THE ROLE OF MOBILE BI CAPABILITIES IN MOBILE BI SUCCESS

Complete Research

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Abstract

While IS success research has gained considerable attention within academia in the past, understanding its constituents and the relationships among them has also emerged within professional fields. Since extant inquiries on the relationships among IS success dimensions have produced equivocal findings, the need to address IS success in the context of specific technologies has been regularly highlighted. Within business intelligence (BI) field one such pervasive technology gaining considerable attention is mobile BI (m-BI).

Despite the recognized value that m-BI brings to firms, our understanding of the success of m-BI is limited. To address this gap, we conducted a quantitative study of key informants using m-BI, employing multiple data collection methods to understand what the key m-BI capabilities are and other success dimensions being perceived as important by users, and how they can be assessed.

Our contribution to the BI and IT business value literature is twofold. First, our results highlight the users’ perceptions about m-BI capabilities that are deemed important for increasing satisfaction with m-BI and its use. Second, while these capabilities have a relatively high explanatory power for user satisfaction, their power to explain m-BI use is found to be rather low, suggesting there are other unobserved organizational characteristics importantly affecting m-BI usage behaviour, thus calling for further investigation.

Keywords: Business Intelligence, BI success, Mobile BI, IS success, capabilities.

1 Introduction

The value of information systems (IS) to advance decision-making and organizational performance has been increasingly highlighted in the information technology (IT) business value literature (e.g. Melville, Kraemer and Gurbaxani, 2004; Mithas, Ramasubbu and Sambamurthy, 2011). In firm performance studies, IS have been found to support timely decisions, provide information to manage uncertainty in the business environment, and promote innovation (Dewett and Jones, 2001; Melville et al., 2004). Quality information, i.e. information that is relevant, reliable, accurate and timely (Low and Mohr, 2001; Wixom, Watson and Werner, 2011), enables improved decisions and can, consecutively, boost improvement in performance (Raghunathan, 1999).
Within the IT/IS and business intelligence (BI) studies, BI systems are well recognized to contribute to decision-making (Popović, Hackney, Coelho and Jaklič, 2012). These systems are distinctive complex IS and are currently ranked among the top 10 strategic technologies (Tapadinhas, 2012). In exploring business value of BI, extant studies suggest BI aid improvements in firms’ strategic planning, business processes, and improvements of performance (Negash and Gray, 2008; Shanks, Bekmamedova, Adam and Daly, 2012).

While research suggests achieving such performance benefits depends largely on the ability to best utilize the information in decision-making processes and less on the technology itself (Rindfleisch and Moorman, 2001), inquiries on the relationships among IS success dimensions have produced equivocal findings (e.g. Auster and Choo, 1993; Todd and Benbasat, 1992). Researchers, consequently, have highlighted the need to understand these relationships in the context of a specific technology. One such technology within BI field that has recently gained attention from both academia and practice is mobile BI (hereafter referred to as “m-BI”). M-BI could be viewed as the extension of BI to smartphones and tablets. For the purpose of this study, we consider m-BI as a system comprised of both technical and organizational elements that presents historical and/or real-time information to its users 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 firm performance (Isik, Jones and Sidorova, 2011).

This topic is worth exploring, because even though m-BI is considered as a sub-field or sub-market of BI, it is complementary to traditional BI rather than a substitute (Tona and Carlsson, 2013). This is because m-BI differs from traditional BI in terms of system characteristics as well as user experience. Today, m-BI is mostly used for information consumption via simple yet almost real-time analysis methods, whereas traditional BI is still preferred for advanced techniques as well as information creation (Tona and Carlsson, 2013). A critical difference also exists from a usage perspective; m-BI introduces a new way of delivering information through the new generation of mobile devices.

Despite the recognition of the value of m-BI and overall interest in the topic, our understanding of the success of m-BI, specifically m-BI capabilities and their effect on users’ satisfaction and m-BI use, is limited. To address this gap, we conducted an empirical investigation using multiple data collection methods to gather responses from key informants of various firms. We explored the following research question; which m-BI success dimensions are deemed important by the users?

The rest of this paper is organized as follows. We first set the theoretical background for our research. More specifically, we examine m-BI capabilities and their links to user satisfaction and actual use, as well as the relationships of the latter to potential net benefits. We then outline the research approach followed in this study. We introduce the research model, hypotheses, outline the sources of data and explain our data analysis procedure. This is followed by our findings on key m-BI capabilities’ influence on user satisfaction and system use, and the link to actual benefits. In the discussion section, we explore the theoretical contributions and managerial implications of our findings. The paper concludes with acknowledged limitations and opportunities for future research.

