The impact model of business intelligence on decision support and organizational benefits

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Abstract

Purpose – Decision support (DS), as a traditional management concept, have had a remarkable role in competitiveness or survival of organizations and nowadays, business intelligence (BI), as a brand modern impression, has various contributions in supporting decision-making process. Although, a variety of benefits are expected to arise from BI functions, researches, and models that determining the effect of BI functions on the decisional and organizational benefits are rare. The purpose of this paper is to study the relationship between BI functions, DS benefits, and organizational benefits in context of decision environment.

Design/methodology/approach – This research conducts a quantitative survey-based study to represent the relationship between BI capabilities, decision support benefits, and organizational benefits in context of decision environment. On this basis, the partial least squares (PLS) technique employs a sample of 228 firms from different industries located in Middle-East countries. **Findings** – The findings confirm the existence of meaningful relationship between BI functions, DS benefits, and organizational benefits by supporting 15 out of 16 main hypotheses. Essentially, this research provides an insightful understanding about which capabilities of BI have strongest impact on the outcome benefits.

Originality/value – The results can provide effective and useful insights for investors and business owners to utilize more appropriate BI tools and functions to reach more idealistic organizational advantages. Also it enables managers to better understand the application of BI functions in the process of achieving the specified managerial support benefits.

Keywords Decision support benefits, Organizational benefits, BI functions,
Business intelligence (BI) benefits, Partial least squares (PLS) technique

Paper type Research paper

1. Introduction

In response to increasing the importance of information intelligence for managers and their business environment, today's enterprises have made remarkable investments in business intelligence (BI) systems (Hou, 2012). Actually, BI is designed to portray organization's information assets for developing an accurate understanding of business dynamics and making better decisions by information gathering from multiple sources (Aruldoss *et al.*, 2014; Li *et al.*, 2008). One overarching theme that has surfaced in the research is that the BI as a generic term constitutes a set of technologies such as data warehouses, data mining, on-line analytical processing (OLAP), decision support (DS) systems, balanced scorecard, and so on, to improve work-flows and decision-making process (Chen and Wang, 2010; Eckerson, 2010). Mostly, BI system is considered to equip decision makers (DM's) with required information in both tactical and strategic level for understanding, managing, and coordinating the operations and processes in organizations (Tseng and Chou, 2006). In the simplest sense, all these functions are seeking to provide users with acceptable assistance in the decision-making process. By the same token, various benefits of organizational DS have emerged in the academic literature (Turban *et al.*, 2008; Vercellis, 2009). On this basis, BI is thought out as one of the leading areas on information technology and has been set top priority for many executives (Evelson, 2011).

Nowadays, large spectrums of technologies are used throughout the firms as a decision-aid. However, identifying the most appropriate one in considering the required benefits in each decision situation will be helpful in achieving specified results. According to the goal of BI which covers DS in all organizational levels, the understanding of what benefits of DS concept are driven by what functions of BI is important (Howson, 2008). Also, there is a dearth of academic research which investigated the effects of DS benefits on organizational benefits (Rouhani *et al.*, 2012a). Although, we have this lack in literature, in practice context the firms need to prove the relationship between BI functions and their desired benefits to justify their investments in BI projects.

Hence, in this study, we analyze the effect of different BI functions on various dimensions of DS benefits in a conceptual model. Therefore the prepared model which was tested in here provides a new insight to figure out the relation between BI functions, DS benefits, and organizational benefits. Further, the findings of this study enable managers to better understand the application of each BI functions in the process of achieving the specified managerial support benefits and finding the most suitable BI functions with high compatibility to the requirements. Specifically, the paper seeks to address the following research questions:

RQ1. What is the relationship between different BI functions and DS benefits?

RQ2. What is the relationship between different DS benefits and organizational benefits?

In response to the above research questions, this study attempts to explore the relationship between the three main constructs of this study. Based on literature in context of DS concept, the lists of potential salient factors which have taken place under our three constructs are lengthy. Hence, we have chosen to highlight those that have been suggested by previous research, are more important and clearly related to the objective of this study. In light of the above arguments, it will be significant to have an accurate understanding of both BI functions and also benefits of such technology. By the same token, our study makes the following contributions:

- This study provides a comprehensive model which include a coherent set of BI functions, DS benefits, and organizational benefits that are validated using partial least square (PLS);
- It provides an insightful understanding for firms to forefront the importance of analytical and intelligent DS (AIDS), and reasoning function in the way of decision-making process;
- Although, the main objective of this study is so clear, there is no conceptual model before for validating the desired hypotheses and current study to bridge this gap; and

- In this research, we assumed the DS concept as a mediating vein (layer) to correlate BI functions to organizational benefits in order to find both significant and non-significant relationship between them.

