, storage and communication
- Wholesale and retail trade
- Other (please specify)

4/23. What is your current work position?

- Non-management/professional staff
- Middle-level management
- First level supervisor
- Top-level management/executives

5/23. What is your functional area?

- Corporate communications
- Finance / Accounting / Planning
- General management
- Human resources / Personnel
- Information technology
- Legal
- Manufacturing / Operations
- Marketing
- Sales
- Supply chain
- Other (please specify)

6/23. Who is your employer? (will only be used anonymously for research purposes)

<< >>

Please answer the following statements/questions about a specific mobile BI solution you use for your everyday business decision making purposes. If you are using more than one mobile BI solution, please focus only on one of them and answer the questions based on that specific solution.

Your **honest responses** to each statement and question are extremely important to this studies outcome.

Please notice that there are **favorable** and **unfavorable** statements in this survey.

7/23. Please indicate the mobile platform (i.e. device) used to access your mobile BI: I use mobile BI via...

- ... a tablet
- ... a smartphone
- ... other (please specify)

8/23. Please choose the response that best describes each of the following statements;

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
My mobile BI solution is user friendly.					
My mobile BI solution is easy to use.					

9/23. Please choose the response that best describes the following statement;

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
My mobile BI solution has a visually attractive interface design. *(includes visualizations, graphs, tables, report layouts, dashboard layout etc…)*					
My mobile BI solution does **not** have a visually appealing interface design. *(includes visualizations, graphs, tables, report layouts, dashboard layout etc...)*					

10/23. Please choose the response that best describes each of the following statements;

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I can modify my mobile BI solution to my desired information needs.					
My mobile BI solution can accommodate changes in business requirements quickly.					
My mobile BI solution makes it easier to deal with exceptional situations.					

11/23. Please choose the response that best describes each of the following statements;

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The way I access my mobile BI fits well to the types of decisions I make using my mobile BI solution.					
The accessed information is processed and delivered rapidly without delay.					
I can use my mobile BI solution at anytime, anywhere I want.					

12/23. Please rank the aspects of the information supply using your mobile BI solution;

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The scope of information is adequate (neither too much nor too little).	○	○	○	○	○
The information is **not** precise enough.	○	○	○	○	○
The information is easily understandable.	○	○	○	○	○
The information is to the point, without unnecessary elements.	○	○	○	○	○
The information is consistent.	○	○	○	○	○
The information is free of error.	○	○	○	○	○
The information is up-to-date and not obsolete.	○	○	○	○	○

13/23. Please choose the response that best describes each of the following statements;

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I enjoy using my mobile BI solution.	○	○	○	○	○
I can discover and learn a lot with my mobile BI solution.	○	○	○	○	○
Using my mobile BI solution is exciting.	○	○	○	○	○
My mobile BI solution gives me the freedom to use it in my own way.	○	○	○	○	○
I like the way my mobile BI solution supports me in achieving my goals.	○	○	○	○	○
Using my mobile BI solution is challenging.	○	○	○	○	○

14/23. Please choose the response that best describes each of the following statements;

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The mobile BI solution has met my expectations.	○	○	○	○	○
I strongly recommend mobile BI to others.	○	○	○	○	○
Overall, I'm satisfied with my mobile BI solution.	○	○	○	○	○

15/23. Please choose the response that best describes the following statement;

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
My use of the mobile BI solution is voluntary.	○	○	○	○	○
My superiors **expect** me to use the mobile BI solution.	○	○	○	○	○

16/23. At present, how often do you use your mobile BI solution?

	Less than once a week	About once a week	A few times a week	About once a day	More than once a day
Frequency	○	○	○	○	○

17/23. How much time do you spend each week using your mobile BI solution?

	Less than 10 minutes	10 - 30 minutes	30 - 60 minutes	1 - 2 hours	More than 2 hours
Per week	○	○	○	○	○

18/23. Since I started using my mobile BI solution, I achieved the following business benefits;

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Helps me to make higher quality decisions.	◯	◯	◯	◯	◯
Enables me to present my arguments more convincingly.	◯	◯	◯	◯	◯
Helps me to make decisions quicker.	◯	◯	◯	◯	◯
Helps me notice problems before they become serious crises (proactive business planning).	◯	◯	◯	◯	◯
Improves my job performance.	◯	◯	◯	◯	◯
Increases my job productivity.	◯	◯	◯	◯	◯
Enhances my effectiveness in my job.	◯	◯	◯	◯	◯
Increases my key performance indicators.	◯	◯	◯	◯	◯
Reduces the costs of business processes.	◯	◯	◯	◯	◯

19/23. My mobile BI solution is supported by the top management in my organization.

Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
◯	◯	◯	◯	◯

20/23. For how many years has your organization been using mobile BI.

Less than 6 months	1 year	1-2 years	2-3 years	over 3 years
◯	◯	◯	◯	◯

<< >>

21/23. Are you a mobile worker?

***Definition:** A mobile worker is a worker who performs his/her works in numerous locations. The place of work may be sites such as customer sites, company offices, homes, vendor offices, planes and hotels among others.*

- ◯ Never
- ◯ Rarely (0-25% a week)
- ◯ Sometimes (25-50% a week)
- ◯ Most of the Time (50-75% a week)
- ◯ Always (75-100% a week)

22/23. Which mobile BI software are you using?

- Actuate
- Andara
- Arcplan
- Birst
- CompentArt
- Enterprise Signal (SurfBI)
- Exxova
- Extended Results (PushBI)
- IBM Cognos
- Information builders
- Jaspersoft
- LogiXML
- Microstrategy
- Microsoft
- Oracle
- Qlikview
- Roambi
- SAP Business Objects Explorer
- SAP Business Objects Mobile
- Strategy Companion
- Tableau
- Tibco Spotfire
- Transpara
- Yellowfin
- In-house development
- I don't know
- Other (please specify)

23/23. In which geographic area do you live?

- Africa
- Asia/Pacific Islands
- Australia/New Zealand
- Canada
- Central/South America
- Europe
- Middle East
- South Asia
- United States
- Other (Please specify)

This is the end of the mobile BI survey.
Thank you for completing this survey!

If you have any additional comments or questions, please feel free to write them here:

If you want to make a chance to win $150, please leave below your email address:
Your email address will not be linked to the given answers in this survey.

Do you want to receive the research results on your email address?
Results will be emailed around June/July 2013.

