Investigating the Effectiveness of Business Intelligence Systems: A PLS-SEM Approach

Author Details:
Professor Haitham Hmoud Alshibly
alshibly@bau.edu.jo
Management Information Systems Department, Faculty of business
Al Balqa Applied University, Jordan

Abstract
Business Intelligence Systems (BIS) adoption is considered a top priority for many organizations and the promises of BIS are rapidly attracting many others. However, not all BIS initiatives have been successful and previous research address the BIS effectiveness have been somewhat scarce. As such, this study seeks to contribute to the developing body of research into BIS effectiveness.

Based on a review of literature grounded on IS success theories, the study develops and empirically validated a comprehensive model of BIS effectiveness, the model suggests BIS effectiveness should be seen as a myriad of an actual benefits and achievements both organization and BIS users receive from using a particular BIS. Following this perspective, by integrating the TAM and The D&M success models, the study model consists of six constructs: information quality, system quality, decision quality, perceived usefulness, decision support satisfaction, and net benefit. The causal relationships among the constructs in the model tested with a field survey collected from 138 BIS users.

Based on the PLS-SEM, the results indicate that seven out of eight hypotheses were supported. Our results suggest the degree to which using the BIS would enhance end-user performance is an important factor affecting decision support satisfaction. An increase in the information quality and system quality of the BIS leads to an increase in decision quality. Any net positive effect from BIS information and system characteristics will result in a positive significant impact on users' perceived usefulness. An increase in decision support satisfaction leads to an increase in the perceived benefits organization and users get from using the BIS.

Keywords: *Business Intelligence Systems; Business Intelligence Systems effectiveness; Partial least squares-structural equation modeling.*

1. Introduction

The demand for information systems (IS) to support effective decision-making have increased, so have the terms used to describe them: data warehousing, knowledge management, data mining, collaborative systems, online analytical processing, with business intelligence systems (BIS) tending to encompass all (Rouhani et al, 2016). BIS can be considered as the combination of processes and technologies to support the decision-making process.

BIS extract a large volume of data from different databases, organize and assimilate the data based on established process, and then demonstrate the information in a way that is valuable to the decision maker (Peters et al, 2016). BIS amalgamate business accumulative knowledge with advanced technology to supply managers with needed information to make informed managerial decisions and can, in turn, endorse improvements in firm performance (Arefin et al, 2015; opovič, et al, 2012). Accordingly, firms are increasingly investing in BIS and infusing it into firms' processes (Popovič et al, 2014).

The adoption of BIS tools is considered the top priority for many organizations and the promises of BI are rapidly attracting many others (Larson & Chang, 2016). Research evidence shows that spending on BIS has comprised one of the largest and fastest growing areas of information technology expenditures. According to the latest forecast from Gartner Inc., the worldwide investment in BIS is estimated to reach $18.3 billion in 2017; an increase of 7.3% from 2016, by the end of 2020, the market is forecast to grow to $22.8 billion.

However, not all BIS initiatives have been successful (Trieu, 2017). Prior research findings have not confirmed a constant link between BIS investment and organizational performance (Dwivedi et al, 2015; Rouhani et al, 2016; Yeoh & Popovič, 2016; Serumaga-Zake, 2017). This finding is supported by research that has highlighted that approximately 70 to 80 % of corporate business intelligence projects have failed to deliver the intended outcome (Gartner, 2016). This makes the measurement of BIS effectiveness essential if they are to be used as a vehicle to deliver organizational outcomes (Trieu, 2017; Serumaga-Zake, 2017). Therefore, practitioners, as well as academicians, are stressing the need to better understand the factors that contribute to the effectiveness or otherwise of BIS (Farrokhi & Pokoradi, 2012).

Although IS success and effectiveness have been receiving much attention among researchers, little is known about the BIS effectiveness. Studies that deal with the conceptualization and assessment of BIS effectiveness have been somewhat scarce (Rouhani et al, 2016; Yeoh & Popovič, 2016). Most published BIS effectiveness research has been either case studies or theoretical frameworks, focused on analyzing a particular BIS implementation (Yeoh & Koronios, 2010).

The above-mentioned specificities of BIS motivate the necessity to research the BIS. Notwithstanding the necessity of examining the effectiveness of BIS, a review of the extant literature reveals the lack of research in this area. Thus, this study will make one of the first steps towards addressing this research gap and improving our understanding of the effectiveness of BIS. We, consequently, derive our research question: What are the factors influencing the effectiveness of BIS and how do these factors interact?

This research seeks to contribute to the developing body of research into BIS effectiveness. As there is a lack of accepted or predictive theories pertaining to BIS effectiveness, this research main objective is to develop and empirically tests a conceptual model of BIS effectiveness using data gathered from employees who had experience using BIS at their workplace.

The remainder of the paper is organized into six sections. In the conceptualization of BIS effectiveness, we address literature review then the BIS effectiveness model and hypothesis is discussed. This is followed by explaining of the research methodology used and data analysis results, finally, we discuss the theoretical contributions and practical implications, and suggest directions for future research.

2. *A conceptualization of BIS effectiveness*

BIS is defined, as an information system (IS) contain both technical and organizational tools that help organizations process, assimilate, and refine information to allow effective decision-making and management support, for the overall purpose of enhancing organizational performance (Acheampong & Moyaid, 2016).

Traditionally, the purposes of BIS is to afford organizations with actionable decision support tools, technologies, and mechanisms, including data-warehouse analysis tools, mathematical, statistical and artificial intelligence tools, ad hoc querying, data mining tools, and On-Line Analysis Processing (OLAP). However, BIS use has expanded to be considered as a managerial philosophy and applications with the purpose of helping firms to organize and process vital business information for making successful decisions (Ghazanfari et al, 2011). Nowadays, BIS is seen as a broad category of technologies, applications, process, information-based routines, management tools, and human competencies, which is executed in a particular pattern to collect, store, retrieve, and analyze data to support decision-making processes (Wixom & Watson, 2012). BIS, also, integrate numerous internal data sources, thus providing firms with the ability to profile, map, plan, conduct analytics, and report on activities (Serumaga-Zake, 2017). These formal information-based routines and procedures are used by managers for improving or altering the course of a firm's operations, otherwise known as management control systems (Acheampong & Moyaid, 2016).

