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Investigating Decision Support System (DSS) Success: A Partial Least Squares Structural Equation Modeling Approach

Haitham Hmoud Alshibly
Management Information Systems Department
Al Balqa Applied University, Jordan, halshibly@gmail.com

Abstract
The central contribution of the study is the development of a DSS success model explores the effects of the quality features of DSS systems, including system quality, information quality, accompanied with perceived ease of use and perceived usefulness on decision support satisfaction and DSS net benefits. A detailed questionnaire was developed to measure the relationship between the aforementioned variables and data was collected from employees in Royal Jordanian Airlines in Jordan who had experience using DSS at their workplace. Partial least squares-structural equation modelling (PLS-SEM) methods were employed to test the research model. The results revealed that system quality had positive effects on both perceived usefulness and decision support satisfaction. Information quality had positive effects on decision support satisfaction; ease of use had positive effects on perceived usefulness, and decision support satisfaction positive effects on net benefits. However, information quality effects on the perceived usefulness, ease of use effects on decision support satisfaction, perceived usefulness effects on decision support satisfaction and benefits were not significant. The findings provide several important implications for DSS research and practice. This paper concludes by discussing the limitations of the study, which should be addressed in future research.

Keywords: Decision support system; Partial least squares-structural equation modelling; Net benefits; D&M IS success model; Decision support satisfaction.

1. Introduction

Undoubtedly, strategic decision-making is one of the most important areas of management research (Dulcic et al, 2012). Accordingly, with the rapid increase in computational resources and increased reliance on in decision analysis, the importance of decision support systems (DSS) in supporting the decision making process has gained in popularity (Arnott & Pervan, 2012).

DSS is as an interactive, flexible and adaptive computer-based information systems (IS), developed for supporting the solution of management problems by utilizing data, providing an easy-to-use interface and allowing for decision makers own insights (Power., 2013). The DSS are intended to enhance decision-making effectiveness, improve communication among decision makers, increase their satisfaction and organizational control (Power et al., 2011). DSS today are found in a wide range of applications and they vary from simple spreadsheet, goal seeking and scenario analyses to geographical IS and knowledge management systems. DSS categorization includes the following systems (Turban et al., 2011; Arnott & Pervan, 2014): data based (e.g.

Data warehouses, Geographical Information Systems), model based (e.g. Online analytical processing), knowledge based (e.g. Data mining), documents based (e.g. Web search engines) and communications systems (e.g. Group decision support system, different groupware tools as teleconferencing and distant whiteboards). Organizations need these new tools and techniques to improve performance and profits. DSS as a result vary on a number of dimensions, including the technological approach adopted, the level of management supported and the number of decision makers involved (one or many). They range from small, IS through to large-scale systems similar in nature to enterprise resource planning systems (Arnott & Pervan, 2014).

The purpose of a DSS is to improve decision-making through the provision of support that is reliable, accurate, timely, and of good quality. According to Bhatt and Zaveri (2002) a DSS can also assist in monitoring decision processes, alerting users of their inconsistent assumptions, and in making context-based decisions. A well-designed DSS can facilitate problem solving and enhance the organizational learning process. A DSS can facilitate problem recognition, model building, assist in collecting, integrating, organizing, and presenting the relevant knowledge, select an appropriate problem solving strategy, evaluate the different solutions, and choose the best solution. The system consists of the user and the DSS will in time be effective if both work toward the cooperative purpose of improving decision-making. Because such systems handle complex and poorly structured problems, they are difficult to empirically evaluate. However, it is still easy to argue that evaluation of all DSS is important.

Organizations need to be cognizant of the factors that will influence the success of a DSS in order to realize its full benefits. DSS mangers as well as IS researchers are stressing the need to better understand the factors that contribute to the success or otherwise of DSS (Bharati and Chaudhury, 2004). Yet, few organizations systematically attempt to measure the effectiveness of their DSS, or even know how to do so (Pick & Weatherholt, 2012). A few academic studies with theoretical views and empirical evidence on DSS success exist. Interestingly, most of the existing studies have focused on describing the technical components of the DSS, instead of evaluating those (Arnott & Pervan, 2014). This suggests that there are gaps in the research to be filled and the need for a more systematic and deliberate study on the DSS success is therefore crucial.

In order for DSS applications to be used effectively in an organization, we need dependable ways to measure the success and/or effectiveness of the DSS system. However, there is no accepted or overall framework that arranges the important aspects of effective DSS in a way helping to assist DSS success, the single available options are by looking through the lens of well-known theories and models of IS success (e.g., DeLone &McLean, 1992; 2003; Rai et al., 2002; Garrity et al., 2005), whether or not those models can be extended to assessing DSS success is rarely addressed.

Accordingly, the overall purpose of the study was to test and validate a revised conceptual model of DSS success. The model appears to provide useful and pioneering insights into DSS success. The role of the model DSS components, the quality features of DSS systems, including system quality, information quality, accompanied with perceived ease of use and perceived usefulness on decision support satisfaction and DSS net benefits, is not new. However, the developed understanding of each of the model components in the context of DSS through empirical testing provides new material. The detailed objectives were to:

- Re-examine the relationships between key dimensions of DSS success in the light of established theories, e.g. The D&M IS success models (DeLone &McLean, 1992; 2003), and the technology acceptance model (TAM) (Davis, 1989);
- Empirically validate and test the model using data gathered from employees at Royal

Jordanian Airlines in Jordan who had experience using DSS at their workplace;

- Contribute to the developing body of research into DSS success as there is a lack of accepted or predictive theories pertaining to DSS success (Arnott & Pervan, 2014).

The remainder of the paper is structured as follows: we address literature review in the next section. This is followed by the presentation of the research hypotheses, discussion of findings, conclusions, and finally recommendations for future studies.

2. Background on DSS Success

The starting point for our research was the existing research in the field. We thus reviewed relevant literature on DSS, information systems success measurement, and existing approaches for evaluating DSS. In the following, we firstly introduce the relevant literature before coming to a conclusion and choosing the aspects that we find relevant.

DSS definition

Since DSS, in general, were developed to support decision maker in processing, assessing, categorizing and organizing information in a useful fashion and have been used for a long time, the literature reveals many possible definitions of the DSS term; however, The original DSS concept was most clearly defined by Gorry and Morton (1971) who combined categories of management activities developed by Anthony (1965) with description of decision types proposed by Simon (1960) using the terms structured, semi-structured and unstructured rather than programmed and non-programmed. For their DSS framework, they used Simon's intelligence, design and choice description of the decision making process. In this framework, intelligence symbolized the search for problems, design involves the development of alternatives and choice consists of analysing the alternatives and choosing one for implementation. For Keen (1980), DSS couple the intellectual resources of individuals with the capabilities of the computer to improve the quality of decisions. "DSS is computer-based support for management decision makers who are dealing with semi-structured problems."