- Yes
- No

<< >>

APPENDIX B: INDICATORS OF THE MEASUREMENT MODEL

Construct	Item code	Measure	Source	I/A/D
Accessibility	SQA1	The way I access my mobile BI fits well to the types of decisions I make using my mobile BI solution.	Isik et al. (2011)	A
	SQA2	The accessed information is processed and delivered rapidly without delay.	Popovič et al. (2012) Eppler (2003, p. 83)	A
	SQA3	I can use my mobile BI solution at anytime, anywhere I want.	Lee & Chung (2009)	A
Ease of Use	SQEU1	My mobile BI solution is user friendly.	Doll & Torkzadeh (1988) Hou (2012)	A
	SQEU2	My mobile BI solution is easy to use.	Doll & Torkzadeh (1988) Hou (2012) Moreau (2006)	A
Flexibility	SQF1	I can modify my mobile BI solution to my desired information needs.	Yeoh & Koronios (2010)	A
	SQF2	My mobile BI solution can accommodate changes in business requirements quickly.	Isik et al. (2011)	A
	SQF3	My mobile BI solution makes it easier to deal with exceptional situations.	Isik et al. (2011)	A
Interface Design	SQID1	My mobile BI solution has a visually attractive interface design. *(includes visualizations, graphs, tables, report layouts, dashboard layout etc*...)	Santosa et al. (2005)	A
	SQID2*	My mobile BI solution does **not** have a visually appealing interface design.*(includes visualizations, graphs, tables, report layouts, dashboard layout etc...)*	Santosa et al. (2005)	A
Information Quality	IQ1	The scope of information is adequate (neither too much nor too little).	Popovič et al. (2012) Eppler (2003, p. 83)	I
	IQ2*	The information is **not** precise enough.	Popovič et al. (2012) Eppler (2003, p. 83)	A
	IQ3	The information is easily understandable.	Popovič et al. (2012) Eppler (2003, p. 83)	A
	IQ4	The information is to the point, without unnecessary elements.	Popovič et al. (2012) Eppler (2003, p. 83)	I
	IQ5	The information is consistent.	Popovič et al. (2012) Eppler (2003, p. 83)	A
	IQ6	The information is free of error.	Popovič et al. (2012) Eppler (2003, p. 83)	A
	IQ7	The information is up-to-date and not obsolete.	Popovič et al. (2012) Eppler (2003, p. 83)	I
Engagement	EG1	I enjoy using my mobile BI solution.	Rozendaal et al. (2009) Webster & Ho (1997) Webster & Ahuja (2006)	A
	EG2	I can discover and learn a lot with my mobile BI solution.	Rozendaal et al. (2009) Webster & Ho (1997) Webster & Ahuja (2006)	A
	EG3	Using my mobile BI solution is exciting.	Rozendaal et al. (2009) Webster & Ho (1997) Webster & Ahuja (2006)	A
	EG4	My mobile BI solution gives me the freedom to use it in my own way.	Rozendaal et al. (2009) Webster & Ho (1997) Webster & Ahuja (2006)	D
	EG5	I like the way my mobile BI solution supports me in achieving my goals.	Rozendaal et al. (2009)	D
	EG6	Using my mobile BI solution is challenging.	Rozendaal et al. (2009) Webster & Ho (1997)	D

Use	U1	At present, how often do you use your mobile BI solution?	Hou et al. (2012) Iivari (2005)	A
	U2	How much time do you spend each week using your mobile BI solution?	Hou et al. (2012) Iivari (2005)	A
User Satisfaction	US1	The mobile BI solution has met my expectations.	Wang & Liao (2008)	A
	US2	I strongly recommend mobile BI to others.	Lee & Chung (2009)	A
	US3	Overall, I'm satisfied with my mobile BI solution.	Lee & Chung (2009)	A
Net Benefits	MBB1	Helps me to make higher quality decisions.	Hou (2012) Moreau (2006)	A
	MBB2	Enables me to present my arguments more convincingly.	Moreau (2006)	I
	MBB3	Helps me to make decisions quicker.	Hou (2012) Moreau (2006)	A
	MBB4	Helps me notice problems before they become serious crises (proactive business planning).	Hou (2012) and Popovič et al. (2012)	A
	MBB5	Improves my job performance.	Hou (2012) Heo & Han (2003) Moreau (2006)	A
	MBB6	Increases my job productivity.	Hou (2012) Moreau (2006)	A
	MBB7	Enhances my effectiveness in my job.	Hou (2012) Moreau (2006)	A
	MBB8	Increases my key performance indicators.	Popovič et al. (2012)	A
	MBB9	Reduces the costs of business processes.	Elbashir et al. (2008) Popovič et al. (2012)	A
Voluntariness of use	UV1	My use of the mobile BI solution is voluntary.	Hou et al. (2012) Heo & Han (2003) Moore & Benbasat (1991)	A
	UV2*	My superiors **expect** me to use the mobile BI solution.	Hou et al. (2012) Moore & Benbasat (1991)	A
Control Variables	CV1	My mobile BI solution is supported by the top management in my organisation.	Sabherwal (2006)	A
	CV2	For how many years has your organisation been using mobile BI.	Subramani (2004)	A

***Reversed coded**

I/A/D= Directly Incorporated, Adapted, Developed

Developed: The items used in this study are developed based on their writings.

APPENDIX C: SKEWNESS AND KURTOSIS

		Age	Education	GeographicArea	Principal_industry	Work_Position	Functional_Area	TabletofSmartphone
N	Valid	196	196	196	196	196	196	196
	Missing	0	0	0	0	0	0	0
Skewness		-,060	1,708	-,637	-,641	,343	,371	1,013
Std. Error of Skewness		,174	,174	,174	,174	,174	,174	,174
Kurtosis		,586	3,164	-,275	-,477	-1,438	-,909	-,985
Std. Error of Kurtosis		,346	,346	,346	,346	,346	,346	,346

		MobileWorker	MobileApplication	SQEU_1	SQEU_2	SQID_1	SQID_2	SQF_1
N	Valid	196	196	196	196	196	196	196
	Missing	0	0	0	0	0	0	0
Skewness		,045	,802	-1,474	-1,155	-1,203	-1,278	-,558
Std. Error of Skewness		,174	,174	,174	,174	,174	,174	,174
Kurtosis		-,571	,093	3,551	1,999	1,690	2,512	-,702
Std. Error of Kurtosis		,346	,346	,346	,346	,346	,346	,346