Studies have emphasized the organizational impacts of BIS, suggesting that the introduction of BIS into an organization implies not only technological enhancement but also a revolutionary way of performing and managing business activities and decision-making processes. BIS process and organizes a large amount of raw unstructured data supports different types of managerial decisions from operational to strategic and helps discover new business opportunities (Yang et al, 2017). Accordingly, firms allocate significant resources to employing BIS. Tunowski (2015) describe the benefits of BIS, including cost control, assuring quality and improved performance, better flow of supply chain and logistics, and effective decisions.

As BIS considered, to be a type of IS their effectiveness can be analyzed with the aid of existing ISs effectiveness models. While the area of IS effectiveness has been investigated since the 1970s, it is widely recognized that assessing IS effectiveness is hard because there is no agreement in determining an accepted dependent variable(s) for the benefits that go to the firms from their investments in or deployment of IS.

Although the concept of IS effectiveness is generally acknowledged as the main criterion for assessing IS, researchers still struggle with the issue of which constructs best represent IS effectiveness or that explain usage values IS provides for its users (Dwivedi et al, 2015).

To add to this nuisance, different terminologies were used within the IS literature to describe IS effectiveness such as evaluation/ success/ appraisal/assessment, as noted by Seddon et al (2002:12). However, we can trace out several similar definitions of IS effectiveness within the IS literature, Hamilton & Chervany (1981:55) define IS effectiveness as the degree to which the goals of the department adopting or utilizing the IS are achieved. Correspondingly, Farhoomand and Drury (1996:45) define IS effectiveness as "*the extent to which a system achieves the goals for which it was designed*". Additionally, Saarinen, (1996:104) imply that "*Effectiveness is a favorable or satisfactory result or outcome*". Seddon (1999:6) describes the success and effectiveness of IS as the measure of the degree to which the person evaluating the system believes that the stakeholder is better off. This includes its final effect on the individual or the organizational units or the whole organization. As is evident, firms will realize the benefit from their BIS initiatives when they manage to link it with their business related objectives (Yang et al, 2017); Accordingly, for the purpose of this research, BIS effectiveness is defined as the extent to which the BIS achieve both end-user and a firm's related objectives from using the given BIS (Alshibly, 2006).

Reviewing IS effectiveness literature revealed that there is a number of models can be used to measure the end user's and firm's related objectives from using BIS. These models are the Technology Acceptance Model (TAM) and Delone and Mclean Information systems success model (the D&M model).

The Technology Acceptance Model (TAM)*:*

Davis et al. (1989) investigated factors that influence on computers users to adopt and accept of technology. Their premises were that all else being equal, the IS that the end-user perceives as being easier to use and more useful than another is more likely to be accepted. According to TAM, the end-user believes that using a particular system would enhance an end-user job performance (perceived usefulness) and would be free of effort (perceived ease of use) influence the end user's attitude toward the system usage. The two variables influence the end user's behavioral intention to use the system, which, sequentially, determines the actual acceptance and usage of the system (Davis et al., 1989).

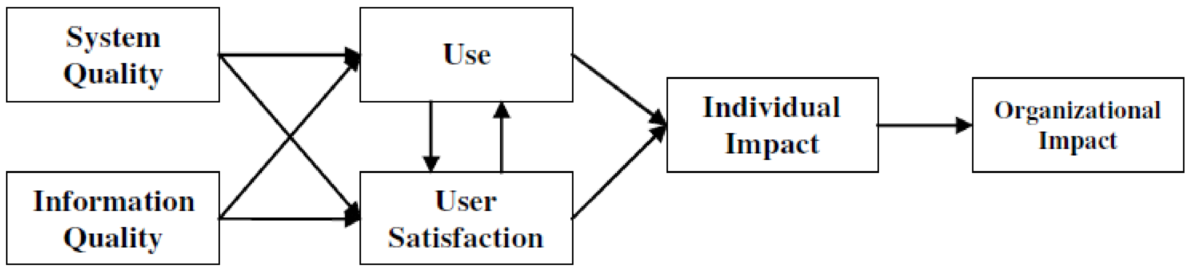
TAM originally targets user acceptance of computers. Yet, TAM measures have been tested and validated for a variety of types of technology, systems, users, etc., (Wixom & Todd, 2005) and are generally described as the most commonly used model within IS acceptance research (Grublješi and Jaklič,2015:300).

The constructs of the TAMs, which prescribe to the principles of perceived usefulness, can be used to assess the effectiveness of BIS at the individual level. By using the TAM, it is possible to learn the extent to which the users achieved their expected benefits with BIS. However, Wixom &Todd (2005) suggest that to enhance practical applications for the IS designers, system characteristics as antecedents to perceived usefulness must be included in the TAM. They further elaborated that as perceived usefulness are abstract concepts and provide general information to the designers. Hence, designers are unable to receive actionable feedback about the important aspects of the IS artifacts itself.

Delone and Mclean Information systems success model (the D&M model):

Delone & McLean (1992) analyzed more than 100 empirical study containing IS effectiveness measures between 1981 and 1988. Based on the meta-analysis results, Delone & McLean develop a taxonomy consisted of six interdependent constructs. Namely: the quality the IS characteristics (system quality), the quality of the IS output (information quality), the consumption of the IS output (use), the user's response to the IS (user satisfaction), the effect of the IS on the behavior of the user (individual impact), and the effect of the IS on organizational performance (organizational impact) (Delone & Mclean, 2016). This comprehensive model is commonly known as the D&M model (Figure 1).