2 BI success

BI success is the positive value an organization obtains from its BI investment (Isik, Jones and Sidorova, 2013). BI success can be measured by an increase in firms’ profits, or enhancement to competitive advantage (Farrokhi and Pokoradi, 2012). However, these are difficult to measure, because many BI-enabled benefits are intangible and non-financial, such as improved decision-making or 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 tie the benefits to BI (Lönnqvist and Pirritimäki, 2006). Therefore, subjective measures are often used to measure BI success, which enables researchers and firms to understand the perceptions and the extent to which the users realised their expected benefits with BI, and to investigate which BI capabilities are important to increase the perceived benefits (Isik et al., 2013; Popović et al., 2012). This enables firms to take BI adoption decisions whilst having a clear understanding of the BI capabilities that define the success of BI from the user’s perspective. Firms that take advantage of these BI capabilities can expect an increase in BI usage and, as a result, an increase in the value BI systems provide (Isik et al., 2013).

The extant body of knowledge about abovementioned BI capabilities in the m-BI context is scarce. To the best of our knowledge no prior research has explored the relationship between the m-BI capabilities and its success. It may very well be that the use of m-BI will change the decision processes in the organization, e.g. lead to decentralization, hence, we cannot assume that the same BI capabilities apply. Therefore we set out to understand, from the users’ perspective, the relationship between m-BI capabilities and m-BI success.

Drawing upon renowned DeLone and McLean’s IS success model (2003), lately investigated within traditional BI context (Tona, Carlsson and Eom, 2012), we examine the relationship between m-BI capabilities and m-BI success at an individual level of analysis. We believe applying the model to m-BI context will help us understand the multi-dimensional nature of m-BI success. Because of our interest in the role of user satisfaction and use, Isik et al.’s (2013) BI success model was not inclusive enough for our purposes. We have decided to use the updated DeLone and McLean’s model (2003) as it was refined based on ten years of research and the net benefits construct implies that the impact of m-BI is beyond its immediate user.

To be applicable to the m-BI context, the original IS success model required certain adjustments. First, DeLone and McLean (DeLone and McLean, 2003) argued that the service quality construct is of greater relevance for measuring the success of an IS department than measuring an IS instance. This argument is supported by various studies that did not find a significant relationship between service quality and user satisfaction, and service quality and use constructs at the individual level (e.g. Petter, DeLone and McLean, 2008; Petter and McLean, 2009). Next to that, service quality is a multidimensional construct which also includes a combination of system quality and information quality constructs (Kang, 2006). Therefore, in order not to overlap the quality constructs, we have focused on system and information quality, and excluded service quality. Also, it is important to emphasize that service quality is not necessarily irrelevant for m-BI; but the context should dictate whether or not to include this construct (DeLone and McLean, 2003). We opted not to as we focus on the functionality of the m-BI, and consider the overall support delivered by the service provider out of scope for this research. Second, for the system quality construct, we have only selected the desired system quality characteristics that are deemed significant in BI studies, m-BI capabilities that are pointed as important in m-BI articles and can be measured from the users’ perspectives. While the DeLone and McLean’s IS success model (2003) integrates system quality characteristics into one construct, we chose to keep system quality related m-BI capabilities as separate constructs in order to be able to investigate the potential difference in significance levels. To more comprehensively link the constructs from seminal IS success research to m-BI context, we now present each construct in greater detail.

### 2.1 System Quality

#### 2.1.1 Accessibility

Accessibility of information is an important attribute of information use (Jeong and Lambert, 2001). Within the BI context, research shows that the way users access and use BI is critical for BI success and high quality user access methods increases decision making effectiveness (Isik et al., 2013). It is...
important for organisations to achieve the necessary balance among the ways in which users access information, to fit the types of decisions they make using BI (İşık et al., 2013). How organisations provide access to information with authorization/authentication controls should match the user’s needs. For example, store managers may need access to the current sales results for theirs and other stores in the region, while sales people may only need access to customer data. User access is a critical BI capability that impacts BI success as well as user satisfaction with BI (İsik et al., 2011; İsik et al., 2013).

Research has also examined information access quality as a combination of bandwidth, customization capabilities and interactivity dimensions (Popović et al., 2012). These correspond to the three information quality criteria of Eppler’s (2006) information quality framework, namely; timeliness, convenience and traceability. When m-BI is used outside the wireless business network, its accessibility depends on the provider’s bandwidth capabilities. When accessed information is not processed and delivered as expected, this could frustrate the user, and decrease m-BI usage. Hence, bandwidth/timeliness could be an important accessibility attribute for m-BI. Anywhere and anytime accessibility is one of the success factors of m-BI (Tapadinhas, 2012). The portability of a mobile device makes it possible to access information anytime and anywhere. Research has examined the impact of accessibility in the context of other mobile technologies, such as mobile banking (Lee and Chung, 2009), and showed that it significantly impacts system success. We believe accessibility anytime and anywhere may be a critical capability for m-BI as well. Based on these implications, we define accessibility according to the users’ perceptions of the user access quality, bandwidth and anytime and anywhere accessibility.