The rest of this paper is structured as follows: first, with regard to related studies the importance of DS concept and BI in business environment is discussed as theoretical background. The research model and hypotheses formulation is presented in detail in the Section 3. Then, the methodology (including the data collection and survey questionnaire), are presented in Section 4. Reporting the data analysis results and assessment the measurement and structural model are described in Section 5. The main research contributions from the obtained results are discussed in Section 6. Implications for research and practice are proposed in Section 7 followed by research limitations and future research directions in Section 8. Finally, the conclusion of the research, outlining a brief overview of the paper, is appeared in Section 9.

2. Literature background

Due to the fuzzy nature of BI, it can be understood and identified in several distinct approaches and viewpoints. On one hand, Petrini and Pozzebon (2009) developed two core approaches includes managerial approach with emphasize on excellence of managerial decision making, and technical approach by considering BI as an instrument to support managerial approach. On the other hand, Ghazanfari *et al.* (2011) complement previous studies by presenting a new approach called system-enabler, in which the main focus is on value added features of enterprise systems on supporting required information into decision making. In this study, we define BI among system-enabler approach comprising of broad functions to support the strategic decision-making process by preparing an appropriate DS environment. Moreover, by reviewing DS concept, we separate outcome benefits in two different layers include DS benefits, and organizational benefits. In here, we assume DS benefits as the main benefits derived across the process of decision making. Further, organizational benefits mean all that stems as the outcomes of decisions. In other words, DS benefits are those that originate from the process of decision making. However, organizational benefits are considered as long-term results. In the following, a detailed description in terms of relevant research on BI functions, DS benefits, and organizational benefits are presented.

2.1 The BI functions

To improve strategic orientation and competitiveness of organization, managers need to utilize some specific tools to support their decisions across the decision-making process. From different vantage point, BI can be useful by providing special outcomes to enhance decision-making abilities of DM's (Isik *et al.*, 2013). These tools cover a wide range of techniques and technologies that are used to gather, provide access to and analyze data from the different sources to help DM's in taking more effective managerial decisions (Cheung and Li, 2011; Delen and Demirkan, 2013). Several variant techniques and technologies with DS roles are declared in recent years. Kou *et al.* (2011) stated that integration of multiple criteria decision-making (MCDM) tools and fuzzy ties with DS systems can be more advantageous and considerable for managers to facilitate decision-making process.

Furthermore, different types of channel include mobile channel, web channel, and e-mail channel were considered as supportive tools in theme of organizational decision making (Gao and Xu, 2009). Also, Elbashir *et al.* (2008) introduced databases (data warehouses and data marts) as one of the main functions of BI. Specially, the strategic use of BI in organization ranked in three important field as follows: performance management, monitoring business activities, reporting (Negash, 2004). By the same token, Petrini and Pozzebon (2009) grouped BI functions into three core categories including analysis (data mining and OLAP), monitoring (dashboards, scorecards, alert systems), and reporting.

In addition, Delen and Demirkan (2013) coined a new taxonomy in terms of business analytics including descriptive group, predictive group, and prescriptive group. In their classification, descriptive group seek to well-defined business problems and opportunities. In the same way, the outcome of predictive group is to define accurate projections of the future states and conditions. Further, the prescriptive group is following to provide best possible business decisions and transactions.

In more detailed and comprehensive study, BI is considered in terms of systems-enabler approach which has wide range of functions by Ghazanfari *et al.* (2011) and Rouhani *et al.* (2012a, b). In their classification, thirty four criteria were explored as BI functions, then grouped these criteria into six main clusters including AIDS (F1), providing related experiment and integration with environmental information (F2), optimization and recommended model (ORM) (F3), reasoning (F4), enhanced decision-making tools (EDMT) (F5), and stakeholders' satisfaction (F6) (for more information see (Ghazanfari *et al.*, 2011)). In considering the results of their study, it is obvious that except stakeholders' satisfaction which has been used as a subset of organizational benefits (Turban *et al.*, 2005), the other clusters could be assumed as BI functions.

Considering the above arguments, we employ the factorial model derived by Ghazanfari *et al.* (2011) as a basis for selecting BI functions. Hence, in our approach, we conclude that BI functions of enterprise systems may impact on DS benefits. These functions are AIDS, providing experiments and environmental information (EEI), ORM, reasoning, and EDMT.