		SQF_2	SQF_3	SQA_1	SQA_2	SQA_3	IQ_1	IQ_2
N	Valid	196	196	196	196	196	196	196
	Missing	0	0	0	0	0	0	0
Skewness		-,508	-,257	-,773	-,897	-1,194	-,798	-,927
Std. Error of Skewness		,174	,174	,174	,174	,174	,174	,174
Kurtosis		-,594	-,788	1,389	,672	1,102	,468	,656
Std. Error of Kurtosis		,346	,346	,346	,346	,346	,346	,346

		IQ_3	IQ_4	IQ_5	IQ_6	IQ_7	EG_1	EG_2
N	Valid	196	196	196	196	196	196	196
	Missing	0	0	0	0	0	0	0
Skewness		-,643	-,610	-1,109	-,496	-,859	-,957	-,721
Std. Error of Skewness		,174	,174	,174	,174	,174	,174	,174
Kurtosis		1,600	,065	3,133	-,057	1,279	1,470	,236
Std. Error of Kurtosis		,346	,346	,346	,346	,346	,346	,346

		EG_3	EG_4	EG_5	EG_6	US_1	US_2	US_3
N	Valid	196	196	196	196	196	196	196
	Missing	0	0	0	0	0	0	0
Skewness		-,591	-,690	-,652	,305	-,771	-1,222	-,975
Std. Error of Skewness		,174	,174	,174	,174	,174	,174	,174
Kurtosis		,011	,010	1,106	-,875	,928	2,111	1,773
Std. Error of Kurtosis		,346	,346	,346	,346	,346	,346	,346

		UV1_1	UV1_2	U1_1	U2_1	MBB_1	MBB_2	MBB_3
N	Valid	196	196	196	196	196	196	196
	Missing	0	0	0	0	0	0	0
Skewness		-1,019	-,438	-,453	-,047	-1,016	-,756	-,926
Std. Error of Skewness		,174	,174	,174	,174	,174	,174	,174
Kurtosis		,926	,381	-,825	-1,082	1,771	,756	1,514
Std. Error of Kurtosis		,346	,346	,346	,346	,346	,346	,346

		MBB_4	MBB_5	MBB_6	MBB_7	MBB_8	MBB_9
N	Valid	196	196	196	196	196	196
	Missing	0	0	0	0	0	0
Skewness		-,659	-,769	-,675	-,894	-,517	-,319
Std. Error of Skewness		,174	,174	,174	,174	,174	,174
Kurtosis		,140	,650	,463	1,375	,169	-,487
Std. Error of Kurtosis		,346	,346	,346	,346	,346	,346

		TopManSup	TimeSincAdop
N	Valid	196	196
	Missing	0	0
Skewness		-1,021	,125
Std. Error of Skewness		,174	,174
Kurtosis		1,955	-1,015
Std. Error of Kurtosis		,346	,346

APPENDIX D: INDEPEDENT-SAMPLES T TEST

Group 1 – 2

Group Statistics

	Group	N	Mean	Std. Deviation	Std. Error Mean
Age	1,00	50	2,80	,535	,076
	2,00	67	2,64	,829	,101
Education	1,00	50	1,96	1,124	,159
	2,00	67	2,01	1,148	,140
GeographicArea	1,00	50	7,40	1,841	,260
	2,00	67	6,04	2,495	,305
Principal_industry	1,00	50	8,12	2,520	,356
	2,00	67	8,58	2,457	,300
Work_Position	1,00	50	2,90	1,147	,162
	2,00	67	2,03	1,128	,138
Functional_Area	1,00	50	6,80	2,871	,406
	2,00	67	5,51	2,149	,263
MobileWorker	1,00	50	3,06	1,058	,150
	2,00	67	3,10	1,017	,124
TabletofSmartphone	1,00	50	1,14	,351	,050
	2,00	67	1,37	,487	,060
Accessibility	1,00	50	3,9533	,59098	,08358
	2,00	67	3,9950	,63958	,07814
Ease_Use	1,00	50	4,1500	,56469	,07986
	2,00	67	4,2313	,70886	,08660
Flexibility	1,00	50	3,5133	,66738	,09438
	2,00	67	3,5970	,87720	,10717
InterfaceDesign	1,00	50	4,2900	,63157	,08932
	2,00	67	4,2687	,62358	,07618
IQ	1,00	50	3,8400	,53735	,07599
	2,00	67	3,9531	,46616	,05695
Engagement	1,00	50	3,7533	,48473	,06855
	2,00	67	3,8209	,54535	,06662
Use	1,00	50	3,5300	,94981	,13432
	2,00	67	3,3731	1,05652	,12907
UserSatisfaction	1,00	50	4,1667	,57242	,08095
	2,00	67	4,0896	,63718	,07784
VoluntarinessUse	1,00	50	3,8300	,70429	,09960
	2,00	67	3,7164	,64093	,07830
NetBenefits	1,00	50	3,9200	,53123	,07513
	2,00	67	3,8507	,62333	,07615
TopManSup	1,00	50	4,26	,664	,094
	2,00	67	4,13	,757	,092
TimeSincAdop	1,00	50	3,18	1,320	,187
	2,00	67	2,67	1,160	,142