2.1.1 Attractive Interface Design

IS are not only judged by their functionality, but also their looks; users like systems with an attractive and appealing user interface (Mishra, 2012). Research shows that a visually appealing interface has a significant positive effect on user satisfaction with information seeking activities (Santosa, Wei and Chan, 2005). Even though users who deal with data access and manipulation on a daily basis may have a higher tolerance for unappealing interfaces, an appealing interface provides a powerful first impression; it can engage users, improve the adoption rate of BI, and also affect the degree in which one enjoys continued use of a particular BI tool (Howson, 2007). Business users also prefer software with attractive interfaces (Schrepp, Held and Laugwitz, 2006). Appealing and attractive visualisations are one of the features that make BI attractive for business users (Williams and Williams, 2007).

We posit that a visually attractive interface design not only makes a BI tool more pleasant to work with, but also affects the adoption rate and user satisfaction with m-BI. The attractive interface design of m-BI includes visualisations, graphs, tables, dashboard layouts etc. and they may be among the factors that explain the success of m-BI.

2.1.3 Ease of Use

Ease of use can be defined as the degree to which a system is user friendly (Doll and Torkzadeh, 1988). An empirically validated end-user computer satisfaction instrument (Doll and Torkzadeh, 1988) has been previously employed within the BI context to examine the effect of user satisfaction on system usage and individual performance with BI (Hou, 2012), and found significant evidence that ease of use impacts BI performance. Another research that examines what users consider as key features that enhance use and adoption of BI showed that ease of use is vital or very important for BI use (Howson, 2007). Ease of use is also a key adoption driver for m-BI (Tapadinhas, 2012). It is therefore intuitive to suggest that for users to benefit from m-BI they must be able to navigate dashboards and guided analytics as comfortably as the mobile device will allow (Chandras, 2011).
2.1.4 Flexibility

Users should easily be able to modify their BI to their needs, insufficient flexibility may withhold users from using BI. However, too much flexibility may increase complexity and reduce usability (Gebauer and Schober, 2006). Although organizations need flexibility and robust functionality to experience the optimal potential of BI (Isik et al., 2013), technology does not always support exceptional situations. A m-BI user should be able to modify the m-BI solution to his needs, and therefore, we define flexibility as an important capability of m-BI.

2.2 Information quality

Information quality refers to the quality of the information the system produces (DeLone and McLean, 2003). If the information coming out of BI environment is not of expected quality as considered by decision makers, it can significantly impact the decision making activities and further affect firm performance. High information quality is not only important for firms, but it is also a business value driver for BI through business processes (Popović, Turk and Jaklič, 2010). Recent research findings indicate that BI users still have issues with reliability and accuracy of the data in their BI environments (Isik et al., 2011). Research also shows that the unsuitability of information quality affects future uses of information and can easily lead to less desirable business decisions (Popović et al., 2012). This may result in dissatisfaction with BI and ultimately in the non-use of BI. Hence, we suggest information quality has significant impact on the success of m-BI.

2.3 Use

System use is a key variable in understanding IS success (DeLone and McLean, 2003) and has played a central role in IS research (Burton-Jones and Straub, 2006). It can be defined as the consumption of an IS or its output described in terms of actual or self-reported usage (Petter and McLean, 2009). Research has showed that use significantly impacts net benefits gained from the IS, at the individual level (Petter et al., 2008). Intention to use a system does not always result in an actual use behaviour (Petter and McLean, 2009). Hence, many has studied the actual use (behaviour) versus the intention to use (an attitude) a system. Intention to use can be defined as expected future consumption of an IS or its output (Petter and McLean, 2009). Even though intention to use seems to significantly impact net benefits, we have chosen not to use this construct in our research, as we are interested in examining the current actual users of m-BI and how it impacts m-BI success.

2.4 User satisfaction

The regular use of an IS along with user satisfaction leads to net benefits with the system (DeLone and McLean, 2003). User satisfaction is a common surrogate measure for IS success and effectiveness, for which several standard instruments have been developed and tested (DeLone and McLean, 2003). Even though user satisfaction has been frequently tested within different contexts, it has not received much attention from BI researchers. Limited research provides evidence that higher levels of user satisfaction may lead to increased BI use and to improved individual performance (Hou, 2012). It is suggested that more experienced BI users tend to be more satisfied with user friendliness of and the decision-making support provided by their BI (Isik et al., 2011). Interestingly, BI capabilities that most strongly relate to BI success are not necessarily the ones with which users are most satisfied with (Isik et al., 2011). Finally, Cox’s (2010) research confirms the positive relationship between frequent BI use and quality and speed of decisions made. Following these indications with regards to satisfaction with BI and also taking into consideration that an increasing number of companies are adopting m-BI, there is a need to better understand how user satisfaction relates to benefits obtained from m-BI.
2.5 Net benefits

Net benefits construct captures the balance of positive and negative impacts of the IS and represents its success level. Net benefits of an IS may be always the same, but they are context specific (DeLone and McLean, 2003; Seddon, Staples, Patnayakuni and Bowtell, 1999). Hence, this study looks at the benefits that can be realised through the use of m-BI at the individual level of analysis.