Figure (1). The D&M model

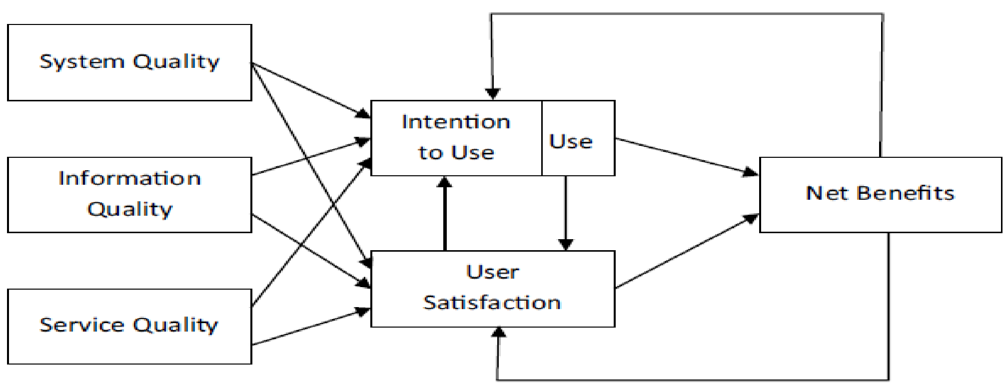


The D&M model has been critiqued by many IS researchers and proposed suggestions for adjusting the model (e.g. Seddon and Yip, 1992; Ballantine et al, 1996; Seddon, 1997; Rai et al, 2002).

In 2003, Delone & Mclean updated their model, taking into account both the changing nature of IS and some of the criticisms directed at their 1992 model. In the updated D&M model, Delone & Mclean grouped all of the impact measures together into a sole net benefits variable. They also added service quality to the model, at the same level as system quality and information quality.

This updated model is shown below (Figure 2)

Figure (2). The updated D&M model



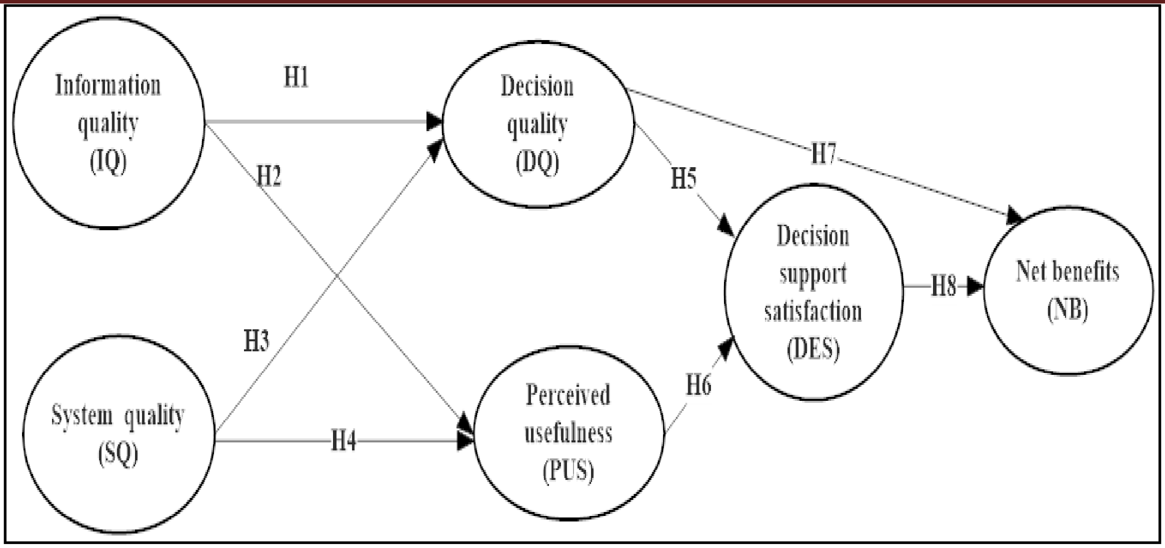
The revised D&M model is one of the most widely used models of IS success and has been used for various ISs (Petter et al, 2013; Alshibly, 2014; Alshibly, 2015).

The BIS effectiveness model and Hypotheses

The BIS effectiveness model suggests that the antecedents to BIS effectiveness should take in considerations both end-user and a firm's related objectives from using the given BIS. Thus, the proposed BIS effectiveness model contain constructs used to explain the accomplishment of end-user related objectives of the BIS, and variables used to explain the accomplishment of the firm objectives from using the given BIS.

Following this perspective, by integrating the TAM and D&M success models, the BIS effectiveness model proposes that BIS information and system quality (IQ &SQ) influence both decision quality (DQ) and perceived usefulness (PUS), in turn; the two constructs affect decision support satisfaction (DES) which directly affects the net benefits (NB) construct. The proposed research model is presented in Figure (3).

Figure (3). The BIS effectiveness model



Hypothesis Development

Our first research hypothesis concerns the effect of BIS IQ on the firm's DQ. Indeed, one of the key benefits of any BIS being the provision of the right information at the right time to enable decision makers to make informed decisions using the BIS (Wieder & Ossimitz, 2015). As a result, the introduction of BIS in organizations is often driven by a need to have improved business related information available to aid decision-making (Aruldoss et al, 2014). Bach et al, (2016) suggest BIS is often adopted to include the use and analysis of information that enables improved decision-making.

DQ refers to the technical aspects of a decision (Visinescu et al, 2017). A decision is considered to be of high quality to the extent the outcomes from decisions in an organization match or exceed expected outcomes and with potentially available information (Visinescu et al, 2017). Sparks & McCann (2015) stated that the quality of decision-making construct is composed of items such as a perceived increase in the quality of decisions and reduction of the time required for decision-making. Therefore, the quality of information that the BIS produces is critical to the quality of decisions made based on that output.

H1: IQ positively effects DQ.