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Age	Equal variances assumed	10,920	,001	1,178	115	,241	,158	,134	-,108	,424
	Equal variances not assumed			1,251	112,833	,213	,158	,126	-,092	,409
Education	Equal variances assumed	,002	,962	-,258	115	,797	-,055	,213	-,476	,366
	Equal variances not assumed			-,259	106,887	,796	-,055	,212	-,475	,365
GeographicArea	Equal variances assumed	,144	,705	3,238	115	,002	1,355	,419	,526	2,184
	Equal variances not assumed			3,381	114,991	,001	1,355	,401	,561	2,149
Principal_industry	Equal variances assumed	,781	,379	-,995	115	,322	-,462	,464	-1,382	,457
	Equal variances not assumed			-,992	104,216	,324	-,462	,466	-1,386	,462
Work_Position	Equal variances assumed	1,357	,246	4,098	115	,000	,870	,212	,450	1,291
	Equal variances not assumed			4,088	104,717	,000	,870	,213	,448	1,292
Functional_Area	Equal variances assumed	17,982	,000	2,786	115	,006	1,293	,464	,374	2,212
	Equal variances not assumed			2,673	87,207	,009	1,293	,484	,331	2,254
MobileWorker	Equal variances assumed	,527	,469	-,230	115	,818	-,044	,193	-,427	,338
	Equal variances not assumed			-,229	103,399	,820	-,044	,194	-,430	,341
TabletofSmartphone	Equal variances assumed	41,089	,000	-2,872	115	,005	-,233	,081	-,394	-,072
	Equal variances not assumed			-3,009	114,870	,003	-,233	,077	-,387	-,080
Accessibility	Equal variances assumed	,454	,502	-,360	115	,719	-,04169	,11574	-,27096	,18757
	Equal variances not assumed			-,364	109,810	,716	-,04169	,11441	-,26844	,18505
Ease_Use	Equal variances assumed	3,886	,051	-,668	115	,505	-,08134	,12173	-,32246	,15977
	Equal variances not assumed			-,691	114,475	,491	-,08134	,11780	-,31470	,15201
Flexibility	Equal variances assumed	6,143	,015	-,564	115	,574	-,08368	,14850	-,37783	,21046
	Equal variances not assumed			-,586	114,946	,559	-,08368	,14280	-,36655	,19919
InterfaceDesign	Equal variances assumed	,012	,912	,182	115	,856	,02134	,11717	-,21076	,25344
	Equal variances not assumed			,182	104,979	,856	,02134	,11739	-,21143	,25411
IQ	Equal variances assumed	1,306	,256	-1,216	115	,227	-,11309	,09302	-,29735	,07116
	Equal variances not assumed			-1,191	96,822	,237	-,11309	,09496	-,30158	,07539
Engagement	Equal variances assumed	2,278	,134	-,695	115	,489	-,06756	,09725	-,26020	,12507
	Equal variances not assumed			-,707	111,457	,481	-,06756	,09559	-,25698	,12185
Use	Equal variances assumed	,407	,525	,829	115	,409	,15687	,18921	-,21792	,53165
	Equal variances not assumed			,842	111,003	,402	,15687	,18629	-,21228	,52601
UserSatisfaction	Equal variances assumed	,022	,883	,676	115	,500	,07711	,11408	-,14885	,30308
	Equal variances not assumed			,687	111,032	,494	,07711	,11231	-,14543	,29966
VoluntarinessUse	Equal variances assumed	,045	,832	,909	115	,365	,11358	,12496	-,13394	,36111
	Equal variances not assumed			,897	99,942	,372	,11358	,12669	-,13778	,36494
NetBenefits	Equal variances assumed	,455	,501	,633	115	,528	,06925	,10949	-,14762	,28613
	Equal variances not assumed			,647	112,918	,519	,06925	,10697	-,14268	,28119
TopManSup	Equal variances assumed	,266	,607	,936	115	,351	,126	,134	-,140	,392
	Equal variances not assumed			,954	111,928	,342	,126	,132	-,135	,387
TimeSincAdop	Equal variances assumed	,780	,379	2,210	115	,029	,508	,230	,053	,964
	Equal variances not assumed			2,169	97,657	,033	,508	,234	,043	,973

Group 1 - 3

Group Statistics

	Group	N	Mean	Std. Deviation	Std. Error Mean
Age	1,00	50	2,80	,535	,076
	3,00	46	2,24	,766	,113
Education	1,00	50	1,96	1,124	,159
	3,00	46	1,46	,546	,080
GeographicArea	1,00	50	7,40	1,841	,260
	3,00	46	6,30	2,457	,362
Principal_industry	1,00	50	8,12	2,520	,356
	3,00	46	8,57	2,754	,406
Work_Position	1,00	50	2,90	1,147	,162
	3,00	46	1,70	,891	,131
Functional_Area	1,00	50	6,80	2,871	,406
	3,00	46	5,70	2,493	,368
MobileWorker	1,00	50	3,06	1,058	,150
	3,00	46	2,72	1,109	,163
TabletofSmartphone	1,00	50	1,14	,351	,050
	3,00	46	1,30	,465	,069
Accessibility	1,00	50	3,9533	,59098	,08358
	3,00	46	4,0652	,59054	,08707
Ease_Use	1,00	50	4,1500	,56469	,07986
	3,00	46	4,3913	,66594	,09819
Flexibility	1,00	50	3,5133	,66738	,09438
	3,00	46	3,8768	,57675	,08504
InterfaceDesign	1,00	50	4,2900	,63157	,08932
	3,00	46	4,3152	,65285	,09626
IQ	1,00	50	3,8400	,53735	,07599
	3,00	46	3,9658	,56839	,08380
Engagement	1,00	50	3,7533	,48473	,06855
	3,00	46	3,9529	,58969	,08694
Use	1,00	50	3,5300	,94981	,13432
	3,00	46	3,6957	1,18546	,17479
UserSatisfaction	1,00	50	4,1667	,57242	,08095
	3,00	46	4,2029	,63820	,09410
VoluntarinessUse	1,00	50	3,8300	,70429	,09960
	3,00	46	3,7174	,84098	,12400
NetBenefits	1,00	50	3,9200	,53123	,07513
	3,00	46	4,0048	,62721	,09248
TopManSup	1,00	50	4,26	,664	,094
	3,00	46	4,39	,649	,096
TimeSincAdop	1,00	50	3,18	1,320	,187
	3,00	46	3,07	1,357	,200