2.2 The DS benefits

In twenty-first century, it is expected from managers to improve firm competitive position by adopting just and accurate decisions in complex decision situations. To this end, organizations require a specific type of managerial support systems with supporting role to help them in decision process. Before, various benefits have been listed that motivate organizations to adopt BI. However, it was not feasible to comprise all potential benefits which derive from BI. Therefore, a theoretical construct was determined through reviewing the literature as well as informal interviews with several BI specialists who have valuable knowledge in IT fields. Consequently, we identify the DS benefits into three main constructs (Holsapple and Sena, 2005; Udo and Guimaraes, 1994) as better knowledge processing, reduced decision time, and reduced decision cost which may be impacted by BI functions.

2.2.1 Better knowledge processing. The major challenges of today's enterprises are management required data and turn them into useful knowledge of business decisions (Ranjan, 2008). Indeed, knowledge is viewed as a strategic resource and it can be useful in decision-making context. Therefore, the ability to create information/knowledge is needed to manage the organization effectively (March and Hevner, 2007; Zack, 2007).

Holsapple and Sena (2005) introduced better knowledge processing as a DS benefit which survey it through enhances DMs' ability to process knowledge. Actually, decision-making process entails processing or applying information or knowledge which brings better understanding of the business problems and more new knowledge (Turban *et al.*, 2005). Thus, it can be understood that there is a mutual linkage between decision making and knowledge creation processes (Bolloju *et al.*, 2002). In fact, enterprises need to gain better insight toward its business processes. Also, the capability for information/knowledge processing was considered as a chief expected benefit of organizational support systems. By the same token, Bhatt and Zaveri (2002) declared that, DS can play a major role in enhancing the DM's decision-making abilities. Moreover, they have the potential to serve as a catalyst to improve the decision-making process as they provide the capability to organize and share knowledge, and provide new insight to managers (Shang *et al.*, 2008). "Better knowledge processing" is considered more enhanced ability (quality and value) to process and create knowledge for decision making, in this research.

2.2.2 Reduced decision time. The growing significance of managerial decisions, has been accompanied with complexity and uncertainty in processing information, concluding the process of decision making in the shortest possible time has been proposed as a definite requirements on behalf of the managers (Delen and Pratt, 2006). According to March and Hevner (2007), preparing information into timely manner is required to support decision making in successful way. Actually, it can lead to accelerate the speed of information processing and consequently decision making (Lin *et al.*, 2009). Further, Eckerson (2003) research concluded that time saving is ranked as the highest priority in terms of tangible benefits of DS systems. As Ranjan (2008) stated, to reduce decision time, business users must be able to sort through an increasing volume of knowledge and information quickly. Also, speeding up the decision-making process is considered as the main stimulus to the development of business analytics software. This issue has also been discussed in (Holsapple and Sena, 2005; Turban *et al.*, 2005; Udo and Guimaraes, 1994) as the main benefit of DS environment within the enterprise. In current research "reduced decision time" is considered as a variable which means shortening the period and time of decision-making process by any technical or functional mechanism.

2.2.3 Reduced decision cost. As Hung *et al.* (2007) states, enterprises may be motivated to adopt DS systems in order to reduce decision-making costs. The cost to support decisions with facts was high and usually involved gathering data manually (Howson, 2008). Also, during the process of decision making several costs imposed to the organizations such as wasting ahead opportunities and also spent time for DM's for involvement. Martinsons and Davison (2007) defined cost reduction in decision-making process as one of the major aim of DS systems in practice. Also, Phillips-Wren *et al.* (2004) stated that managerial support systems can be effective on reducing cost of the decision making and organizational performance. In fact, DS systems have a key role in cost reduction by providing DS information (Elbashir *et al.*, 2008). Additionally, cost reduction introduced as one of the most important outputs of DS in context of supply chain management (Sahay and Ranjan, 2008). Chaudhuri *et al.* (2011) argued that BI as an information technology aims to decrease cost of acquiring and storing huge amount of data and consequently reducing cost in decision-making process. In some studies, cost reduction has been documented as the benefits of organizational support systems (Holsapple and Sena, 2005; Power, 2002).