The technical quality of the IS is manifested in the system's overall performance (DeLone & McLean, 2016), which can be defined as the IS user perceptions of IS technical and design quality. Previous research has highlighted and confirmed the importance of IQ and SQ for the effectiveness of general IS (e.g. Petter et al, 2013). As far as we know, however, few studies explored the impact of BIS IQ and SQ on decision quality. Iffat et al, (2015) found that poor SQ significantly affects both BIS adoption and usage. Mudzana & Maharaj (2015) found BIS SQ is positively associated with user satisfaction. Therefore, we hypothesize the following:

H2: SQ *positively effects DQ.*

The model posits that both IQ and SQ affect PUS. PUS is an essential factor in the acceptance of the BIS (Li et al, 2013); PUS defined as '*the degree to which a person believes that using a particular technology will enhance his or her job performance*' (Davis, 1989).

Wixom & Todd (2005) developed an integrated model based on technology acceptance and user satisfaction literature. The model was tested using a sample of users from seven different organizations regarding their use of data warehousing software; Findings showed that data warehousing software information and system characteristics have a significant impact on users' PUS. Venkatesh et al, (2003) suggest that both IQ and SQ need to be considered when implementing TAM. We, however, excluded perceived ease of use from this research, largely because it only indirectly affects the use of information technology, according to several researchers (Davis et al, 1989, Davis, 1989).

BIS is designed as a decision support tool for business users to provide friendly interfaces for supporting them to access information (Li et al, 2013). Thus, BIS is supposed to be useful for managers. If a manager believes that using BIS would enhance his/her job performance, he/she will intend to use the BIS. In turn, the greater the expected benefits can be derived from BI. This study proposes the following:

H3: IQ positively effects PUS.

H4: SQ positively effects PUS.

DES scrutinizes the capability of the BIS to aid users' problem solving and decision-making activities (Bharati & Chaudhury, 2004; Garrity et al, 2005). Decision support satisfaction is the desired emotional attitude toward the BIS and positive emotion will be the principal factor in individuals' acceptance of the BIS (Bharati & Chaudhury, 2004; Garrity et al, 2005).

DQ is the most important result of BIS usage and DES depends on the quality of the decisions enabled by BIS (Visinescu et al, 2017). BIS helps an organization to create knowledge from that information to enable better decision-making and to convert those decisions into action (Popovič et al, 2012). While improving decision support is the main purpose of BIS, there are also other benefits associated with BIS, including improving the employee's productivity or performance.

In cases in which users can improve productivity or performance in their job by using the BIS, they tend to evidence a positive emotional response to the system. Users will intend to use the BIS if they perceive the BIS to be sufficiently useful, as they expect a great deal from it, and help them perform their job better (Davis et al, 1989). This means that PUS works very positively in terms of DES. Seddon & Kiew (1994) asserted that PUS is predictive of decision support satisfaction and Rai et al, (2002) actually confirmed the positive relationship between the perceived usefulness of and DES with the ERP system.

Alshibly (2015) identified PUS as the determinant factor of DES in their research on the factors and beliefs that affect the success of decision support system. Based on the discussion above, the hypothesis can be asserted as follows:

H5: DQ positively effects DES.

H6: PUS positively effects DES.

The NB is the main construct for determining the BIS effectiveness. According to D&M (2003) model, the NB construct summaries all positive and negative impacts of using the BIS by firms from the point of view of all BIS users and stakeholders. It is a myriad of an actual benefits organization and users receive from using the BIS.

As known, NB added as the new construct to the updated D&M IS success (2003) model, it replaces the two constructs previously exists in the D&M (1992) model: organizational impact and individual impact. These are defined as the system impact on the firm's performance and a user, respectively. In this study, the NB construct refers to a myriad of an actual benefits organization and users receive from using the BIS.

The main reason of BIS adoption by firms is to enhance the quality of the decision-making processes by providing sufficient and accurate information and accelerating the decision-making processes (Popovič et al, 2012). This in turn not only enables a better dissimilation of knowledge all through the firm but also enables the achievement of employees' related objectives from using the BIS. Accordingly, an increase in DES may lead to an increase in the perceived benefits organization and users get from using the BIS (Bharati & Chaudhury, 2004).

Alshibly (2015) identified DES as the determinant factor of individual and organizational performance in their research on decision support systems success. Alshibly (2015) study found a high level of DES make individuals accomplish their tasks more effectively, increased their productivity. Therefore, DQ and DES drive the perception of NB. Thus, this study proposes the following hypotheses:

H7: DQ positively effects NB.

H8: DES positively effects NB.

3. Research Methodology

Construct measurement

A survey instrument using previously validated measures of several instruments borrowed from IS research literature was developed to measure the BIS model and hypotheses. Any amendment required to fit the instruments to the BI context were appropriately performed. After the measurement items were constructed, the face validity of these items was validated. Three scholars reviewed the measurement items and provide feedback on the content clarity and length of each item as well as ease of completion. Based on the feedback received, any measurement item that would cause confusion or were deemed potentially difficult to understand were dropped or replaced by new, easier-to-understand items. The constructs operationalization and measurement items are

Constructs	Operationalization	Measurement items	References
Information quality (IQ)	The quality of the BIS output	iq1: BIS provides sufficient information iq2: BIS provide reports that seem to be just about exactly what I need iq3: BIS provide up-to-date information.	Gable et al, (2008)
System quality (SQ)	BIS technical and design quality	sq1: The BIS is convenient to access. sq2: The BIS is ease of use. sq3: The BIS can be easily modified, corrected or improved.	Bailey and Pearson, 1983
Decision quality (DQ)	The technical aspects of a decision	dq1: The BIS reduces the time of my decision-making dq2: I believe I made the right decisions using The BIS. dq3: Decision I have made with the help of The BIS has been better than without it.	Caniëls & Bakens, (2012).
Perceived usefulness (PUS)	The degree to which using the BIS would enhance end-user performance.	pu1: the BIS helps me to perform work's requirements more quickly pu2: the BIS enables me to accomplish job's tasks pu3: I think that the BIS I use is useful.	Davis (1989) Alshibly(2015)
Decision support satisfaction (DES)	the ability of the BIS to support decision-making and problem-solving activities	ds1: BIS Meets my information needs ds2: I think the BIS is very helpful. ds3: The BIS meets my expectations ds4: Overall, I am satisfied with the system	Mudzana & Maharaj(2015); Bharati & Chaudhury (2004)
Net benefits (NB)	A myriad of an actual benefits organization and users receive from using the BIS.	n1: The system has a positive impact on my work. n2: The system is an important and valuable aid to me in the performance of my work n3: The BIS has resulted in overall productivity improvement n4: Overall, the system is successful.	Mudzana & Maharaj(2015) ; Iivari (2005)

summarized in Table 1.