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Age	Equal variances assumed	8,652	,004	4,189	94	,000	,561	,134	,295	,827
	Equal variances not assumed			4,129	79,698	,000	,561	,136	,291	,831
Education	Equal variances assumed	6,210	,014	2,753	94	,007	,503	,183	,140	,867
	Equal variances not assumed			2,825	72,180	,006	,503	,178	,148	,859
GeographicArea	Equal variances assumed	1,310	,255	2,485	94	,015	1,096	,441	,220	1,971
	Equal variances not assumed			2,456	83,108	,016	1,096	,446	,208	1,983
Principal_industry	Equal variances assumed	,102	,750	-,827	94	,410	-,445	,538	-1,514	,624
	Equal variances not assumed			-,824	91,290	,412	-,445	,540	-1,518	,628
Work_Position	Equal variances assumed	9,696	,002	5,709	94	,000	1,204	,211	,785	1,623
	Equal variances not assumed			5,768	91,495	,000	1,204	,209	,790	1,619
Functional_Area	Equal variances assumed	7,444	,008	2,004	94	,048	1,104	,551	,010	2,198
	Equal variances not assumed			2,016	93,699	,047	1,104	,548	,017	2,192
MobileWorker	Equal variances assumed	,529	,469	1,549	94	,125	,343	,221	-,096	,782
	Equal variances not assumed			1,546	92,407	,125	,343	,222	-,097	,783
TabletofSmartphone	Equal variances assumed	16,289	,000	-1,965	94	,052	-,164	,084	-,330	,002
	Equal variances not assumed			-1,942	83,389	,056	-,164	,085	-,333	,004
Accessibility	Equal variances assumed	,012	,914	-,927	94	,356	-,11188	,12069	-,35153	,12776
	Equal variances not assumed			-,927	93,348	,356	-,11188	,12069	-,35154	,12777
Ease_Use	Equal variances assumed	3,509	,064	-1,920	94	,058	-,24130	,12570	-,49088	,00827
	Equal variances not assumed			-1,907	88,616	,060	-,24130	,12656	-,49280	,01019
Flexibility	Equal variances assumed	2,370	,127	-2,844	94	,005	-,36348	,12782	-,61726	-,10969
	Equal variances not assumed			-2,861	93,647	,005	-,36348	,12704	-,61573	-,11123
InterfaceDesign	Equal variances assumed	,051	,823	-,192	94	,848	-,02522	,13113	-,28558	,23514
	Equal variances not assumed			-,192	92,723	,848	-,02522	,13131	-,28599	,23555
IQ	Equal variances assumed	,000	,991	-1,115	94	,268	-,12584	,11286	-,34993	,09825
	Equal variances not assumed			-1,112	92,187	,269	-,12584	,11313	-,35052	,09884
Engagement	Equal variances assumed	1,782	,185	-1,817	94	,072	-,19957	,10982	-,41762	,01849
	Equal variances not assumed			-1,802	87,341	,075	-,19957	,11072	-,41962	,02049
Use	Equal variances assumed	2,734	,102	-,758	94	,450	-,16565	,21842	-,59934	,26803
	Equal variances not assumed			-,751	86,228	,454	-,16565	,22044	-,60385	,27255
UserSatisfaction	Equal variances assumed	,320	,573	-,293	94	,770	-,03623	,12356	-,28157	,20910
	Equal variances not assumed			-,292	90,656	,771	-,03623	,12413	-,28281	,21034
VoluntarinessUse	Equal variances assumed	,404	,527	,713	94	,477	,11261	,15787	-,20085	,42607
	Equal variances not assumed			,708	88,116	,481	,11261	,15905	-,20345	,42867
NetBenefits	Equal variances assumed	,306	,581	-,717	94	,475	-,08483	,11832	-,31977	,15011
	Equal variances not assumed			-,712	88,570	,478	-,08483	,11915	-,32159	,15193
TopManSup	Equal variances assumed	,009	,923	-,978	94	,330	-,131	,134	-,398	,135
	Equal variances not assumed			-,979	93,650	,330	-,131	,134	-,398	,135
TimeSincAdop	Equal variances assumed	,000	,997	,420	94	,675	,115	,273	-,428	,657
	Equal variances not assumed			,420	92,846	,676	,115	,274	-,429	,658

Group 1 - 4

Group Statistics

	Group	N	Mean	Std. Deviation	Std. Error Mean
Age	1,00	50	2,80	,535	,076
	4,00	33	2,88	,545	,095
Education	1,00	50	1,96	1,124	,159
	4,00	33	1,94	1,298	,226
GeographicArea	1,00	50	7,40	1,841	,260
	4,00	33	6,52	2,347	,409
Principal_industry	1,00	50	8,12	2,520	,356
	4,00	33	8,55	2,959	,515
Work_Position	1,00	50	2,90	1,147	,162
	4,00	33	2,79	1,269	,221
Functional_Area	1,00	50	6,80	2,871	,406
	4,00	33	6,33	3,058	,532
MobileWorker	1,00	50	3,06	1,058	,150
	4,00	33	3,33	1,080	,188
TabletofSmartphone	1,00	50	1,14	,351	,050
	4,00	33	1,24	,435	,076
Accessibility	1,00	50	3,9533	,59098	,08358
	4,00	33	4,1313	,88168	,15348
Ease_Use	1,00	50	4,1500	,56469	,07986
	4,00	33	4,1667	1,09449	,19053
Flexibility	1,00	50	3,5133	,66738	,09438
	4,00	33	3,8889	1,01949	,17747
InterfaceDesign	1,00	50	4,2900	,63157	,08932
	4,00	33	4,1061	,79802	,13892
IQ	1,00	50	3,8400	,53735	,07599
	4,00	33	4,0260	,77134	,13427
Engagement	1,00	50	3,7533	,48473	,06855
	4,00	33	3,8081	,74200	,12916
Use	1,00	50	3,5300	,94981	,13432
	4,00	33	3,4848	1,09320	,19030
UserSatisfaction	1,00	50	4,1667	,57242	,08095
	4,00	33	4,0101	1,01887	,17736
VoluntarinessUse	1,00	50	3,8300	,70429	,09960
	4,00	33	3,8182	,69393	,12080
NetBenefits	1,00	50	3,9200	,53123	,07513
	4,00	33	3,9259	,96051	,16720
TopManSup	1,00	50	4,26	,664	,094
	4,00	33	4,15	,870	,152
TimeSincAdop	1,00	50	3,18	1,320	,187
	4,00	33	2,64	1,342	,234