2.3 *The organizational benefits*

Strategic decision making as a critical activity has profound human, financial, and organizational impact into enterprise. Therefore, manager's needs to employ some specific managerial support systems to help them in decision-making path with clear beneficial outcomes for the enterprise. Yet, a wide range of benefits have been listed to employ BI (Oliveira *et al.*, 2012). While some argued that BI systems can brings beneficial opportunities, improving shareholder relations, and can put a company ahead of its competitors (Evelson and Norman, 2008; Lin *et al.*, 2009), others stated that the main purpose of BI is to prepare a support environment to make more effective decisions (Alter, 2004). Generally, applying managerial procedures to enhance organization productivity are valuable when they are capable to establish some tangible benefits across the enterprise. In similar vein, using BI systems can be found beneficial by supporting and enhancing decision-making quality within the firms. In here, we focus on the most important benefits from organizational viewpoint and overlooked indirect benefits such as improved work-flows, etc. Hence, we identify the organizational benefits into three main construct (Ghazanfari *et al.*, 2011; Holsapple and Sena, 2005; Power, 2002) which may be impacted by DS benefits. These are effective decision, competitive advantage, and stakeholders' satisfaction.

2.3.1 Effective decision. BI as a set of processes intends to improve business decisions in both strategic and tactical level (Hill and Scott, 2004). In fact, this structure transformed the role of computer science in companies from a technology for storing data into an enabler for solving strategic decisional problems effectively (Golfarelli *et al.*, 2012). According to Shang *et al.* (2008), these systems proposes a more methodical approach to make better and effective decision. Hung *et al.* (2007) expressed that effective decisions are the typically expected benefits of every organizational support systems. In fact, BI intends to improve business decisions in an effective mode that provides information throughout the organization in both strategic and tactical degree (Li *et al.*, 2008). By using BI, DM's could make decisions more effectively than before by analyzing both unstructured or semi-structured condition (Castellanos *et al.*, 2011; Turban *et al.*, 2008). In current research "effective decision" is considered as an organizational benefit which means: BI function and business analytics impacts on organizational decisions which enable organization to archive its strategic objectives and goals.

2.3.2 Competitive advantage. It is suggested that IT can be a source of competitive advantage (Ross *et al.*, 1996). In such environment, competitive advantage can be provided through extracting of information from wide range of data and instantly response (Castellanos *et al.*, 2011). In here, BI can assist companies to remain competitive by giving an entire overview of critical information at all times. Howson (2008) declared that, adoption of BI in business environment results in enterprises gaining competitive edge. According to Phillips-Wren *et al.* (2004), this could be displayed as the strategic benefit of DS systems. In some case studies, implementing the DS systems provided competitive advantage (Shang *et al.*, 2008). Furthermore, past experiences implies that the application of BI by a company is a potential source of competitive advantage and provides specific competitive weapon in the industry or industries (Elbashir *et al.*, 2008; Kiron and Shockley, 2011; Shang *et al.*, 2008; Williams and Williams, 2010). With appropriate BI (tools or functions), it enables the firm to gain the competitive advantage throughout the industry by making effective decision (Li *et al.*, 2008; Tseng and Chou, 2006). Organizations can gain competitive advantage by leveraging data warehousing technology for BI initiatives (Ramamurthy *et al.*, 2008).

The importance of competitive advantage has also been discussed in (Clark *et al.*, 2007; Power, 2002; Udo and Guimaraes, 1994).

2.3.3 Stakeholders' satisfaction. The term Stakeholders includes investors, owners, board of directors and employees as a whole with different interest and values in the activities of a given enterprise (Vercellis, 2009). Therefore, reaching higher level of satisfaction is crucial aim for each firm. According to Jarupathirun and Zahedi (2007), satisfaction means feeling satisfied, pleased, contented, and delighted about a decision outcome and the technology. Thus, organizations are seeking to adopt special tools such as organizational support systems to help manager's decision, and consequently increase stakeholders' satisfaction. In general, the aim behind all types of DS systems is to increase satisfactory level of stakeholders (Clark *et al.*, 2007). In current research, the Stakeholders' satisfaction implies the consents of investors and owners about decision-making outcomes in organization. The importance of stakeholders' satisfaction as a critical advantage, has also been considered in (Evers, 2008; Holsapple and Sena, 2005; Turban *et al.*, 2005).