Table 1: Construct measures for BIS effectiveness

Sample and data collection procedure

In this study, the focus was on BIS users; accordingly, convenience sampling was used. A self-completion questionnaire was circulated to all BIS users working at a large Jordanian organization. The organization provides services in the fields of education, accounting, intellectual property, project management, information and communications technology, e-commerce, and law. It offers its services to clients through its 85 branches located around the world.

A 250 BIS users from different job levels were emailed. A total of 141 response were received over a period of 10 weeks, representing a response rate of 56.4%. 3 received responses were discarded because they had an unacceptable amount of missing data (Hair et al, 2016) and the remaining 138 usable responses were accepted for data analysis, yielding a 55.2% usable response rate, which is regarded as satisfactory for this type of study (Hair et al, 2016).

This research study uses the PLS-SEM method for data analysis because it does not assume multivariate normality when assessing the structural model (Garson, 2016). The minimum sample size required to perform the PLS-SEM analysis is that the sample should be at least ten times more than the number of independent variables in the research model (Garson, 2016). According to Garson's (2016) guidelines, the minimum number of respondents for this study should be 60 observations. Our survey had a 138 usable observations, which exceeds the minimum sample size requirement.

Approximately, 73% of the respondents were male. Age distribution was approximately normal: 23 to less than 32 (20%), between 33 and 45 (44%), between 46 and 55 (8%), and over 55 (26%). The sample is composed of well-educated individuals: approximately 66% of them have a university degree (Table 2).

Table 2: The demographic composition

Characteristic	Item	Frequency	Percentage %
Gender	Male	101	73
	Female	37	26
Age	23 Y to less than 32 Y	29	20
	33 Y to less than 45 Y	61	44
	46 Y to less than 55 Y	12	8
	55 Y and more	36	26
Education Level	High school or below	4	2
	Diploma	39	28
	Bachelor	91	66
	Master or higher	4	2

4. Data analysis and results

In general, PLS-SEM technique was conducted in PLS software version 3.1.7 to examine the model fit for each construct (to assess the measurement model) including the individual item reliability, internal consistency, and discriminate validity of the measures and to test the relationships among the constructs (to test the hypotheses in the structural model).

The study applied PLS-SEM path modeling with a path-weighting scheme for the inside approximation (Davcik, 2014; Garson, 2016). Then, it applied the non-parametric bootstrapping approximation with 500 resampling to obtain the standard errors of the estimates (Hair et al, 2016).

5.1. Measurement model

For the purpose of testing of the measurement model, the study used the following tests: collinearity using the variance inflation factor (VIF), reliability using Cronbach's alpha (α) and composite reliability (CR), convergent validity using average variance extracted (AVE), and the Fornell-Larcker criterion, cross-loadings, and heterotrait-monotrait (HTMT) ratio of correlations to examine discriminant validity.

Collinearity exists when two or more independent variables are highly inter-correlated. When more than two indicators (measurement items) are highly inter-correlated, it is called multicollinearity (Hair et al., 2016). Multicollinearity inflates standard errors, makes significance tests of independent variables unreliable, and prevents the researcher from assessing the relative importance of one independent variable compared to another (Garson, 2016). A common measure of collinearity is the variance inflation factor (VIF) (Hair et al., 2016). A common rule of thumb is that problematic multicollinearity may exist when the variance inflation factor (VIF) coefficient is higher than 5.0 (Garson, 2016). There are two types of VIF, the outer and inner VIF. The outer VIF shows the severity of collinearity among the latent variables and their indicators. Additionally, the inner VIF shows the severity of collinearity among constructs (latent variables) that make up the model (Garson, 2016). Table 3 shows that the VIF values are below 5.0 threshold. Thus, there is no collinearity and multicollinearity problem in the study measurement model.

Table 3 Multicollinearity test results

Constructs	Item	Outer VIF	Inner VIF
IQ	iq1	1.727	1.389

Constructs	Item	Outer VIF	Inner VIF
	iq2	1.619	
	iq3	2.139	
SQ	sq1	2.546	1.389
	sq2	2.358	
	sq3	2.783	
DQ	dq1	2.814	2.522
	dq2	1.388	
	dq3	1.682	
PUS	pu1	1.424	2.522
	pu2	3.005	
	pu3	2.406	
DES	ds1	2.936	1.899
	ds2	2.799	
	ds3	1.505	
	ds4	1.589	
NB	nb1	1.187	1.899
	nb2	1.611	
	nb3	1.629	
	nb4	1.527	

Reliability was evaluated by calculating Cronbach's alpha coefficients and composite reliability (CR). Both Cronbach's alpha and CR provide an estimate of the reliability based on the inter-correlations of the observed indicator variables. According to Hair et al, (2016), items have acceptable reliability if the Cronbach's alpha and CR values are greater than 0.70. As shown in Table 4, the Cronbach's alpha and CR values for each of the six constructs ranged from 0.730 to 0.937. Accordingly, all the Cronbach's alpha coefficients and CR values satisfied the minimum criterion value of 0.70. Thus, the scale can be considered reliable.