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Age	Equal variances assumed	,292	,590	-,652	81	,516	-,079	,121	-,319	,162
	Equal variances not assumed			-,649	67,681	,518	-,079	,121	-,321	,163
Education	Equal variances assumed	,062	,805	,077	81	,939	,021	,268	-,513	,554
	Equal variances not assumed			,075	61,672	,941	,021	,276	-,532	,573
GeographicArea	Equal variances assumed	,754	,388	1,919	81	,058	,885	,461	-,032	1,802
	Equal variances not assumed			1,827	57,109	,073	,885	,484	-,085	1,855
Principal_industry	Equal variances assumed	,586	,446	-,702	81	,485	-,425	,606	-1,631	,780
	Equal variances not assumed			-,679	60,870	,500	-,425	,626	-1,678	,827
Work_Position	Equal variances assumed	1,202	,276	,418	81	,677	,112	,268	-,422	,646
	Equal variances not assumed			,409	63,736	,684	,112	,274	-,435	,660
Functional_Area	Equal variances assumed	,342	,560	,706	81	,482	,467	,661	-,848	1,782
	Equal variances not assumed			,697	65,569	,488	,467	,670	-,870	1,804
MobileWorker	Equal variances assumed	,282	,597	-1,143	81	,257	-,273	,239	-,749	,203
	Equal variances not assumed			-1,138	67,632	,259	-,273	,240	-,753	,206
TabletofSmartphone	Equal variances assumed	5,449	,022	-1,183	81	,240	-,102	,087	-,275	,070
	Equal variances not assumed			-1,131	58,289	,263	-,102	,091	-,284	,079
Accessibility	Equal variances assumed	4,575	,035	-1,102	81	,274	-,17798	,16148	-,49928	,14332
	Equal variances not assumed			-1,018	50,870	,313	-,17798	,17476	-,52885	,17289
Ease_Use	Equal variances assumed	11,435	,001	-,091	81	,928	-,01667	,18306	-,38089	,34756
	Equal variances not assumed			-,081	43,358	,936	-,01667	,20659	-,43319	,39986
Flexibility	Equal variances assumed	8,580	,004	-2,031	81	,046	-,37556	,18496	-,74356	-,00755
	Equal variances not assumed			-1,868	50,047	,068	-,37556	,20101	-,77928	,02817
InterfaceDesign	Equal variances assumed	1,417	,237	1,168	81	,246	,18394	,15746	-,12936	,49724
	Equal variances not assumed			1,114	57,507	,270	,18394	,16515	-,14671	,51459
IQ	Equal variances assumed	3,550	,063	-1,295	81	,199	-,18597	,14356	-,47162	,09967
	Equal variances not assumed			-1,205	52,280	,233	-,18597	,15429	-,49553	,12358
Engagement	Equal variances assumed	7,277	,008	-,407	81	,685	-,05475	,13450	-,32237	,21287
	Equal variances not assumed			-,374	49,977	,710	-,05475	,14623	-,34846	,23897
Use	Equal variances assumed	,481	,490	,200	81	,842	,04515	,22628	-,40507	,49537
	Equal variances not assumed			,194	61,810	,847	,04515	,23293	-,42050	,51080
UserSatisfaction	Equal variances assumed	9,106	,003	,895	81	,373	,15657	,17493	-,19149	,50462
	Equal variances not assumed			,803	45,434	,426	,15657	,19496	-,23601	,54914
VoluntarinessUse	Equal variances assumed	,292	,590	,075	81	,940	,01182	,15705	-,30065	,32429
	Equal variances not assumed			,075	69,364	,940	,01182	,15656	-,30049	,32413
NetBenefits	Equal variances assumed	7,163	,009	-,036	81	,971	-,00593	,16408	-,33239	,32054
	Equal variances not assumed			-,032	45,026	,974	-,00593	,18331	-,37512	,36327
TopManSup	Equal variances assumed	1,185	,280	,643	81	,522	,108	,169	-,227	,444
	Equal variances not assumed			,609	55,932	,545	,108	,178	-,249	,466
TimeSincAdop	Equal variances assumed	,051	,823	1,824	81	,072	,544	,298	-,049	1,137
	Equal variances not assumed			1,818	67,846	,073	,544	,299	-,053	1,140

APPENDIX E: SINGLE FACTOR

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	17,321	42,247	42,247	17,321	42,247	42,247
2	2,057	5,016	47,263	2,057	5,016	47,263
3	1,699	4,144	51,406	1,699	4,144	51,406
4	1,371	3,345	54,751	1,371	3,345	54,751
5	1,329	3,241	57,992	1,329	3,241	57,992
6	1,176	2,869	60,861	1,176	2,869	60,861
7	1,131	2,760	63,621	1,131	2,760	63,621
8	1,028	2,508	66,129	1,028	2,508	66,129
9	,903	2,201	68,330			
10	,879	2,143	70,473			
11	,814	1,984	72,458			
12	,790	1,926	74,384			
13	,726	1,772	76,156			
14	,695	1,695	77,850			
15	,645	1,574	79,425			
16	,615	1,500	80,925			
17	,569	1,388	82,312			
18	,546	1,331	83,644			
19	,528	1,287	84,930			
20	,495	1,206	86,137			
21	,481	1,174	87,310			
22	,436	1,064	88,375			
23	,409	,997	89,372			
24	,402	,981	90,353			
25	,375	,915	91,268			
26	,351	,855	92,124			
27	,338	,825	92,949			
28	,333	,813	93,762			
29	,308	,752	94,515			
30	,304	,741	95,256			
31	,263	,641	95,897			
32	,249	,608	96,505			
33	,238	,580	97,085			
34	,221	,539	97,624			
35	,198	,483	98,106			
36	,168	,411	98,517			
37	,153	,373	98,890			
38	,141	,343	99,233			
39	,119	,289	99,523			
40	,105	,257	99,780			

APPENDIX F: EFA SPSS OUTPUT

Communalities[a]

	Initial	Extraction
SQEU_1	,791	,999
SQEU_2	,735	,714
SQID_1	,634	,732
SQID_2	,372	,444
SQF_1	,437	,473
SQF_2	,528	,645
SQF_3	,413	,507
EG_1	,667	,664
EG_2	,586	,626
EG_3	,533	,675
EG_4	,490	,505
EG_5	,689	,695
US_1	,709	,736
US_2	,707	,723
US_3	,789	,921
UV1_1	,247	,557
UV1_2	,184	,232
U1_1	,443	,714
U2_1	,411	,475

Extraction Method: Maximum Likelihood.