3. The research model and hypotheses formulation

Our research model and its hypotheses are highlighted in Figure 1. In this study, we construct the research model based on an extensive reviewe of the literature on BI and DS concept. This study encompasses three main areas: BI functions, based on BI evaluation criteria which was extended by Ghazanfari *et al.* (2011), DS benefits and organizational support benefits which was mainly borrowed from Holsapple and Sena (2005), Udo and Guimaraes (1994), and Power (2002). Although previous research made a contribution about several special benefits in taking appropriate decisions, this study aims to determine the impacts of distinct types of intelligent functions on DS benefits. Therefore, we select the functions of BI which encourage DS benefits to formulate our research model. The proposed model entails five constructs (Ghazanfari *et al.*, 2011) for BI functions, namely AIDS, providing EEI, ORM, reasoning, and EDMT. As better knowledge processing, reduced decision time, reduced decision cost are exactly related to the decision-making process, they are considered DS benefits. Also, effective decision, competitive advantage, and stakeholders' satisfaction are considered as organizational benefits, because they are really the results of decision-making process at organizational level. In brief, our research approach is intended to investigate the relationships between BI functions and its impact on DS and organizational benefits. The statements of hypotheses are completely discussed below.

As mentioned before, analysis function which includes data mining, data warehouse, and OLAP are known as one of the important functions in terms of BI (Petrini and Pozzebon, 2009). Indeed, this function provides the ability for analyzing business information to support and improved decision making in regard to business activities (Elbashir *et al.*, 2008). By the same token and with regard to these functions, Ghazanfari *et al.* (2011) made a self-constituted framework in which analysis tools were settled into more skillfully group namely AIDS function. In brief, the aim behind this function is to support DM's by visual reports and to inform them by alarms and warnings utilizing agents and through channels. Williams and Williams (2010) discussed that the analysis tools equip managers in decision making by providing more detailed and specific information. As Vercellis (2009) states, analysis tools helps in exploiting the available data in order to retrieve information and knowledge which useful in supporting complicated decision-making process. Similarly, Papamichail and