Table 4. Constructs reliability and validity test results

Constructs	Item	Outer Loading	Sample Mean	Standard Error	T Statistics	α	CR	AVE
IQ	iq1	0.775	0.771	0.050	15.352	0.730	0.847	0.649
	iq2	0.841	0.838	0.045	18.624			
	iq3	0.800	0.799	0.046	17.269			
SQ	sq1	0.840	0.841	0.038	22.075	0.773	0.868	0.688
	sq2	0.840	0.836	0.041	20.509			
	sq3	0.808	0.805	0.048	16.823			
DQ	dq1	0.858	0.859	0.027	31.850	0.802	0.882	0.714
	dq2	0.767	0.762	0.071	10.755			
	dq3	0.903	0.902	0.018	49.870			
PUS	pu1	0.806	0.803	0.032	25.158	0.785	0.827	0.616
	pu2	0.823	0.822	0.035	23.633			
	pu3	0.721	0.719	0.051	14.137			
DES	ds1	0.879	0.876	0.027	33.116	0.900	0.930	0.770
	ds2	0.861	0.860	0.039	21.926			
	ds3	0.884	0.882	0.025	35.264			
	ds4	0.885	0.883	0.025	35.160			
NB	nb1	0.905	0.904	0.016	55.403	0.911	0.937	0.789
	nb2	0.856	0.855	0.037	22.924			
	nb3	0.904	0.903	0.018	49.324			

Constructs	Item	Outer Loading	Sample Mean	Standard Error	T Statistics	α	CR	AVE
	nb4	0.886	0.885	0.027	32.485			

The convergent validity, the extent to which a measure correlates positively with alternative measures of the same construct (Davcik, 2014), was evaluated by testing the AVE and the outer loadings of the indicators. As shown in Table 3, the AVE coefficient for the constructs is greater than 0.5 (Davcik, 2014). This means that more than 50% of the variance of the construct is due to its indicators (Davcik, 2014). Accordingly, all constructs have valid AVE measurements.

To confirm convergent validity, Hair et al, (2016) recommend, also, considering the outer loadings of the indicators. High outer loadings on a construct indicate that the associated indicators have much in common (Hair et al, 2016), which is captured by the construct. The outer loadings for all items are statistically significant at the level of 5% and exceeded the recommended value of 0.708 (Hair et al, 2016).

The discriminant validity was evaluated using Fornell & Larcker, (1981) criterion, to establish discriminant validity the square root of the AVE for each construct should be higher than the correlation between that construct and other constructs (Fornell & Larcker, 1981). As shown in table 5, the square root of the AVE for each construct (the diagonal elements in bold) is greater than the correlation between constructs; all the indicators comply with the empirical criteria, thus offering additional evidence of discriminant validity.

Table 5 Discriminant validity–Fornell–Larcker criterion.

Constructs	(1)IQ	(2)SQ	(3)DQ	(4)PUS	(5)DES	(6)NB
IQ	**0.806**					
SQ	0.529	**0.829**				
DQ	0.431	0.393	**0.845**			
PU	0.497	0.482	0.777	**0.785**		
DES	0.429	0.478	0.688	0.729	**0.877**	
NB	0.480	0.428	0.568	0.760	0.731	**0.888**

In addition, the discriminant validity of the measurement model was assessed using the heterotrait-monotrait ratio (HTMT) proposed by Henseler et al, (2015). Henseler et al, (2015: 121) suggest that if the HTMT value is below 0.90; discriminant validity has been established between a given pair of reflective constructs. Table 6 shows that all the HTMT ratios between the study model constructs': IQ, SQ, DQ, PUS, DES, and NB are below the threshold of 0.90 (Hensler et al, 2015), thus providing sufficient evidence of the establishment of discriminant validity of the measurement models.

Table 6 Heterotrait-Monotrait (HTMT) Ratio

Constructs	(1)IQ	(2)SQ	(3)DQ	(4)PUS	(5)DES	(6)NB
IQ		0.706	0.531	0.700	0.528	0.588
SQ	0.706		0.485	0.661	0.571	0.505
DQ	0.531	0.485		0.320		0.648
PUS	0.700	0.661	0.320		0.796	0.760
DES	0.528	0.571	0.796	0.727		0.800
NB	0.588	0.505	0.648	0.760	0.800	

Discriminant validity can be also confirmed if the indicator is loading on its construct is higher than all of its cross-loadings with other constructs (Garson, 2016). Table 7 shows that the study construct indicator's loadings are higher than all of its cross-loadings. For example, the indicator iq1 has the highest value for the loading with its corresponding IQ (0.775). All cross-loadings with other constructs have lower values (SQ = 0.390; DQ= 0.355; PUS= 0.383; DES= 0.308; NB= 0.403). The same finding holds for the other indicators of IQ (iq2& iq3) as well as the indicators measuring the model constructs. Therefore, the discriminant validity of the different constructs that make up the proposed model is confirmed.

Table 7: Discriminant validity–- loadings and cross-loadings for the construct indicators

Construct	Item	(1)IQ	(2)SQ	(3)DQ	(4)PUS	(5)DES	(6)NB
IQ	**iq1**	**0.775**	0.390	0.355	0.383	0.308	0.403
	iq2	**0.841**	0.500	0.321	0.390	0.376	0.379
	iq3	**0.800**	0.393	0.364	0.426	0.352	0.378
SQ	**sq1**	0.477	**0.840**	0.320	0.429	0.420	0.333
	sq2	0.413	**0.840**	0.334	0.405	0.434	0.417
	sq3	0.427	**0.808**	0.323	0.364	0.329	0.313
DQ	**dq1**	0.396	0.331	**0.858**	0.696	0.634	0.532
	dq2	0.166	0.230	**0.767**	0.534	0.457	0.361
	dq3	0.471	0.407	**0.903**	0.604	0.625	0.518
PUS	**pu1**	0.403	0.376	0.621	**0.806**	0.594	0.474
	pu2	0.367	0.369	0.662	**0.823**	0.550	0.473
	pu3	0.396	0.388	0.441	**0.721**	0.568	0.837
DES	**ds1**	0.431	0.431	0.612	0.665	**0.879**	0.659
	ds2	0.382	0.458	0.561	0.634	**0.861**	0.637
	ds3	0.349	0.366	0.606	0.619	**0.884**	0.656
	ds4	0.341	0.422	0.635	0.641	**0.885**	0.613
NB	**nb1**	0.459	0.390	0.588	0.697	0.692	**0.905**
	nb2	0.430	0.301	0.478	0.649	0.550	**0.856**
	nb3	0.425	0.434	0.484	0.682	0.723	**0.904**
	nb4	0.390	0.383	0.461	0.671	0.610	**0.886**

Structural model assessment

Once it has been proven that the measurement model is reliable and valid, the relationship level between the constructs and the prediction capability of the endogenous variables is assessed. This assessment entails the usage of three basic indexes: explained variance (the adjusted R^2), standardized path coefficients (β), and Bootstrap technique (Garson, 2016). Chin (2010) suggests that the adjusted R^2 value must be equal to or greater than 0.19 and β must have at least a value of 0.2 to be considered significant (Chin, 2010).