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	8,443	44,436	44,436	5,674	29,861	29,861	6,711
2	1,420	7,473	51,909	3,037	15,985	45,846	5,766
3	1,272	6,694	58,603	,828	4,360	50,206	5,573
4	1,044	5,493	64,096	,642	3,377	53,582	5,297
5	1,019	5,363	69,458	,711	3,743	57,325	3,278
6	,786	4,139	73,597	,602	3,170	60,496	6,497
7	,756	3,977	77,574	,543	2,859	63,355	2,114
8	,656	3,453	81,027				
9	,553	2,913	83,939				
10	,447	2,355	86,294				
11	,421	2,215	88,509				
12	,401	2,112	90,622				
13	,377	1,987	92,608				
14	,365	1,920	94,528				
15	,291	1,533	96,061				
16	,249	1,311	97,372				
17	,228	1,198	98,569				
18	,156	,819	99,388				
19	,116	,612	100,000				

Extraction Method: Maximum Likelihood.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

Goodness-of-fit Test

Chi-Square	df	Sig.
93,198	59	,003

Pattern Matrix[a]

	Factor						
	1	2	3	4	5	6	7
EG_3	1,039	-,136	-,026	-,043	,002	-,101	-,084
EG_2	,716	,038	,014	-,090	,140	-,006	,070
EG_5	,508	,222	,010	-,015	-,114	,301	-,120
EG_1	,477	-,032	,158	,126	,062	,061	,147
EG_4	,461	,360	-,160	,067	-,096	,110	-,081
SQF_2	-,098	,828	,137	-,090	,065	-,030	-,006
SQF_3	,072	,796	,092	-,148	,001	-,146	-,045
SQF_1	-,142	,552	-,132	,108	,117	,203	,053
SQEU_1	-,024	,022	,992	,031	-,016	-,010	,006
SQEU_2	,024	,159	,635	,105	-,046	,081	-,075
SQID_2	-,096	-,130	-,007	,779	,047	,066	-,162
SQID_1	,076	-,014	,208	,681	-,002	-,092	,081
U1_1	-,047	,070	,013	-,056	,798	,110	-,054
U2_1	,143	,045	-,081	,166	,575	-,064	-,004
US_3	-,001	-,017	,008	,034	,061	,912	,008
US_2	,268	-,126	,218	-,134	,089	,573	,063
US_1	,087	,172	-,065	,200	-,102	,552	,116
UV1_1	,022	,114	-,056	-,027	-,022	-,137	,765
UV1_2	-,117	-,161	,023	-,153	-,040	,244	,499

Extraction Method: Maximum Likelihood.
Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 7 iterations.

APPENDIX G: VALIDITY AND RELIABILITY

	AVE	Composite Reliability	R Square	Cronbachs Alpha	Communality	Redundancy
Accessibility					0,582180	
Attractive Interface Design	0,752465	0,858128		0,685691	0,752465	
Ease of Use	0,910395	0,953096		0,901604	0,910395	
Engagement	0,653494	0,903961	0,642968	0,867197	0,653494	0,233901
Flexibility	0,672360	0,860039		0,755958	0,672360	
IQ					0,499990	
Net Benefits			0,757528		0,668133	0,317716
Time Since Adoption	1,000000	1,000000		1,000000	1,000000	
Top Manag. Support	1,000000	1,000000		1,000000	1,000000	
Use	0,779142	0,875863	0,304803	0,716538	0,779142	-0,054826
User Satisfaction	0,826079	0,934381	0,668257	0,894392	0,826079	0,209600

Outer Model (Weights or Loadings)

	Accessibility	Attractive Interface Design	Ease of Use	Engagement	Flexibility	IQ	Net Benefits	Time Since Adoption	Top Manag. Support	Use	User Satisfaction
EG_1				0,819573							
EG_2				0,831281							
EG_3				0,787935							
EG_4				0,750707							
EG_5				0,848727							
IQ_1						0,297376					
IQ_2						0,115497					
IQ_3						0,410543					
IQ_4						0,056719					
IQ_5						0,053712					
IQ_6						0,031485					
IQ_7						0,348139					
MBB_1							0,172512				
MBB_2							0,246792				
MBB_3							0,157550				
MBB_4							0,103179				
MBB_5							0,030604				
MBB_6							0,134204				
MBB_7							0,167821				
MBB_8							0,081818				
MBB_9							0,118089				
SQA_1	0,701081										
SQA_2	0,301999										
SQA_3	0,216727										
SQEU_1			0,955740								
SQEU_2			0,952550								
SQF_1					0,795916						
SQF_2					0,869344						
SQF_3					0,792362						
SQID_1		0,927247									
SQID_2		0,803207									
TimeSincAdop								1,000000			
TopManSup									1,000000		
U1_1										0,883092	
U2_1										0,882288	
US_1											0,891513
US_2											0,892043
US_3											0,942178

Outer Weights (Mean, STDEV, T-Values)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (|O/STERR|)
EG_1 <- Engagement	0,2604	0,2599	0,0130	0,0130	20,0980
EG_2 <- Engagement	0,2578	0,2583	0,0129	0,0129	20,0254
EG_3 <- Engagement	0,2115	0,2123	0,0121	0,0121	17,4592
EG_4 <- Engagement	0,2241	0,2244	0,0138	0,0138	16,2754
EG_5 <- Engagement	0,2797	0,2790	0,0129	0,0129	21,7451
IQ_1 -> IQ	0,2974	0,2830	0,1049	0,1049	2,8352
IQ_2 -> IQ	0,1155	0,1122	0,0754	0,0754	1,5321
IQ_3 -> IQ	0,4105	0,4018	0,1147	0,1147	3,5794
IQ_4 -> IQ	0,0567	0,0610	0,1033	0,1033	0,5493
IQ_5 -> IQ	0,0537	0,0509	0,1275	0,1275	0,4213
IQ_6 -> IQ	0,0315	0,0395	0,1031	0,1031	0,3055
IQ_7 -> IQ	0,3481	0,3420	0,1045	0,1045	3,3322
MBB_1 -> Net Benefits	0,1725	0,1719	0,0854	0,0854	2,0196
MBB_2 -> Net Benefits	0,2468	0,2488	0,0684	0,0684	3,6061
MBB_3 -> Net Benefits	0,1575	0,1551	0,0852	0,0852	1,8494
MBB_4 -> Net Benefits	0,1032	0,1008	0,0681	0,0681	1,5159
MBB_5 -> Net Benefits	0,0306	0,0349	0,0730	0,0730	0,4191
MBB_6 -> Net Benefits	0,1342	0,1311	0,0854	0,0854	1,5712
MBB_7 -> Net Benefits	0,1678	0,1672	0,0760	0,0760	2,2078
MBB_8 -> Net Benefits	0,0818	0,0831	0,0748	0,0748	1,0945
MBB_9 -> Net Benefits	0,1181	0,1145	0,0645	0,0645	1,8306
SQA_1 -> Accessibility	0,7011	0,6943	0,0790	0,0790	8,8719
SQA_2 -> Accessibility	0,3020	0,3020	0,0963	0,0963	3,1370
SQA_3 -> Accessibility	0,2167	0,2172	0,0880	0,0880	2,4639
SQEU_1 <- Ease of Use	0,5329	0,5335	0,0184	0,0184	29,0343
SQEU_2 <- Ease of Use	0,5151	0,5146	0,0144	0,0144	35,6703
SQF_1 <- Flexibility	0,4174	0,4174	0,0329	0,0329	12,6989
SQF_2 <- Flexibility	0,4374	0,4362	0,0257	0,0257	17,0262
SQF_3 <- Flexibility	0,3630	0,3636	0,0319	0,0319	11,3882
SQID_1 <- Attractive Interface Design	0,6983	0,6999	0,0611	0,0611	11,4260
SQID_2 <- Attractive Interface Design	0,4389	0,4359	0,0494	0,0494	8,8870
TimeSincAdop <- Time Since Adoption	1,0000	1,0000	0,0000	0,0000	0,0000
TopManSup <- Top Manag. Support	1,0000	1,0000	0,0000	0,0000	0,0000
U1_1 <- Use	0,5674	0,5673	0,0328	0,0328	17,2857
U2_1 <- Use	0,5655	0,5657	0,0336	0,0336	16,8476
US_1 <- User Satisfaction	0,3569	0,3572	0,0108	0,0108	33,0149
US_2 <- User Satisfaction	0,3546	0,3554	0,0119	0,0119	29,9016
US_3 <- User Satisfaction	0,3879	0,3876	0,0102	0,0102	38,1705