The output of m-BI is processed information, yet, such information has to be used to actually have an impact on performance. In other words, m-BI must be utilised before it can deliver performance effects (Hou, 2012). For example, when used properly, 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 and Gray (2008) states that BI is not only beneficial for operational business processes, but also for making decisions at the tactical and strategic level. In the light of these findings, we suggest that both use of and user satisfaction with m-BI significantly impact net benefits obtained from it.

Based on the previous findings and conceptual limitations mentioned above, Figure 1 illustrates our research model followed by a list of hypotheses to be tested. We based the hypotheses on the original paths of the DeLone and McLean’s (2003) IS Success model.

![Figure 1. Research model](image)

- **H1.** Use will positively influence net benefits in the m-BI context
- **H2.** User satisfaction will positively influence net benefits in the m-BI context
- **H3.** User satisfaction will positively influence use in the m-BI context
- **H4.** Flexibility will positively influence use in the m-BI context
- **H5.** Flexibility will positively influence user satisfaction in the m-BI context
- **H6.** Accessibility will positively influence use in the m-BI context
- **H7.** Accessibility will positively influence user satisfaction in the m-BI context
- **H8.** Ease of use will positively influence use in the m-BI context
- **H9.** Ease of use will positively influence user satisfaction in the m-BI context
- **H10.** Attractive interface design will positively influence use in the m-BI context
- **H11.** Attractive interface design will positively influence user satisfaction in the m-BI context
- **H12.** Information quality will positively influence use in the m-BI context
- **H13.** Information quality will positively influence user satisfaction in the m-BI context

Compared to earlier IS success and BI success studies, our model introduces some novelty to the BI research arena. First, we include interface design as an important antecedent to user satisfaction and system use. Second, we cross examine the influence of m-BI capabilities on user satisfaction and m-BI
use. Third, we try to shed light on the relationships between user satisfaction, system use and net benefits in the context of m-BI.

3 Methodology

3.1 Research design, instrument development, and data collection

Our study employed a structured questionnaire, combining five-point Likert and five-point semantic differential scales. To ensure content validity, we developed questions by building on established theory and validated surveys. The final questionnaire was refined by several BI experts from the industry and three BI professors from different universities. Based on their suggestions, ambiguity, sequencing and flow of the questions were improved. The participants were given introduction letters which explained the aims and procedures of the study. Pre-notifications, reminders, keeping the survey as short as possible, and incentives were used to increase the response rate. Constructs in the conceptual model are operationalized based on reflective and formative multi-item scales, see table 1. For data collection different methods were used to gather responses from (key) m-BI users of various firms; including personal contacts, mailings to service subscribers, and social networking sites.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Item</th>
<th>Measure</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accessibility</td>
<td>SQA1</td>
<td>The way I access my mobile BI fits well to the types of decisions I make using my mobile BI solution.</td>
<td>Isik et al. (2011)</td>
</tr>
<tr>
<td></td>
<td>SQA2</td>
<td>The accessed information is processed and delivered rapidly without delay.</td>
<td>Popovič et al. (2012)</td>
</tr>
<tr>
<td></td>
<td>SQA3</td>
<td>I can use my mobile BI solution at anytime, anywhere I want.</td>
<td>Lee and Chung (2009)</td>
</tr>
<tr>
<td>Ease of Use</td>
<td>SQEU1</td>
<td>My mobile BI solution is user friendly.</td>
<td>Doll and Torkzadeh (1988)</td>
</tr>
<tr>
<td></td>
<td>SQEU2</td>
<td>My mobile BI solution is easy to use.</td>
<td>Hou (2012)</td>
</tr>
<tr>
<td>Flexibility</td>
<td>SQF1</td>
<td>I can modify my mobile BI solution to my desired information needs.</td>
<td>Yeoh and Koronios (2010)</td>
</tr>
<tr>
<td></td>
<td>SQF2</td>
<td>My mobile BI solution can accommodate changes in business requirements quickly.</td>
<td>Isik et al. (2011)</td>
</tr>
<tr>
<td></td>
<td>SQF3</td>
<td>My mobile BI solution makes it easier to deal with exceptional situations.</td>
<td>Isik et al. (2011)</td>
</tr>
<tr>
<td>Interface Design</td>
<td>SQID1</td>
<td>My mobile BI solution has a visually attractive interface design (includes visualizations, graphs, tables, report layouts, dashboard layout etc...).</td>
<td>Santosa et al. (2005)</td>
</tr>
<tr>
<td></td>
<td>SQID2</td>
<td>My mobile BI solution does not have a visually appealing interface design (includes visualizations, graphs, tables, report layouts, dashboard layout etc...).</td>
<td>Santosa et al. (2005)</td>
</tr>
<tr>
<td>Information Quality</td>
<td>IQ1</td>
<td>The scope of information is adequate (neither too much nor too little).</td>
<td>Popovič et al. (2012)</td>
</tr>
<tr>
<td></td>
<td>IQ2</td>
<td>The information is not precise enough.</td>
<td>Eppler (2006)</td>
</tr>
<tr>
<td></td>
<td>IQ3</td>
<td>The information is easily understandable.</td>
<td>Popovič et al. (2012)</td>
</tr>
<tr>
<td></td>
<td>IQ4</td>
<td>The information is to the point, without unnecessary elements.</td>
<td>Eppler (2006)</td>
</tr>
<tr>
<td></td>
<td>IQ5</td>
<td>The information is consistent.</td>
<td>Popovič et al. (2012)</td>
</tr>
</tbody>
</table>
Table 1. Indicators of the conceptual model