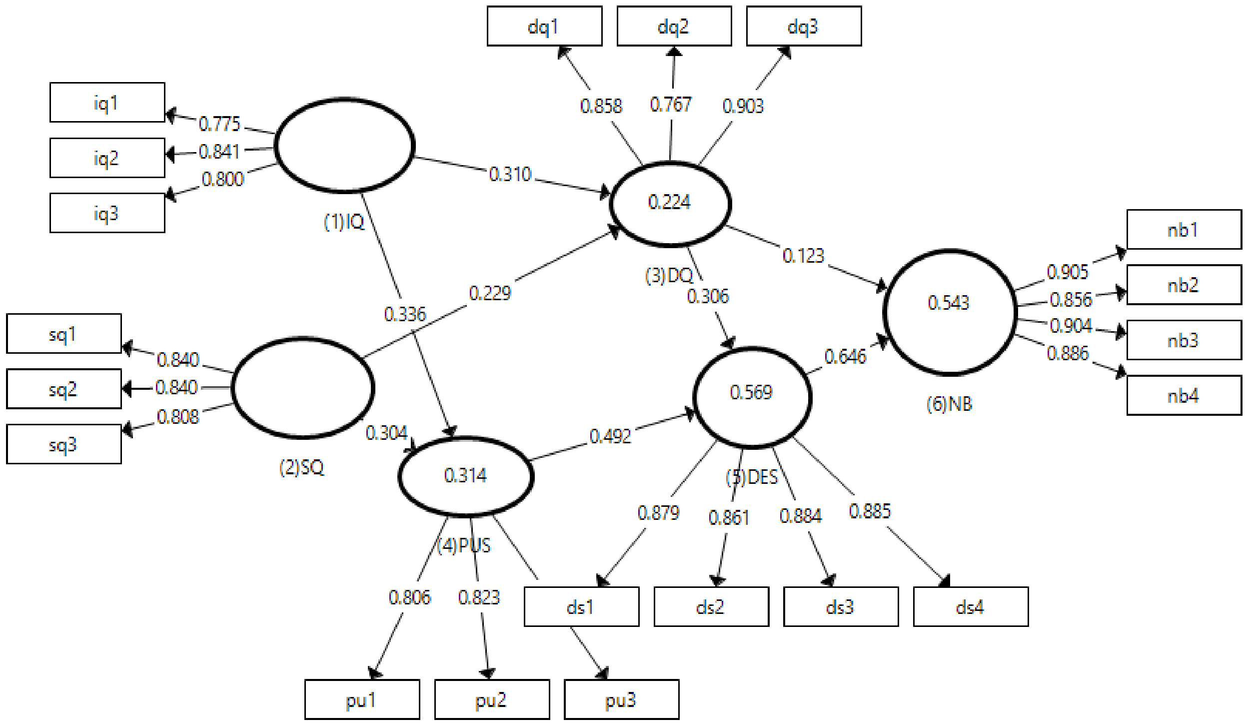
The non-parametric Bootstrap technique, with a re-sampling procedure with replacement, considering 138 cases with 5000 samples, were utilized as recommended by Hair et al, (2016). From the Bootstrap test, student's t values and the significance (P) were also examined.

P-values are defined as a probability between zero and one where smaller numbers suggest the null hypothesis is less likely to be true (Hair et al., 2016). In all instances where the t-value reflects significance (greater than 1.65 at .05; one-tailed test); the corresponding p-value also predicts probability with smaller p-values (closer to 0) indicating support for the path (Hair et al., 2016). That is, the t-value >1.65 is significant at the 0.05 level. Table 8 and Fig. 4 show the results of the structural model assessment.

The results indicate that seven out of eight hypotheses were supported. IQ ($\beta = 0.310$, t=3.017, $p < 0.05$) and SQ ($\beta = 0.229$, t=2.336, $p < 0.05$) had a significant influence on DQ, hence H1 and H2 were supported. From the t-statistics, we can see that the IQ has slightly more impact than SQ. The β value for SQ is 0.229 and for IQ is 0.310. So again, IQ is showing slightly more impact than SQ on DQ.

As expected, IQ ($\beta = 0.336$, t=3.541, $p < 0.05$) and SQ ($\beta = 0.304$, t=3.319, $p < 0.05$) had a significant influence on PUS. The model accounted for 31% of the variance explained in PUS. The results also provide support for H3 and H4.

Figure (4). Measurement Model Results



DES is positively influenced by both DQ (β = 0.306, t=3.162, $p < 0.05$) and PUS (β = 0.492, t=5.375, $p < 0.05$). The results provide support for H5 and H6. From the magnitude of the t-statistics and the standardized Beta (β), PUS has more impact on DES than DQ. Based on the value of the adjusted R, DQ and PUS explain 56% of the variance in the DES construct. NB is positively influenced by DES (β = 0.306, $p < 0.05$), but DQ had insignificant effects on NB (β = 0.306, $p > 0.05$), the model accounted for 54% of the variance explained in NB construct, which can be considered substantial.

Table 8. Summary of hypotheses testing.