Latent Variable Correlations

	Accessibility	Attractive Interface Design	Ease of Use	Engagement	Flexibility	IQ	Net Benefits	Time Since Adoption	Top Manag. Support	Use	User Satisfaction
Accessibility	1,000000										
Attractive Interface Design	0,520124	1,000000									
Ease of Use	0,670566	0,647072	1,000000								
Engagement	0,728227	0,557548	0,667274	1,000000							
Flexibility	0,618463	0,400375	0,524494	0,589965	1,000000						
IQ	0,698435	0,568257	0,666501	0,704193	0,560937	1,000000					
Net Benefits	0,709713	0,538529	0,660553	0,808944	0,586495	0,717145	1,000000				
Time Since Adoption	0,242588	0,164409	0,197839	0,270245	0,238165	0,187787	0,285081	1,000000			
Top Manag. Support	0,434624	0,406055	0,434307	0,475901	0,386988	0,508264	0,525388	0,260315	1,000000		
Use	0,383456	0,346376	0,375746	0,477423	0,460654	0,376221	0,545863	0,240067	0,391388	1,000000	
User Satisfaction	0,708210	0,589925	0,705608	0,790901	0,593075	0,729232	0,812234	0,250427	0,475753	0,494919	1,000000

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	SQA_1	,479	2,089
	SQA_2	,528	1,894
	SQA_3	,724	1,381
	IQ_1	,474	2,111
	IQ_2	,769	1,301
	IQ_3	,423	2,364
	IQ_4	,490	2,043
	IQ_5	,453	2,207
	IQ_6	,589	1,697
	IQ_7	,442	2,264
	MBB_1	,269	3,724
	MBB_2	,372	2,689
	MBB_3	,247	4,050
	MBB_4	,456	2,192
	MBB_5	,262	3,818
	MBB_6	,281	3,555
	MBB_7	,248	4,036
	MBB_8	,368	2,715
	MBB_9	,518	1,930

APPENDIX H: PATH COEFFICIENT AND T-STATISTICS

Path Coefficients

	Accessibility	Attractive Interface Design	Ease of Use	Engagement	Flexibility	IQ	Net Benefits	Time Since Adoption	Top Manag. Support	Use	User Satisfaction
Accessibility				0,316374						-0,082815	0,210415
Attractive Interface Design				0,096738						0,074395	0,115460
Ease of Use				0,156400						-0,029078	0,224912
Engagement							0,384779			0,198170	
Flexibility				0,133926						0,259582	0,135729
IQ				0,248890						-0,072763	0,290620
Net Benefits											
Time Since Adoption							0,027277				
Top Manag. Support							0,100552				
Use							0,121765				
User Satisfaction							0,392979			0,272576	

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (|O/STERR|)
Accessibility -> Engagement	0,3164	0,3145	0,0756	0,0756	4,1833
Accessibility -> Use	-0,0828	-0,0793	0,0951	0,0951	0,8705
Accessibility -> User Satisfaction	0,2104	0,2059	0,0815	0,0815	2,5827
Attractive Interface Design -> Engagement	0,0967	0,0917	0,0620	0,0620	1,5592
Attractive Interface Design -> Use	0,0744	0,0695	0,0854	0,0854	0,8708
Attractive Interface Design -> User Satisfaction	0,1155	0,1117	0,0585	0,0585	1,9728
Ease of Use -> Engagement	0,1564	0,1484	0,0904	0,0904	1,7303
Ease of Use -> Use	-0,0291	-0,0288	0,1119	0,1119	0,2598
Ease of Use -> User Satisfaction	0,2249	0,2162	0,0724	0,0724	3,1048
Engagement -> Net Benefits	0,3848	0,3872	0,0781	0,0781	4,9287
Engagement -> Use	0,1982	0,1930	0,1128	0,1128	1,7574
Flexibility -> Engagement	0,1339	0,1273	0,0636	0,0636	2,1043
Flexibility -> Use	0,2596	0,2551	0,0879	0,0879	2,9534
Flexibility -> User Satisfaction	0,1357	0,1301	0,0590	0,0590	2,3014
IQ -> Engagement	0,2489	0,2693	0,0746	0,0746	3,3344
IQ -> Use	-0,0728	-0,0547	0,1080	0,1080	0,6736
IQ -> User Satisfaction	0,2906	0,3130	0,0663	0,0663	4,3826
Time Since Adoption -> Net Benefits	0,0273	0,0252	0,0415	0,0415	0,6571
Top Manag. Support -> Net Benefits	0,1006	0,0988	0,0480	0,0480	2,0945
Use -> Net Benefits	0,1218	0,1217	0,0483	0,0483	2,5213
User Satisfaction -> Net Benefits	0,3930	0,3966	0,0877	0,0877	4,4790
User Satisfaction -> Use	0,2726	0,2664	0,1082	0,1082	2,5202