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>IQ6</td>
<td>The information is free of error.</td>
</tr>
<tr>
<td>IQ7</td>
<td>The information is up-to-date and not obsolete.</td>
</tr>
<tr>
<td>Use</td>
<td>U1 At present, how often do you use your mobile BI solution?</td>
</tr>
<tr>
<td></td>
<td>U2 How much time do you spend each week using your mobile BI solution?</td>
</tr>
<tr>
<td>User</td>
<td>US1 The mobile BI solution has met my expectations.</td>
</tr>
<tr>
<td>Satisfaction</td>
<td>US2 I strongly recommend mobile BI to others.</td>
</tr>
<tr>
<td></td>
<td>US3 Overall, I’m satisfied with my mobile BI solution.</td>
</tr>
<tr>
<td>Net Benefits</td>
<td>MBB1 Helps me to make higher quality decisions.</td>
</tr>
<tr>
<td></td>
<td>MBB2 Enables me to present my arguments more convincingly.</td>
</tr>
<tr>
<td></td>
<td>MBB3 Helps me to make decisions quicker.</td>
</tr>
<tr>
<td></td>
<td>MBB4 Helps me notice problems before they become serious crises (proactive business planning).</td>
</tr>
<tr>
<td></td>
<td>MBB5 Improves my job performance.</td>
</tr>
<tr>
<td></td>
<td>MBB6 Increases my job productivity.</td>
</tr>
<tr>
<td></td>
<td>MBB7 Enhances my effectiveness in my job.</td>
</tr>
<tr>
<td></td>
<td>MBB8 Increases my key performance indicators.</td>
</tr>
<tr>
<td></td>
<td>MBB9 Reduces the costs of business processes.</td>
</tr>
</tbody>
</table>

3.2 Data analysis

First we screened the data on missing values, outliers, normality, non-response bias and common method bias (Harmon’s one factor test). Based on the screening process, nine cases are deleted, resulting in 196 usable responses. Then data analyses was carried out using SPSS 18 and SmartPLS 2.0 M3. We chose partial least squares (PLS) because it performs a confirmatory factor analysis (Gefen and Straub, 2005), it is widely used and accepted, it handles both reflective and formative constructs (Esposito Vinzi, Chin, Henseler and Wang, 2010; Hair, Ringle and Sarstedt, 2011) and it can also handle smaller sample sizes better than other techniques, although it is not a panacea for unacceptably low sample sizes (Marcoulides and Saunders, 2006). It is able to concurrently test the measurement and structural model, is robust to violations of homogeneity and the normal distribution of the data set (Chin, Marcolin and Newsted, 2003). Our analysis of kurtosis and skewness indicate minor issues with some of our constructs (all kurtosis values between -1.5 and 3.2, and all skewness values between -1.5 and 1.7), hence using PLS helped us not presume normal distribution.

Our demographics analysis indicated that 34.7% of the respondents classified themselves as non-management/professional staff, 27.6% as middle-management, 10.7% as first level supervisor and 27% as top-management. In addition, the majority of the respondents live in Europe and in the United States.
4 Results

In our research model, we used three formative constructs: accessibility, information quality and net benefits. We used formative constructs because according to Fornell and Bookstein (1982), ‘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 are specified as formative constructs in this study. However, reliability and validity assessments that are used for the reflective constructs are not appropriate for these constructs (Edwards, 2011; MacKenzie, Podsakoff and Jarvis, 2005). Petter, Straub and Rai (2007) developed a framework to assess the validity and reliability of formative constructs, which was also recommended by Hair et al. (2011) and Henseler, Ringle and Sinkovics (2009). In this study, we also employ this framework to assess the validity and reliability of the formative constructs.