Bhatt and Zaveri (2002) define DSS as a computer software that facilitates and accepts inputs of a large number of facts and methods to convert them into meaningful comparisons, graphs, and trends that can facilitate and enhance a decision makers' decision-making abilities to solve unstructured problems. However, Power, (2013) ascertains that the DSS can range in level of sophistication from a simple spreadsheet to sophisticated data warehousing and mining applications, knowledge management systems, or modeling systems.

Besides that, DSS is also identified by Turban et al. (2011) as an approach (or methodology) for supporting decision making by using an interactive, flexible, adaptable computer-based information system (CBIS) developed (by end user) for supporting the solution to a specific non-structured management problem uses data, model and knowledge along with a friendly (often graphical; Web-based) user interface, incorporating the decision maker's own insights, supporting all phases of decision making, and can be used by a single user or by many people.

DSS Success

In theory, it is widely recognized that assessing IS success is hard simply because IS contain many systems and is an "abstract concept that does not easily lend itself to direct measurement" (Delone and McLean, 1992:69). Studying IS success draws on theories and measures borrowed from diverse disciplines including engineering, finance, economics, decision-making, sociology, marketing, and organizational effectiveness (Avgerou, 2000). This diversity results in varying scope of the IS success measures as well as the approaches used (Larsen, 2003).

IS success is seen as a multi-dimensional concept that can be assessed at multi levels (such as technical, individual, group, organizational) (Seddon, 1997). In other studies, IS success is surrogate by other constructs or criteria (e.g. user satisfaction) (Delone and McLean, 2003). IS success can also be surrogated by economic, financial, behavioral and perceptual measures (Sterafeimidis et al., 2003). Farhoomand and Drury (1996:45) define IS success as "the extent to which a system achieves the goals for which it was designed". Likewise, Miller and Doyle (1987) imply that an effective system is one, which achieves the purpose of its users; this includes its final effect on the individual, department and organization. In a similar vein, White et al (1997:38) define a successful IS as" one which achieves the expectations of its users". Seddon (1997:248) defines IS success as "a value judgment made by an individual, from the point of some stakeholder". A more complex definition is given by Seddon et al. (1999:6) who describes the success/effectiveness of a system as the measure of the degree to which the person evaluating the system believes the stakeholder is better off. Seddon et al., (1999:36) says IS is "effective if the person or organization that expended resources in auguring, learning to use /or using the systems is better off as a result "(ibid: p36). Hung et al., (2005) reported that DSS success measures generally target at DSS efficiency or effectiveness. DSS effectiveness is defined as the DSS accuracy and completeness with which users achieve specified goals. Effectiveness is measured by decision outcome, such as the quality or accuracy of decision and user satisfaction. For example, user satisfaction and/or decision-making satisfaction, decision quality, and business profitability to measure DSS outcomes. Efficiency is more process-oriented and is typically measured by decision speed or the number of alternatives under consideration, for example, increased efficiency of decision making.

Several researchers have investigated the DSS success (Aldag and Power, 1986; Elam & Mead, 1987; Chakravarti et al, 1979; Mclntyre, 1982; Goslar et al., 1986; Ben-Zvi, 2012; Dickmeyer, 1983; Lilien et al, 2004; Webby and O'Connor, 2005). The findings of these studies have been mixed and inconclusive. This can be explained partly by the various different measures of DSS success which were employed, sometimes without appropriate theoretical foundation. Elam & Mead (1987) reported a number of research questions that they feel need more attention. One of these questions is how to study and measure DSS effectiveness, quality of decision-making, learning and change. They argue that research into the impact of decision support systems for efficiency or effectiveness of an individual executing one or more tasks, has lacked both rigor and relevance.

In a laboratory experiment, Aldag and Power (1986) analyze the effects of DSS on participants' performance and perceptions. They found that here was only limited support for the hypothesis that, compared to unaided users, those with decision aids will exhibit more confidence in, and satisfaction with, their decision processes and recommendations. There was no support for the hypothesis that DSS availability will improve user's performance, and make better decisions.

In an advertising allocation task using a decision calculus model, Chakravarti et al. (1979) found that the use of DSS did not improve the quality of advertising decisions and in fact led to poorer decisions. Mclntyre (1982) studied the impact of DSS availability on decision quality in a promotion budget allocation task, contrary to the results of Chakravarti et al. (1979), he found that the group with the DSS had significantly higher decision quality. Thus, the results of the two previous empirical studies of the effectiveness of the DSS are mixed.

Based on insights gleaned from a lab experiment examined the effects of applying a DSS to an ill-structured marketing problem, Goslar et al. (1986) found not having a DSS was associated with the consideration of more alternatives. No differences in decision speed, perceived confidence, amount of data considered, decision processes, and overall performance were due to DSS availability. Meanwhile, Ben-Zvi (2012) found that DSS users who perceive the system as effective correlate to improved company performance. Other scholars provide no support for the premise that the use of DSS improves individual or group decision making effectiveness. For example, Dickmeyer (1983) examined the effect of a DSS on subjects' preference functions. In a university budget planning task employing an interactive financial planning model he observed that preference functions changed more when using the DSS to achieve a greater understanding of the tradeoffs between variables than when subjects only received a printed report on long range forecasts. Moreau (2006) analyze the impacts of DSS on intellectual task success. The main findings of Moreau study are that intellectual workers who are satisfied with DSS user-friendliness perceive their tasks as being more enriching and the systems themselves as being more useful. In addition, if these users perceive a good job outcome with DSS, then it may lead to the successful performance of the user's task.

The broader DSS research reports mixed findings in laboratory studies on the effects of DSSs on decision outcomes. In a study of task complexity and DSS, Webby and O'Connor (2005) find that the DSS did not affect subjects' performance. Of the 11 studies that Sharda et al. (1988) reviewed, 6 showed improved performances because of DSS use, 4 showed no difference, and in 1 study performance actually decreased for DSS users. Dulcic and Pavlic (2012) investigate the intended use of DSS within medium and large business organizations in Croatia by applying TAM. The study indicates the importance of perceived usefulness and perceived ease of use as core factors which influence on the perception of using DSS to support management decision process. Lilien et al (2004) concluded that it is possible that DSS can improve objective decision outcomes without having a positive effect on the subjective evaluations of these decisions and vice versa, and it would be useful to understand the separate nature of these two effects.

As is evident, little research has been done in this area and different authors have put different measures of DSS Success forward. Moreover, most of these studies are descriptive reviews that lack detailed quantitative analysis and fail to prioritize the relative importance of those factors. These studies are useful and provide a good start to study DSS success. They do not however, identify common factors across systems and organizations that can foster the successful development and use of DSS. Field studies have used DSSs to address real managerial problems, but have lacked effective experimental control, making it difficult to demarcate the drivers of DSS success, while lab studies have imposed sound experimental controls, but have addressed relatively simple and contrived problems (Lilien et al, 2004). Ben-Zvi (2012) believes most of DSS success studies principally focused on the direct effects of system design and use on outcomes and user performance. Fewer DSS studies have integrated decision process variables, such as perceived usefulness, satisfaction, enjoyment, and perceived ease of use.