Hypothesis	β	T	P	f^2	Support	R^2	Adjusted R^2
H1: IQ --> DQ	0.310	3.017	0.003	0.089	Yes	0.224	0.212
H2: SQ--> DQ	0.229	2.336	0.020	0.049	Yes		
H3: IQ --> PUS	0.336	3.541	0.000	0.119	Yes	0.314	0.304
H4: SQ--> PUS	0.304	3.319	0.001	0.097	Yes		
H5: DQ--> DES	0.306	3.162	0.002	0.086	Yes	0.569	0.563
H6: PUS -> DES	0.492	5.375	0.000	0.223	Yes		
H7: DQ--> NB	0.123	1.492	0.136	0.018	No	0.543	0.536
H8: DES --> NB	0.646	8.206	0.000	0.481	Yes		

The last criterion for assessing the structural model is the effect size f^2 is a test that demonstrates whether the change in the adjusted R^2 values of all variables occurs if a specified variable has been removed from the model (Hair et al, 2016).

The change in the R^2 of the endogenous latent variable is calculated by estimating the structural model two times for when the construct is used and when it is not used. Values of 0.02 indicate that the predictor variable has a "weak" effect size on the endogenous variable, whereas values of 0.15 and 0.35 indicate a "moderate" and "large" effect size, respectively (Chin, 2010). As shown in Table 8, the effect sizes f^2 of IQ on the endogenous variable DQ is weak, whereas It is obvious that DES (f^2=0.481) has a large influence in producing the R^2 for NB and PUS (f^2=0.223) has a moderate influence in the R^2 for DES.

5. Discussion, Implications, Limitations, and Future Research

This research study seeks to contribute to the developing body of research into BIS effectiveness. As there is a lack of accepted or predictive theories pertaining to BIS effectiveness, this research main objective is to develop and empirically tests a conceptual model of BIS effectiveness using data gathered from employees who had experience using BIS at their workplace.

Accordingly, the study develops and empirically validated a comprehensive model of BIS effectiveness, the model suggests BIS effectiveness should be seen as a myriad of actual benefits and achievements both organization and BIS users receive from using a particular BIS. Following this perspective, the antecedents of BIS effectiveness must be variables related to both end user's and firm's objectives from using the given BIS. Following this perspective, by integrating the TAM and The D&M success models, the study model consists of six constructs: IQ, SQ, DQ, PUS, DES, and NB. The causal relationships among the constructs in the model tested with a field survey.

Discussion

This study provides several important theoretical and practical implications for BIS effectiveness.

Based on the PLS-SEM results, it can be said that IQ and SQ of the BIS positively affect DQ. Support for this inference can be found by examining the adjusted R^2, which is summarized in Table 8, the results have shown that the two constructs explain 21.1% of the variance in DQ, so an increase in the IQ and SQ of the BIS leads to an increase in DQ.

Previous research have highlighted and confirmed the importance of IQ and SQ for the effectiveness of general IS (e.g. Petter et al, 2013). As far as we know, however, few studies explored the impact of BIS IQ and SQ on DQ. A common perception is that BIS improves the quality of information that this would improve the quality of the decisions being made (Mudzana & Maharaj, 2015), the results confirm this perception in the BIS context, BIS need to provide sufficient information to aid users decision-making. The information produced and processed by BIS should be up-to-date, of sufficient quality, and care should be given to the BIS technical quality. The respondents believe the extent to which the BIS is convenient to access, ease of use, easily modified, corrected or improved will reduce the time of the decision-making and enhance the technical aspects of marginal decisions.

The second conclusion relates to the impact of IQ and SQ on PUS, as they were conceptualized in BIS effectiveness model. Our results have shown that IQ and SQ could explain 30.4% of the variance in PUS (see Table 8). Thus, a net positive effect from BIS information and system characteristics will result in a positive significant impact on users' PUS.

BIS is supposed to be useful for managers, If a manager believes that using BIS would enhance his/her job performance, he/she will intend to use the BIS. In turn, the greater the expected benefits can be derived from BI. Studies suggest that the TAM offers merely partial direction on how to influence usage via design and implementation. Wixom &Todd (2005) suggest that to enhance practical applications for the IS designers, system characteristics as antecedents to perceived usefulness must be included in the TAM. They further elaborated that as PUS are abstract concepts and provide general information to the designers. Hence, designers are unable to receive actionable feedback about the important aspects of the IS artifacts itself. Not only this result supports the findings of the previous IS effectiveness research in the BIS context(Gonzales &Wareham, 2019), but also it partially refines the TAM.

The third conclusion relates to the impact of DQ and PUS on decision support satisfaction. Our results have shown that DQ and PUS could explain 56.3% of the variance in decision support satisfaction (Table 8) and PUS has more impact on decision support satisfaction than DQ. Our results suggest that the degree to which using the BIS would enhance end-user performance is an important factor affecting decision support satisfaction. While improving decision support is the main purpose of BIS, there are also other benefits associated with BIS, including improving the employee's productivity or performance, This result is consistent with the findings of previous research (e.g. Alshibly, 2015).

Finally, NB is found to positively influence by DES, but DQ had insignificant effects on NB. Therefore, an increase in DES leads to an increase in the perceived benefits organization and users get from using the BIS. A high DES means that the BIS enable employees to complete their jobs more effectively and improved their decision-making quality (Serumaga-Zake, 2017). This result is consistent with prior research (Garrity et al, 2005) and supports the posited impact of User Satisfaction on net benefit as suggested by the Delone & Mclean (2003) models.

Theoretical Implications

This study extends current research in BIS and develops a BIS effectiveness model for explaining the relationship between BIS effectiveness constructs based on IS success theories.

This study contributes to the theory by providing further empirical testing of TAM and the D&M IS success model in the new context as suggested by previous studies (e.g., DeLone & McLean, 2016).

Secondly, this study contributes to academic research by providing richer insight into the role of the decision support satisfaction in BIS effectiveness and providing a framework with which future research on the relationship between decision quality and BIS effectiveness can be conducted. Finally, this study introduces a new instrument, which measures different BI effectiveness constructs.

This study has few limitations in terms of sample size and sampling; that the study used a convenience sampling from a single company for the data collection. Further studies are recommended to use a random sample from a pool of companies.

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