4.1 Confirmatory factor analysis

This study is confirmatory in nature and the conceptual model is built on the basis of findings of previous empirical research. Hence, the structural equation modelling (SEM) method was used to test the research model. To ensure data validity and reliability of the reflective constructs, the Cronbach's alpha, composite reliability, convergent validity, and discriminant validity were examined. Cronbach’s alpha was computed for each construct and a brief summary of the analysis is shown in Table 2. Of the five (reflective) constructs, four had values that exceeded the recommended level of 0.7, and ranged from 0.72 to 0.9. The Cronbach’s alpha for attractive interface design is 0.69. Although this is lower than the suggested level, it is acceptable for new instruments (Nunnally, 1978). As illustrated in Table 2, the composite reliabilities ranged from 0.89 to 0.95. Both composite reliability and the Cronbach’s Alpha estimates indicate that the instrument is reliable and internally consistent (Hair et al., 2011; Nunnally, 1978). However, the high composite reliability of ease of use may indicate that there is little internal variance. The average variance extracted (AVE) for each construct is higher than 0.6, as recommend by Hair et al. (2011). Also, the resulting factor loadings with t-values were found, without exception, to be significant at the 0.1% significance level, and confirm a high convergent validity of the measurement model (see Table 2).

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Items</th>
<th>Construct reliability and validity</th>
<th>Average variance extracted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Factor loadings</td>
<td>t-value</td>
</tr>
<tr>
<td>Ease of use</td>
<td>SQUEU1</td>
<td>0.9557</td>
<td>29.0343</td>
</tr>
<tr>
<td></td>
<td>SQUEU2</td>
<td>0.9525</td>
<td>35.6703</td>
</tr>
<tr>
<td>Flexibility</td>
<td>SQF1</td>
<td>0.7959</td>
<td>12.6989</td>
</tr>
<tr>
<td></td>
<td>SQF2</td>
<td>0.8693</td>
<td>17.0262</td>
</tr>
<tr>
<td></td>
<td>SQF3</td>
<td>0.7924</td>
<td>11.3882</td>
</tr>
<tr>
<td>Attractive interface design</td>
<td>SQID1</td>
<td>0.9272</td>
<td>11.4260</td>
</tr>
<tr>
<td></td>
<td>SQID2</td>
<td>0.8032</td>
<td>8.8870</td>
</tr>
<tr>
<td>Use</td>
<td>U1</td>
<td>0.8831</td>
<td>17.2857</td>
</tr>
<tr>
<td></td>
<td>U2</td>
<td>0.8823</td>
<td>16.8476</td>
</tr>
<tr>
<td>User satisfaction</td>
<td>US1</td>
<td>0.8915</td>
<td>33.0149</td>
</tr>
<tr>
<td></td>
<td>US2</td>
<td>0.8920</td>
<td>29.9016</td>
</tr>
<tr>
<td></td>
<td>US3</td>
<td>0.9422</td>
<td>38.1705</td>
</tr>
</tbody>
</table>

Table 2. Reliability and validity measures of the research model
Discriminant validity was assessed by comparing the square root of AVE associated with each construct with the correlations among the constructs, and observing whether that square root was a greater value (Hair et al., 2011). As suggested for discriminant validity, the values on the diagonal, which represent the square root of AVE, were all larger than the off-diagonal values, see table 3.

<table>
<thead>
<tr>
<th></th>
<th>Attractive Interface design</th>
<th>Ease of use</th>
<th>Flexibility</th>
<th>Use</th>
<th>User satisfaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attractive Interface design</td>
<td>0.8675</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ease of use</td>
<td>0.6471</td>
<td>0.9541</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flexibility</td>
<td>0.4004</td>
<td>0.5245</td>
<td>0.8200</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Use</td>
<td>0.3464</td>
<td>0.3757</td>
<td>0.4607</td>
<td>0.8827</td>
<td></td>
</tr>
<tr>
<td>User satisfaction</td>
<td>0.5899</td>
<td>0.7056</td>
<td>0.5931</td>
<td>0.4949</td>
<td>0.9089</td>
</tr>
</tbody>
</table>

Table 3. Correlations between the latent variables and square roots of AVE

4.2 Validation of the formative constructs

Reliability of formative constructs is assessed via the assumption of no multicollinearity, hence variance inflation factor (VIF) is evaluated (Petter et al., 2007). The VIF values of the formative constructs (accessibility, information quality (IQ) and net benefits) were all below the recommended cut-off points, that is tolerance values greater than 0.2 (O'brien, 2007) and VIF values less than five (Hair et al., 2011). This indicates little or no multicollinearity among constructs, indicating high reliability.