Delone and Mclean Information success model

Because IS success is a multi-dimensional concept that can be assessed at various levels, the measure for IS success has neither been totally clear nor exactly defined. However, to address this problem, DeLone & McLean (1992) performed a review of the research published during the period 1981–1987, and created a causal-explanatory model of IS success (the D&M IS Success Model) based upon this review. This model identified six interrelated dimensions of IS success. It suggested that the success can be represented by the system quality, the output information quality, consumption (use) of the output, the user's response (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). This model provided taxonomy for classifying the multitude of IS success measures and suggested the temporal and causal interdependencies between the six dimensions. Delone and McLean describe the six categories as follows:

• System quality - the measure of information processing system itself
• Information quality - the measures of information system output
• Information use - the recipient consumption of the output of an information system
• User satisfaction - the recipient response to the use of the output of an information system
• Individual impact - the effect of information on the behavior of the recipient
• Organizational impact - the effect of information on organizational performance

Since its introduction in 1992, the D&M IS Success Model has created a broad response in the literature. In fact, the 1992 article of DeLone and McLean (1992) was found to be the single-most heavily cited article in the IS literature (Lowry et al. 2007). Through all this work, the model's principal constituents and their relations have been investigated in a broad spectrum of settings (Petter et al. 2008).

Motivated by DeLone and McLean's call for further development and validation of their model, Garrity and Sanders (1998) extended the D&M IS success model and proposed an alternative model in the context of organizational and socio-technical systems. Their model identifies four sub dimensions of user satisfaction, namely: interface satisfaction, decision support satisfaction, task support satisfaction, and quality of work life satisfaction (Garrity and Sanders, 1998).

Garrity and Sanders (1998) believe the above mentioned dimensions are consistent with TAM (Davis 1989). Davis suggested that the actual use of technology could be predicted by the user's behavioral intention and his or her attitude towards its use. This in turn is influenced by a technology's perceived ease of use and usefulness (Davis 1989). Davis describes TAM variables as follows:

- Perceived usefulness - refers to the degree to which a person believes that using a particular system would enhance his or her job performance.
- Perceived ease of use - in contrast, refers to the degree to which a person believes that using a particular system would be free of effort.

Davis indicated that perceived usefulness and ease of use are influential factors affecting the decisions made to use information technology. Thus, they are important in designing and implementing successful information systems (Davis, 1989).

The Garity and Sanders model measures the fit with the system, the user, and the task, and is consistent with the TAM (Garrity and Sanders 1998). Garrity et al. (2005) confirmed that task support satisfaction and interface satisfaction are closely related to the TAM's perceived dimensions of usefulness and the perceived ease of use (Garrity et al, 2005).

In 1997, Seddon claimed there is confusion with the interrelationship between use and user satisfaction in the D&M IS success model. He suggested the removal of system use as a success variable in the causal success model, since the D&M IS success model treats IS use as behaviour, as opposed to a proxy for benefits or an event in a process leading to individual or organizational impact. Seddon also differentiated among actual impacts and expected impacts, and included the additional construct of perceived usefulness. Seddon's concept of usefulness is equivalent to the idea of perceived usefulness in TAM by Davis (1989). Seddon argued that, for voluntary systems, use is an appropriate measure; however, if system use is mandatory, usefulness is a better measure of IS success than use. Seddon (1997) also claims that IS use is a behaviour, not a success measure, and replaces D&M IS Success Model's IS use with perceived usefulness, which serves as a general perceptual measure of the IS use, to adapt his model to both voluntary and non- voluntary usage contexts.

Rai et al. (2002) further built on Delone and Mclean and Seddon. They viewed usefulness as being related to individual impacts and noted that it was based on several of the constructs Delone and Mclean had linked to individual impacts, such as improved individual productivity. Rai et al. (2002) focused on five constructs – system quality, information quality, perceived usefulness, user satisfaction, and system use – and represented system quality in terms of ease of use and system use in terms of system dependence. They conducted a survey of 274 users of an integrated student information system, and test Delone and Mclean's and Seddon's models. Based on the empirical results, they also tested an amended Seddon model, including a correlation path between perceived usefulness and system use, and found this model to perform the best. They found that IS a user satisfaction impact IS use: a higher level of satisfaction generates better user dependence on the system. This relationship is consistent with Davis' (1989) findings that attitudes towards using the system shape system-usage behaviour.

The relationships proposed by Delone and Mclean have been tested in several domains. Roldán and Lean (2003) tested the entire model for executive IS and found support for some of the relationships. The results of an earlier study of decision support system use by Snitkin and King (1986) are consistent with the proposed relationship between use and individual impact, as are the results of the study by Etezadi-Amoli and Farhoomand (1996) and Rai et al. (2002). However, neither Gelderman (1998) nor Roldán and Lean (2003) found any evidence of this relationship. Igbaria and Tan (1997) found user satisfaction has the strongest direct effect on individual impact. Millman and Hartwick (1987) provided empirical support for the relationship between individual impact and organisational impact in a study of middle managers' perceptions of the impact of systems.

In 2003, Delone and Mclean presented a reformulated version of their classic model, taking into account both the changing nature of IS and some of the criticisms directed at their 1992 model. The criticisms that they take into consideration concern elements included in the quality dimension, and the nature of the impacts. Delone and Mclean refined their model by merging all impacts (including organizational and individual) in one generalized component, net benefits. They also added a return loop from net benefits to intention of use and user satisfaction. Net benefits generalize the notion of benefits since many researchers suggested the impacts of IS could be expanded to include diverse entities. They define net benefits as the extent to which IS are contributing to the success of individuals, groups, organizations, industries, and nations. For example: improved decision-making, improved productivity, increased sales, cost reductions, improved profits, market efficiency, consumer welfare, creation of jobs, and economic development. Brynjolfsson et al. (2002) have used production economics to measure the positive impact of IT investments on firm-level productivity.

Petter et al. (2008) provide a review of recent literature on measuring IS success. They summarize the measures applied and examine the relationships that comprise the D&M IS success model in an individual and organizational context. The results show that the majority of the relationships posited in the updated D&M model in 2003 have been supported. In another review, Urbach et al. (2009) explore the current state of IS success research by analyzing and classifying recent empirical articles with regard to their theoretical foundation, research approach, and research design. The results show that the dominant research analyzes the impact that a specific type of IS has by means of users' evaluations obtained from surveys and structural equation modeling. The D&M IS Success Model is the main theoretical basis of the reviewed studies. Several success models for evaluating specific types of IS – like eHRM (Alshibly, 2015) or cheque clearing systems (Alshibly, 2011) – have been developed from this theory. One of the latest is the meta-analysis carried out by Petter and McLean (2009) who stated that the majority of the relationships posited in the updated D&M model in 2003 have been supported.

The results of all these studies, along with the basic Delone and Mclean model, suggest

D&M IS success model is composed of a set of factors that apply to all systems, in addition to a set of factors specific to each type of system.

3. The DSS success model and Hypotheses

The D&M IS success models proposed by DeLone and McLean (1992, 2003) were used as the framework to evaluate the success of DSS. In their model of IS success, they state that the quality of the information system positively affects other variables of IS success. Specifically the types of quality include the technical quality of the system (system quality) and the quality of the output provided by the IS (information quality). The incorporation of quality into the DSS success model must describe the dependency of user satisfaction on system quality and information quality. This supports the underlying belief in Delone and Mclean's 1992 model that user involvement should lead to increased positive outcomes for the user. Accordingly, system and information quality constructs from Delone and Mclean and Rai et al.'s modified Seddon model are posited as two key drivers of user satisfaction. Moreover, although user satisfaction has for a long time been recognized as an indicator of IS success (Bailey and Person, 1983; Ives et al., 1983; Seddon, 1997), the mechanism by which to measure it was not clear. Information and system features were not always been explicitly separated as dimensions of user satisfaction until Delone and Mclean (1992) distinguished information quality and systems quality. This structure was retained in the D&M IS success (2003) model.

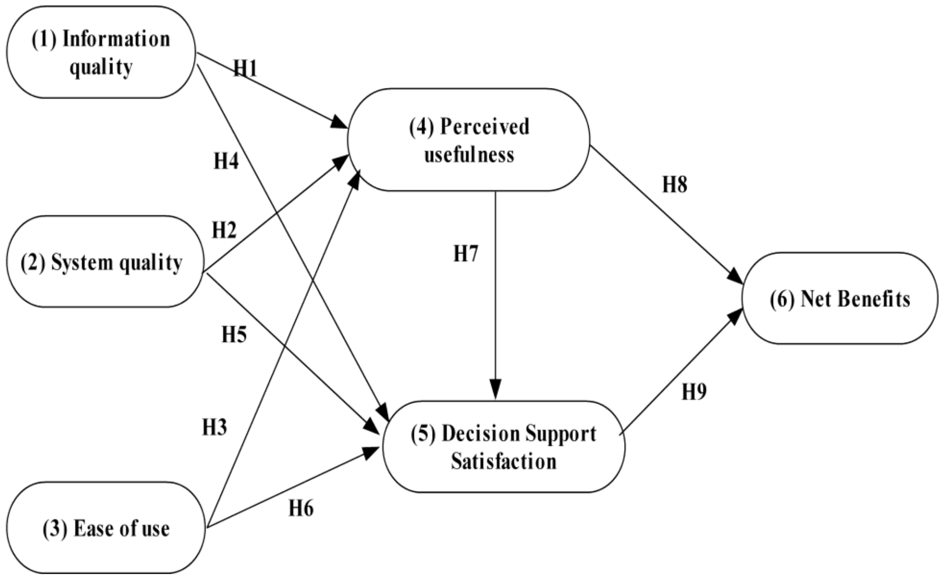
User satisfaction refers to the extent to which users are pleased with IS and support services (Petter et al., 2008).In the model user satisfaction is replaced by decision support satisfaction .The current study assumes that decision support satisfaction is a focal construct that affects net benefits. Decision support satisfaction scrutinizes the DSS capability to assist in decision-making of the user's jobs (Bharati & Chaudhury, 2004; Garrity et al, 2005).

In addition, this study examines the impact of two widely tested TAM variables perceived ease of use and perceived usefulness of the DSS. The relationships between these two TAM variables and Decision support satisfaction should be tested to provide additional insight and corroborate the findings of prior research in the context of actual DSS use. In fact, TAM has proven to be among the most effective models in the IS literature for predicting user acceptance and usage behavior. Yet, few of TAM studies have investigated the impact of system characteristics as antecedents to ease of use or perceived usefulness (Wixom and Todd, 2005). In their integration of the technology acceptance literature, Venkatesh et al. (2003) stress the need to extend this literature by explicitly considering system and information characteristics and the way in which they might influence the core beliefs in TAM, and might indirectly shape system usage.

Delone and Mclean (1992:69) describe individual impact as "an indication that an information system has given a user a better understanding of the decision context, has improved his or her decision-making productivity, has produced a change in user activity, or has changed the decision maker's perception of the importance or usefulness of the information system" (p. 69), Seddon (1997) belief individual impact mean benefits accruing to individuals from using the IS. We do claim that perceived usefulness covers some aspects of individual impact. Perceived usefulness essentially covers the impact on decision-making productivity. Nevertheless, in this study perceived usefulness refers to the degree to which a user believes that using DSS would enhance his or her job performance" (Davis 1989, p. 320)

As known, net benefits added as new construct to the updated D&M IS success (2003) model. The construct includes and replaces two variables previously found in the DeLone & McLean (1992) model: individual impact and organizational impact. These are defined as the system impact on an individual (user) and organizational performance, respectively. Delone and Mclean (2003) say that the "net benefits" variable must be defined within the context of the

system under study and within the frame of reference of those assessing the system impact, as these variables substantially influence what constitutes net benefits and hence IS success, accordingly, in this study, the success construct refers to the actual benefits adopters receive from using the DSS and includes a myriad of benefits covers the individual impact and organizational impacts of DSS. Fig. 1 illustrates hypothesized relationships between constructs in the study.
Figure (1).The DSS success



The proposed constructs and hypotheses are fully supported by prior studies in the IS literature (DeLone & McLean, 1992; 2003; Garrity et al., 2005; Rai et al, 2002; Wixom and Todd, 2005) Drawing upon the literature and based on the present research context, we hypothesize the following:

H1: information quality positively influences perceived usefulness.

H2: system quality positively influences perceived usefulness.

H3: ease of use positively influences perceived usefulness.

H4: information quality positively influences decision support satisfaction.

H5: system quality positively influences decision support satisfaction.

H6: ease of use positively influences decision support satisfaction.

H7: perceived usefulness positively influences decision support satisfaction.

H8: perceived usefulness positively influences net benefits.

H9: decision support satisfaction positively influences net benefits.

4. Research Methods

Measurement

In developing measures for the constructs proposed in the model, we made use of previous validated measures wherever possible in order to enhance validity (Sugianto and Tojib, 2006). After surveying the literature for existing constructs, a survey instrument was developed based on published literature. Specifically, four items for Information quality were adapted and refined from the work of Wixom and Todd (2005). Six items for system quality were adapted and refined from Gable et al. (2008). Three items to measure the perceived usefulness and three items to measure perceived ease of use were adapted from Davis (1989). To measure decision support satisfaction, three items were adopted and refined from instruments used by Garrity et al. (2005). However, the DSS net benefits construct had not been examined empirically in the context of DSS. Consequently, we identified the main indicators used by researchers to measure net benefits and facilitate conditions from the IS literature, and ‘‘borrowed’’ them for use in this study. Accordingly, the DSS net benefits construct was measured by using three items from Gable et al. (2008) and two from Iivari (2005). All of these items were measured using a 5-point Likert scale ranging from ‘‘strongly disagree’’ (1) to ‘‘strongly agree’’ (5), to indicate the respondent’s level of agreement and disagreement towards a given statement. The survey instrument and the measurement items are summarized in Table 1.