Construct validity was assessed by examining the item loadings, to observe their relative contribution to the construct (Esposito Vinzi et al., 2010; Petter et al., 2007). All the accessibility items are significant at 0.05% significance level. However, only three IQ items (IQ1, IQ3, IQ7) are significant at 0.05% level. Since it is not possible to eliminate the non-significant IQ items without changing the nature of the construct (Fornell and Bookstein, 1982), we chose to keep the non-significant items and follow the original definition of the construct. Due to the same reasoning, we kept the non-significant items (MBB4, MBB5, MBB6, MBB8) for the net benefits construct.

4.3 Results of the model estimation

For hypothesis testing, 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 et al., 2011). The research model is then assessed by examining the determination coefficients (R²), the path coefficients and their significance levels, using t-tests.

Use and user satisfaction explain 69.2% of the variance in net benefits, which can be considered as high. The m-BI capabilities explain 29.3% in use, and 66.6% in user satisfaction. The variance explained in use is respectively moderate, which suggests that factors that are not included in the research model may be more important in explaining the variance for use. Overall, the model has a good explanatory power.

The results of the PLS path model analysis is presented in figure 2, indicating support for nine out of 13 hypotheses. All the m-BI capabilities (H5, H7, H9, H11, H13) are significantly related to user satisfaction. However, only one capability, flexibility (H4), is significantly related to use. This indicates that flexibility is a critical m-BI capability. Hypotheses H1 and H2 posit that user satisfaction and use influence net benefits, which are both supported.
5 Discussion

Our findings suggest that user satisfaction has the strongest direct and positive relation with net benefits. This finding is consistent with prior BI research (Hou, 2012). Literature also suggests that measuring user satisfaction is a reliable method to measure IS success and effectiveness (McHaney, Hightower and Pearson, 2002), and this study supports this argument. Furthermore, it indicates the importance of user satisfaction in promoting the m-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 (e.g. Leidner and Elam, 1995; Petter et al., 2008). The results show that higher levels of m-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, extent, and quality and appropriateness of use.

Figure 2. Final measurement model

All m-BI capabilities which were researched (accessibility, attractive interface design, ease of use, flexibility, and information quality) have a significant relationship with user satisfaction, as our model predicted. What is surprising is that flexibility is the only m-BI capability that has a significant relationship with use. A possible explanation is that use is more influenced by organizational factors than the systems capabilities. Use of m-BI could be mandatory for the participants in this study; we did not study voluntariness of use, however, it could explain why other capabilities did not have a significant relationship with use. Another organizational factor could be the work pressure of the m-BI users. Even if m-BI has excellent capabilities, this is not enough to increase its use; the users will use m-BI when they have a purpose, not because they enjoy using it. This suggests that flexibility is a critical m-BI capability, as it has a significant relationship with use and user satisfaction. Therefore, in order to have a successful solution, an m-BI initiative should be able to accommodate a certain amount of variation in the business processes, environment or technology (Gebauer and Schober, 2006), it is, next to traditional BI, one of the most important factors of m-BI success (Isik et al., 2013).

Accessibility has a positive significant relationship only with user satisfaction. The significance of accessibility indicates that organizations should pay attention to providing appropriate user access to the required information resources, heed information access speed, and enable m-BI to be used at anytime.
and anywhere. This is in line with existing research suggesting that user access quality is the cornerstone of the overall user satisfaction with BI (Isik et al., 2013).

It is also suggested that information access quality is important as perceived by the user, however, lower access quality is less likely to be used for excluding criterion when information is needed (Popović et al., 2012). This may indicate why IQ has the strongest relationship with user satisfaction. High quality information is important in the decision making process as it reduces the uncertainty of the decision (Mithas et al., 2011), and it is one of the critical BI capabilities that allow users deal with uncertainty (Isik et al., 2013). The unsuitability of information, even if high quality, can easily lead to a less appropriate business decision. Such approaches, therefore, result in dissatisfaction with m-BI solutions, and ultimately, in the non-use of these solutions, yielding a lower success rate (Popović et al., 2012). This may explain why IQ has a strong significant relationship with user satisfaction.

Ease of use has a positive significant relationship with user satisfaction. This finding is also in line with the argument of Tapadinhas (2012), who suggests that ease of use is a key adoption driver of m-BI. Thus, when m-BI is not experienced as easy to use, it may result in dissatisfaction and non-use.

Attractive interface design has a positive significant relationship with user satisfaction. Several authors recognized that attractive visualizations such as graphs are particularly useful for the identification of trends and relationships among data and can result in higher quality decisions (e.g. Harvey and Bolger, 1996; Umanath, 1994; Umanath and Vessey, 1994). Furthermore, the finding confirms the suggestion of Mishra (2012) that IS are not only judged by their functionality, but also on looks. As results indicate, m-BI users are more satisfied with an attractive user interface.

### 5.1 Implications for theory and practice

As discussed earlier, subjective measures are often used to measure BI success, however, at the present moment, no studies have used subjective measures to measure m-BI success at the individual level. This study presents and empirically tests an adapted DeLone and McLean research framework and validates it in the area of m-BI. Our study provides strong evidence that m-BI success is a multidimensional construct, and that for m-BI and other IS success, the system quality construct should be replaced by the desired characteristics of the IS that is to be measured. This enables a researcher to investigate the potentially different significance levels of those characteristics. This study pointed out, especially compared to user satisfaction, that explaining the use of m-BI is more complex than we initially expected. Hence, researchers should be careful with taking system quality as a single construct in measuring IS success. Many organizations have begun implementing m-BI or are considering deploying an m-BI solution. This study provides a list and description of capabilities that are important for a successful m-BI implementation. It helps organizations to deploy m-BI and to improve their m-BI solution in order to increase the derived benefits from their m-BI investment. Furthermore, this study could also be useful for vendors to promote m-BI, to explain its potential value for their customers and it eventually may even help to accelerate the adoption rate of m-BI.

### 5.2 Limitations and future work

Although this study resulted in some interesting findings, there were several limitations. First, the list of studied m-BI capabilities is not exhaustive. The m-BI capabilities investigated here were identified through an extensive literature review, which consisted of BI studies and m-BI reports. However, because BI academic literature lacks studies about m-BI capabilities and because it is a relatively new innovation, it is possible that there are important capabilities that are not yet revealed by research and reports. Especially the variance explained in use, only 29.3%, suggests that factors that are not included in the research model may be more important in explaining the variance for use. Also, other dimensions
such as engagement may be important to understand m-BI success, because an engaging experience provided by m-BI is considered globally to be more relevant than the breadth and depth of the functionality of m-BI (Tapadinhas, 2012). Next to that, our study is mainly focused on system and information quality, we did not test the importance of the organizational component service quality on m-BI success. Our study indicates that individuals can make faster decisions with m-BI, which could suggest that the service quality factor, that is for example responsiveness of the support organization (Kang, 2006) for the m-BI user, may influence m-BI success. Future research is needed to explore other m-BI capabilities or organizational factors that may be important for m-BI success.

Another limitation is that this study is based on user perceptions. Studies have found that self-reported measures are not always consistent with actual measures, and therefore not always reliable substitutes for objective measures (Petter et al., 2008). Goodhue (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 m-BI benefits with user evaluations, in other words, does an m-BI solution enhance performance or not, and do users recognize this or not. This may lead to four possible situations (Althuizen, Reichel and Wierenga, 2012); (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 IS and actual performance. In fact, the researchers did find significant negative correlations, meaning that improvements in actual performance were associated with less favourable evaluations of the IS in question. It suggests that there is a possibility that there are m-BI users who fail to recognize the benefits already experienced from their m-BI solution. Another limitation is that the sample consists of m-BI users from four different work positions: non-management, middle management, first level supervisor and top management. The kind of decision-making differs per work position level. Therefore, it is possible that there exists a difference in the way how these four kind of decision-makers have experienced their m-BI solution. Future research is needed to determine if there exist a difference for different levels of decision makers in organizations. The final limitation is that this study measures user perceptions at a precise point in time. It is logical to assume that user perceptions may change as they gain more experience using m-BI (Hou, 2012). Hence, a longitudinal approach should be considered in future research.

6 Conclusion

The purpose of this study was to explore the m-BI success dimensions deemed important by its users. The DeLone and McLean’s (2003) IS success model was adapted and extended for use in investigating this. Data was collected from 196 m-BI users to perform an empirical analysis. Findings pointed out several implications for developing better m-BI solutions. Improving the m-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 key for m-BI success. They influence the use and user satisfaction level, which explains the variance in the perceived net benefits. However, while these capabilities have a relatively high explanatory power for user satisfaction with m-BI their power to explain m-BI use is found to be rather low, suggesting there are other unobserved (organizational) characteristics that significantly affect m-BI use behaviour. M-BI adoption in organizations particularly enables individuals to present their arguments more convincingly, make faster and better quality decisions, increase their job effectiveness, and reduce the costs of business processes. Hence, a better understanding of how to improve m-BI success based on the findings of this study can improve how vendors approach to the development of m-BI and also significantly contribute to scholarly literature.
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