Table 1: Measurement items

Constructs	Operationalization	Survey items	Sources
Information quality	The quality of the information that the DSS produces and delivers	IQ1: Information from the DSS is easy to understand IQ2: The DSS provides sufficient information IQ3: The DSS provide reports that seem to be just about exactly what I need IQ4: The DSS provide up-to-date information.	Wixom and Todd (2005)
System quality	The desirable characteristics of the DSS	SQ1: The DSS allows information to be readily accessible to me. SQ2: The DSS makes information very accessible. SQ3: The DSS always does what it should. SQ4: The DSS user interface can be easily adapted to one’s personal approach. SQ5: All data within the DSS is fully integrated and consistent. SQ6: The DSS can be easily modified, corrected or improved.	Gable et al. (2008)
Ease of use	The degree to which a user believes that using the DSS would be free of effort	EU1: Learning to operate the DSS is easy for me EU2: Interacting with the DSS does not require a lot of my mental effort EU3: I find it easy to get the DSS to do what I want it to do.	Davis (1989)
Perceived usefulness	The degree to which a user believes that using the DSS would enhance his or her performance within an organizational setting	PU1: Using the DSS enables to perform work's requirements more quickly PU2: Using the DSS enables me to accomplish job's tasks PU3: Using the DSS improves my ability to make good decisions.	Davis (1989)
Decision support satisfaction	The degree to which a user believes that he DSS has the capability to assist in decision-making of the user’s jobs	DS1: Using the DSS assists me in making a decision more effectively. DS2: The DSS has met my expectations. DS3: Overall, I’m satisfied with the DSS ability to enables me to make better decisions.	Garrity et al.(2005)
Net benefits	The achievement of a firm’s objectives for using the DSS and achievement of end-user related	N1: The DSS enhances my awareness and recall of job related information N2: The DSS enhances my effectiveness in the job	Gable et al. (2008) Iivari (2005)

Constructs	Operationalization	Survey items	Sources
	objectives from using them	N3: The DSS is cost effective N4: The DSS has resulted in overall productivity improvement N5: The DSS has resulted in improved business processes	

Sampling and data collection

The data for this study was gathered by means of a questionnaire survey. The study was conducted in the flight operations department in royal Jordanian airlines in Jordan. The flight operations department is implementing a customized DSS as a tool for supporting decisions related to how flight operations are conducted in a safe and efficient manner, the department workflow; the way duties are carried out, the flow of information between sections, how to enhance the performance of the department employees. The unit of analysis in this study was the individual who had experience using DSS. Accordingly, the questionnaires were distributed to all DSS users within the department from different job levels.

Prior to the questionnaires distributions, the first draft of instrument was pre tested by three researchers and experts in the fields of IS each one with practical and/or academic experience. Each expert was provided with a working definition of the construct being measured, and was asked to rate: how well they felt individual statements reflected the stated definition; their opinion of whether the questions were likely to accurately measure each dimension; whether the questions were vague, ambiguous, difficult to understand, or had contradictions; whether there was incompatibility between any item and the dimension it was supposed to measure; and whether there were any set of items that did not fully capture the dimension it was supposed to measure. The aim was to detect and remedy errors in the instrument design (Cavana et al, 2001), and they also assist in translation and validating the Arabic version of the survey which distributed to DSS users. After the pre-testing stage, a modified questionnaire was developed for the purpose of conducting a pilot study. The measurement instrument was then pilot tested among a small sample of seven DSS users who were not included in the main survey. The objective was to examine whether the respondents had difficulty answering the questionnaire, as well as test the reliability and validity of the scales. Based on the pilot study results, minor revisions were made to the questionnaire to reduce ambiguity and simplify interpretation.

The questionnaires were then distributed to the respondents through an officer/coordinator from the flight operations department. A covering letter explaining the purpose of this study was attached together, assuring them of the confidentiality of their responses, and instructing them to complete the questions, Out of the 160 questionnaires distributed, 99 usable questionnaires were returned, yielding a response rate of 61.8 percent, which is considered to be adequate for this type of study.

There were 77 male and 22 female respondents. The age range of the sample was from ages 30 to 55 years with a mean of age 42 years. Out of 99 respondents, 97 had achieved at least a high school qualification. Approximately 87% of the participants had more than 4 years' experience in using DSS.

5. Data analysis and results

Data analysis using Structural Equation Modeling Approach

Partial least squares-structural equation modeling (PLS-SEM) was used for data analysis and hypotheses testing using smartPLS software version 3.1.7 (Ringle, et. al, 2014). PLS-SEM is a structured equation modeling technique that can analyses structural equation models involving multiple-item constructs, with direct and indirect paths. PLS-SEM works by extracting successive linear combinations of the predictors and is effective in explaining both response and predictor variation (Davcik, 2014).

PLS-SEM can simultaneously evaluate the measurement model (the relationships between constructs and their corresponding indicators), and the structural model (the relationship among constructs) with the aim to minimize error variance (Chin, 2010; Hair et al., 2014). It generates loadings between reflective constructs and their indicators, weight between formative constructs and their indicators, standardize regression coefficients between constructs, and coefficients of multiple determination (R^2) for dependent variable (Davcik, 2014).

A PLS-SEM analysis involves two stages (Chin., 2010): (1) the assessment of the measurement model, including the individual item reliability, internal consistency, and discriminate validity of the measures, and (2) the assessment of the structural model. The measurement model describes how each construct is measured by corresponding manifest indicators. The structural model shows how the latent variables are related to each other, it shows the constructs and the path relationships between them in the structural model.

In this study, we have chosen PLS-SEM as the primary data analysis technique because of its minimal requirements regarding the sample size, as it does not assume multivariate normality and takes into account the measurement error when assessing the structural model. A rule of thumb for the required sample size in PLS-SEM is that the sample should be at least ten times the number of independent variables in the most complicated multiple regression of the model (Chin, 2010). The sample size in this study met the minimum sample size requirement. According to Hair et al.'s (2014) guidelines, the minimum number of respondents for this PLS-SEM analysis should be 60 observations. Our survey had an N of 99 observations, which exceeds the general rule requirement.

This study applied PLS-SEM to validate the study constructs and to test the hypotheses. The study applied PLS-SEM path modeling with a path-weighting scheme for the inside approximation (Chin, 2010). Then, we applied the non-parametric bootstrapping approximation with 100 resampling to obtain the standard errors of the estimates (Hair et al., 2014).

The measurement model assessment

To start with, we examine each set of predictors in the structural model for collinearity. According to Hair et al. (2014) collinearity arises when two indicators are highly correlated. When more than two indicators are involved, it is called multicollinearity. A related measure of collinearity is the variance inflation factor (VIF), defined as the degree to which the standard error has been increased due to the presence of collinearity. Each predictor construct's tolerance (VIF) value should be higher than 0.20 and lower than 5. Table 2 shows that there no multicollinearity problem among the exogenous variable, since the VIF values are below 5.

Table 2. Collinearity using VIF

Constructs	**Perceived usefulness**	**Decision Support Satisfaction**	**Net Benefits**
Information quality	2.647	2.469	
System quality	2.003	2.368	-
Ease of use	1.940	2.340	
Perceived usefulness	-	2.109	1.531
Decision support satisfaction	-	-	1.531

Based on satisfactory result of collinearity assessment, then the adequacy of measurement model was evaluated based on reliability, convergent validity, and discriminate validity. Reliability was tested using the Cronbach's alpha α and composite reliability (CR) values. Table 3 shows that all the values of Cronbach's α and CR for each of the six constructs: information quality, system quality, ease of use, perceived usefulness, decision support satisfaction, and net benefits ranged from 0.709 to 0.870, which were above the suggested threshold of 0.70. Thus, the scale can be considered reliable.

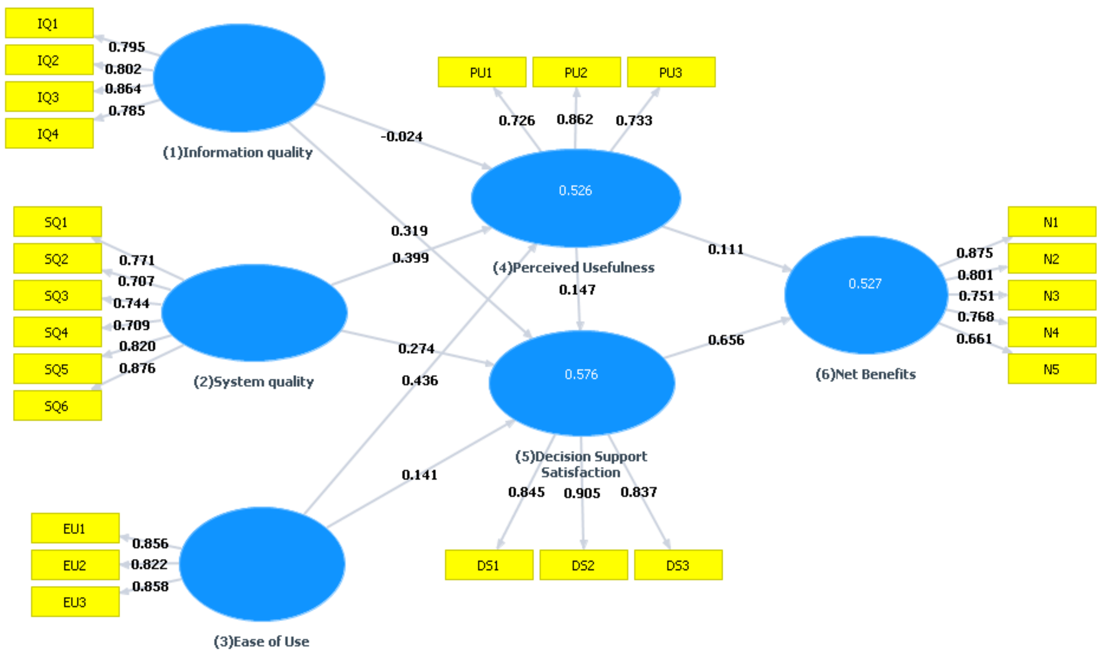
Table 3.the measurement model was tested for reliability and validity.

Constructs	Item	Loading	α	CR	AVE
Information quality	IQ1	0.795	0.882	0.886	0.660
	IQ2	0.802			
	IQ3	0.864			
	IQ4	0.785			
System quality	SQ1	0.771	0.864	0.899	0.600
	SQ2	0.707			
	SQ3	0.744			
	SQ4	0.709			
	SQ5	0.820			
	SQ6	0.876			
Ease of use	EU1	0.856	0.801	0.883	0. 715
	EU2	0.822			
	EU3	0.858			
Perceived usefulness	PU1	0.726	0.773	0.819	0.602
	PU2	0.862			
	PU3	0.733			
Decision support satisfaction	DS1	0.845	0.828	0.897	0.744
	DS2	0.902			
	DS3	0.837			
Net benefits	N1	0.875	0.832	0.881	0.600
	N2	0.801			
	N3	0.751			
	N4	0.768			
	N5	0.661			

Next we test the convergent validity, which is the degree to which multiple items measuring the same concept are in agreement. As suggested by Chin et al. (2010) we used the factor loadings and the average variance extracted (AVE) to assess convergent validity. The loadings for all items exceeded the recommended value of 0.50. The AVE, which indicates that the latent construct accounts for at least 50% of the variance in the items (Hair et al., 2014), were in the range of 0.600 and 0.744 which exceeded the recommended value of 0.5 (Hair et al., 2014) as shown in figure 2 and table 3. As such, both tests indicate an adequate degree of validity.

Discriminate validity was tested using the criteria suggested by Fornell & Larcker (1981). The square root of AVE should be greater than the correlations among the constructs; that is, the amount of variance shared between a latent variable and its block of indicators should be greater than the shared variance between the latent variables. Table 4 shows the inter-correlations of the constructs and variance shared between the latent variables and their indicators. The diagonal elements in Table 3 are the square root of the AVE. This showed that the square roots of each AVE value were greater than the off-diagonal elements. The measurement model, thus, had a reasonable degree of discriminate validity among all of the constructs.

Figure 2: Measurement Model Results



Structural model assessment

The PLS method was also used to confirm the hypothesized relations between constructs in the proposed model. The significance of the paths included into the proposed model was tested using a bootstrap resample procedure. In assessing the PLS model, the squared multiple correlations (R^2) for each endogenous latent variable were initially examined and the significance of the structural paths was evaluated. The proposed relationships are considered to be supported if the corresponding path coefficients had the proposed sign and were significant.

Two measures were used to assess the structural model: the statistical significance (t-tests) of the estimated path coefficients **(β)**, and the ability of the model to explain the variance in the dependent variables, coefficient of determination (R^2). R^2 results represent the amount of variance in the construct in question that is explained by the model (Chin, 2010). R^2 attempts to measure the explained variance of the dependent variable relative to its total variance. Values of approximately 0.35 are considered substantial, values around 0.333 moderate, and values of approximately 0.190 weak (Chin, 2010). To test the significance of the hypotheses, the rule proposed by Martinez-Ruiz and Aluja- Banet (2009) was followed. The t-value >1.65 is significant at the 0.05 level, and the t-value > 2 is significant at the 0.01 level. The statistical significance of each path was estimated using a PLS-SEM bootstrapping method utilizing 200 resamples to obtain t-values (Chin, 2010). Table 5 and Fig. 3 summarize the results of the structural model test. All of the hypotheses, except four hypotheses, are supported. In particular, the results show system quality ($\beta = 0.399$, $p < 0.05$) and ease of use ($\beta = 0.436$, $p < 0.05$) had significant positive effects on perceived usefulness, but information quality had insignificant effects on perceived usefulness, hence H2 and H3 were supported, but H1 was rejected.

The results also provide support for H4 and H5. Information quality ($\beta = 0.319$, $p < 0.05$) and system quality ($\beta = 0.274$, $p < 0.05$) were positively related to decision Support Satisfaction. However, ease of use and Perceived usefulness had significant positive effects on decision support satisfaction. Hence both H6 and H7 were rejected. Moreover, decision support satisfaction had significant positive relationship with net benefits, hence H9 was supported ($\beta = 0.656$, $p < 0.05$), perceived usefulness but insignificant effects on net benefits, hence H8 was rejected. Lastly, the model accounted for 52.6% of the variance explained in perceived usefulness, 57.6% of the variance in decision Support Satisfaction, and 52.7% of the variance in net benefits.

Table 5. Results of Structural Equation Model Analysis

Relations	**β**	**T**	**P**	**Support**	***f²***	**R^2**
H1: Information Quality --> Perceived Usefulness	-0.024	0.16	0.871	No	0.000	0.526
H2: System Quality--> Perceived Usefulness	0.399	3.5	0.001	Yes	0.165	
H3:Ease Of Use --> Perceived Usefulness	0.436	4.49	0.000	Yes	0.206	
H4: Information Quality --> Decision Support Satisfaction	0.319	2.65	0.009	Yes	0.097	0.576
H5: System Quality --> Decision Support Satisfaction	0.274	2.34	0.021	Yes	0.057	
H6: Ease Of Use --> Decision Support Satisfaction	0.141	1.26	0.211	No	0.020	
H7: Perceived Usefulness --> Decision Support Satisfaction	0.147	1.31	0.193	No	0.024	
H8: Perceived Usefulness --> Net Benefits	0.111	1.16	0.250	No	0.017	0.527
H9: Decision Support Satisfaction --> Net Benefits	0.656	8.52	0.000	Yes	0.594	

An additional criteria for assessing structural models in PLS can be found in the literature is the significance of effect size (f^2). The effect size f^2 allows assessing an exogenous construct's contribution to an endogenous latent variable's R^2 value. According to Hair et al., (2014), the f^2 values of 0.02, 0.15, and 0.35 indicate an exogenous construct's small, medium, or large effect, respectively, on an endogenous construct.

f^2 was calculated for significant paths in the model and are presented in Table 4. It is evident that Decision Support Satisfaction (f^2=0.594) has a large effect in producing the R^2 for net benefits and ease of use (f^2=0.206) has a large effect in producing the R^2 for Perceived Usefulness. Further, the path leading from system quality (f^2=0.165) to Perceived Usefulness has a large effect size. All other paths have both a small effect size.

In addition to the effects of the paths, several authors, such as Henseler et al. (2010) and Hair et al, (2014) recommend examining significant indirect effects, as well as direct effects, to gain insight into possible moderating or mediating effects of particular latent variables. Indirect effects can be calculated as a product of direct paths. According to Hair et al, (2014) indirect effects are those relationships that involve a sequence of relationships with at least one intervening construct involved. The sum of direct and indirect effects is referred to as the total effect. The interpretation of total effects is particularly useful at exploring the differential impact of different driver constructs on a criterion construct via several mediating variables.

A detailed analysis of indirect effects produced by SmartPLS (Table 6) leads to conclude that Decision Support Satisfaction (β = **0.656**, $p < 0.01$) can be identified as an important mediating variable because all constructs in the model affect other constructs through this variable. Furthermore, system quality (β = **0.262**, $p < 0.01$) has an indirect effect on net benefits.

Table 6 indirect and total effects (beta values) in the model

	Net Benefits				
	Direct effects	Indirect effects	Total effects	T -value	P values
(1) information quality	-	0.204	0.204	2.079	0.004
(2) system quality	-	0.262	0.262	3.479	0.001
(3) ease of use	-	0.183	0.183	2.489	0.014
(4) Perceived usefulness	0.111	0.096	0.207	1.834	0.070
(5) Decision Support Satisfaction	0.656	-	0.656	9.110	0.000

6. Discussion, Implications, Limitations, and Future Research

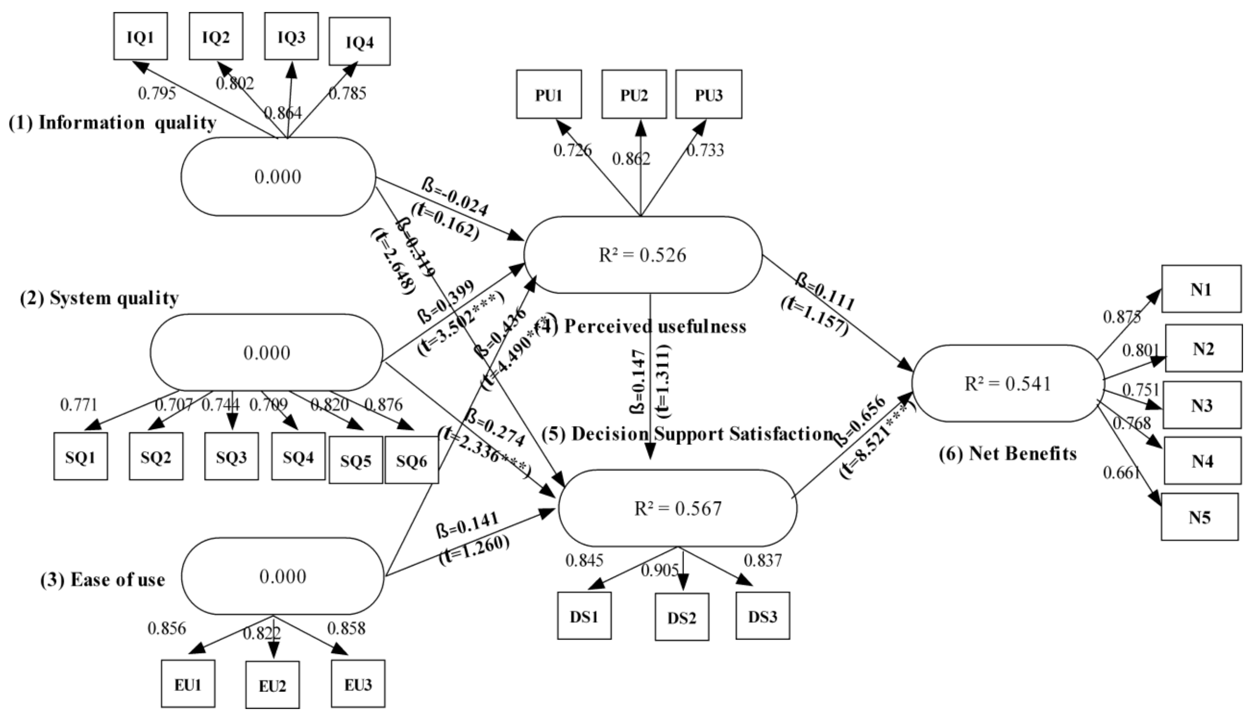
Empirical studies that investigated the DSS success have reported contradictory results. The primary purpose of this study was to develop a comprehensive model of DSS success and empirically validated the causal relationships among the constructs in the model with a field survey. The DSS success model consists of six success measures: system quality, information quality, ease of use, perceived usefulness, decision support satisfaction, and net benefits.

Many of the hypotheses derived from the model are supported. The paths from system quality to perceived usefulness and decision support satisfaction, from ease of use to perceived usefulness, as well as from information quality to decision support satisfaction emerged as hypothesized by the model. However, the paths from information quality to perceived usefulness, from ease of use to decision support satisfaction as well as from perceived usefulness to decision support satisfaction and benefits were not significant. Instead, our results support the path from decision support satisfaction to net benefits.

The empirical results of our study indicate that system quality is the only quality dimension that significantly influences both perceived usefulness and decision support satisfaction. Thus, the quality of the desirable characteristics of the DSS seems to be an important success factor. If available, these features increases users perceived usefulness and lead to a higher overall decision support satisfaction with the DSS. Accordingly, providing additional features and/or improving existing ones may directly increase perceived usefulness and user satisfaction and, consequently, the net benefits gained from using the DSS. Specifically between satisfaction and the extent to which the users believes the DSS allows information to be readily accessible to them, makes information more accessible, DSS user interface can be easily adapted to one's personal approach, the extent to which data within the DSS is fully integrated and consistent, and the extent to which DSS can be easily modified, corrected or improved. Thus, this research supports that literature that has empirically investigated the relationship between system quality and satisfaction, mostly in a non- DSS environment (e.g. Alshibly, 2014). Moreover, an empirically test had verified the direct impact of system quality to the perceived usefulness. These findings partially refine the TAM encompassing. The direct effect between external variable and acceptance, and then, the users' perceptions in the quality of information systems plays the role as a core driving force and external variable to the acceptance of users while facing to new technologies.

The results of this study revealed that DSS information quality have a significant impact on decision support satisfaction. Many studies have found that information quality is important for the success of general IS (e.g. Rai et al, 2002). While our research confirms the previous research in the DSS context, DSS need to provide information to aid users decision-making. The information given by DSS should be just sufficient for the users to make a decision, and care should be taken to avoid giving too much, as this is likely to result in information overload. Users satisfaction may be influenced by the extent to which the DSS providing them with easy to understand information that is relevant to their work, and by providing them with reports that seem to be just about exactly what they need. These in turn, will create a sense of satisfaction with the DSS.

Figure 3: Measurement and Structural Model Results



In contrast, Perceived DSS ease of use found to have insignificant impact on decision support satisfaction, this finding is consistent with other authors' results (e.g. Alshibly, 2011). Our results suggest that the difficulty in using systems is becoming less of a concern as they are increasingly user-friendly. In addition, since systems are more common and standardized nowadays, the users have become increasingly competent in using them. Accordingly, in the planning and development of DSS systems, software developers should pay attention to practical functions and extend key features that are frequently required. Furthermore, this conclusion also suggests that the influence of some factors varies at different stages of the DSS implementation process. It also can be explained by the fact that the users actually using the system are not using it voluntarily, but are forced to use the system that is already owned by the company.

As revealed from the findings, it can be seen that there is a relationship between ease of use and perceived usefulness. The respondents agreed that they found learning to operate the DSS is easy and Interacting with the DSS does not require a lot of mental efforts, in turn, using the DSS enables them perform work's requirements more quickly, accomplish job's tasks, and their ability to make good decisions. This meant that the more users perceive the system to be easy to use, the more they will see it as useful and vice versa.

As expected and consistent with prior research (Garrity et al,2005), the results show that higher levels of decision support satisfaction lead to higher levels of individual and organizational performance(net benefits). The strong and statistically significant impact of decision support satisfaction net benefits supports the suggestion that user satisfaction may serve as a valid surrogate for DSS success (Iivari, 2005). A high level of decision support satisfaction make individuals accomplish their tasks more effectively, increased their productivity, and improved their decision-making quality. Therefore, organizations can improve employee performance if the user has a higher level of user satisfaction with DSS systems. In particular, the results demonstrate the importance of examining decision support satisfaction in explaining user and organization performance. The results also indicate that decision support satisfaction has a stronger effect on net benefits than perceived usefulness. This supports the findings of Gelderman (1998) and Igbaria and Tan (1997). When examining the direct and indirect effects of decision support satisfaction on net benefits, the results show Decision support satisfaction can be identified as an important mediating variable because all constructs in the model affect other constructs through this variable.

The central contribution of this study is the development of a simple model that illustrates the effects of the quality features of DSS systems, including system quality, information quality, accompanied with perceived ease of use and perceived usefulness on decision support satisfaction and DSS net benefits as criteria for DSS success. The model appears to provide useful insights into DSS success. The role of the quality features of DSS systems, including system quality, information quality is not new. However, the developed understanding of the dimensions of each of the two components in the context of DSS, and in the presence of the TAM variables, decision support satisfaction and DSS net benefits, through empirical testing provides new material.

In addition, the framework of this DSS success model enabled the construction of a new instrument which measures quality of the DSS and of different criteria for DSS success. This DSS success instrument is simple, easy to administer and can be used with users of a variety of DSS. This has several benefits for DSS success researchers. At the level of a single study, this instrument can help a researcher select measures of DSS success that will enable him/her to improve explanations of DSS success in his/her theoretical model. At the level of the entire community of researchers who study DSS success, the approach illustrates a disciplined way of creating DSS success measures. In the field of IS research a well-defined outcome measure is essential, yet existing user satisfaction measures are being challenged by changing technology and changing applications. The instrument is an initial step toward such a measure.

This research contribution to the theory is the extension and further empirical testing of the D&M IS success model in a different setting and system context than in previous studies as recommended by various authors (e.g., DeLone and McLean, 2003; Iivari, 2005). Thus, our study advances the theoretical development in the area of such systems, serving as a basis for future research in DSS field. Moreover, by using an established IS theory as the theoretical basis for a benchmarking study, our study is an attempt to apply rigorous research to a practical, highly relevant problem.

Our research has a few limitations; this research is limited in that we used a purposive sampling for the data collection. A random sample from a pool of companies would have increased the generalizability of the results. The model is cross-sectional, which measures users' perceptions at a single point in time. Further studies are recommended to use longitudinal survey because individuals' perceptions are likely to change as they achieve more experience over time. The sample studied is limited to a single company, and needs to cover larger populations and more representative sample, and improved the generalizability of the research outcomes. Despite these limitations, the present study provides valuable insights into the study of DSS success.

In brief, this study provided a structure for understanding DSS success, the detailed framework we built from theory and empirical research provides a foundation for future research.

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