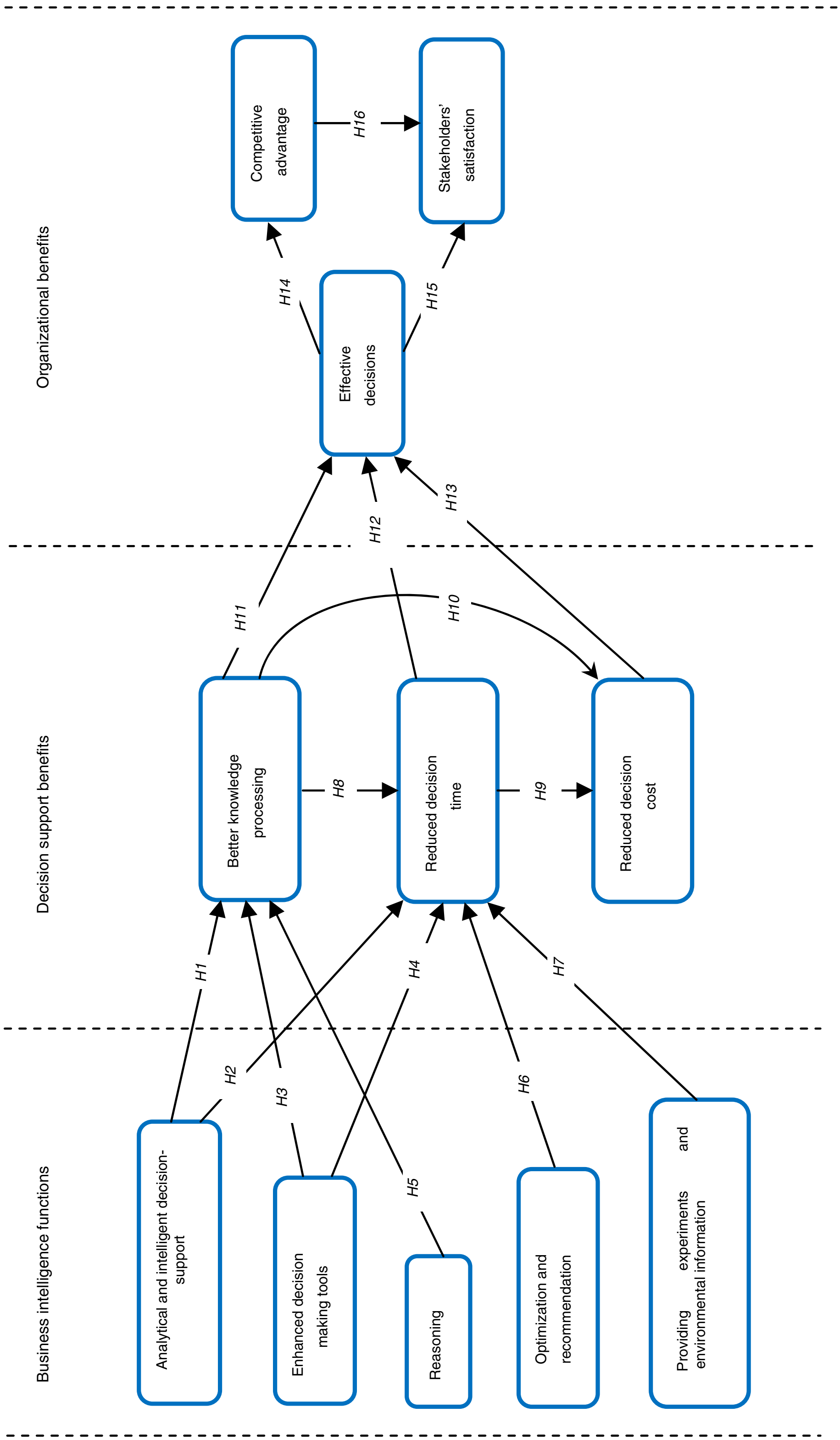


Figure 1. The proposed conceptual model and research hypotheses

French (2005) revealed that intelligent DS lead to promote the capabilities of DM's in better understanding of knowledge. For example, data mining as criterion of AIDS function aims at discovering the potential knowledge to improve managers abilities for taking more accurate decisions (Lee *et al.*, 2009). With regard to decision time, Pal and Palmer (2000) confirmed that this function has also led to faster decision process in form of knowledge processing. Also, Delen and Pratt (2006) have determined that the analysis tools have emerged to equip managers with required information to make accurate decisions by considering the importance of time into account. Moreover, Negash (2004) states, analytical tools in BI systems can play a remarkable role in preparing essential information for planners and DM's. In fact, the aim of these tools is to improve the timeliness and quality of inputs to the decision process. According to the above mentioned, in our model, DS benefits which come from better knowledge processing and reduced decision time are driven and affected by the AIDS function of BI. Thus, the following hypotheses are predicted that:

H1. The AIDS function of BI positively affects DS benefits in better knowledge processing.

H2. The AIDS function of BI positively affects DS benefits in reduced decision time.

DM's are often more interested in verbal and conceptual judgments rather than crisp and certain values. Moreover, DM's needs to consider different aspect of a decision which may be impacted by various criteria. Regarding to this fact, in here, the capability of analyzing fuzzy values and multi-criteria decision making are considered as BI functions (Hung *et al.*, 2007; Yu *et al.*, 2009). Ghazanfari *et al.* (2011) has argued that both these functions are known as EDMT. In the process of decision making, managers face several difficulties with various level of uncertainty (Duan *et al.*, 2012) which indicates the importance of fuzzy logic to deal with a decision situation more effectively. Therefore, the ability to manage uncertainty and fuzzy data is obvious to be critical in an organizational support system (Metaxiotis *et al.*, 2003). At the same time, information as a central item in decision-making process is associated with complexity and uncertainty which means that DM's requires a suitable DS with fuzzy capability in order to afford ambiguity of problems and finally processing knowledge in desired way (Zack, 2007). On the other hand, with regard to the fact that MCDM tools have been developed to solve decision problems with multiple criteria, it can be helpful to improve organizational decision making by providing knowledge processing capability in an efficient manner (Liu and Stewart, 2004). In addition, according to complexity nature of problem solving with multiple aspects, decision-making process requires more time to clarify issues and relationships, and also to identify quantitative and qualitative variables. Thus, MCDM tools and fuzzy logic can play an irreplaceable role in DS environment to reduce decision time (Liu and Stewart, 2004; Wadhwa *et al.*, 2009). Hence, in our model it is reasonable to expect that the DS benefits derived from better knowledge processing and reduced decision time are driven by the EDMT of BI. Thus, the following hypotheses are given:

H3. The EDMT function of BI positively affect the DS benefits in better knowledge processing.

H4. The EDMT function of BI positively affect the DS benefits in reduced decision time.

In each organizational decision making, declaration of reasons are important for giving rationality to DM's. Consequently, in reasoning (REAS) function of BI, the knowledge reasoning and forward and backward reasoning with financial analysis tools are spotted as BI functions. Reasoning function is structured to show why the assumptions should be accepted or are worthy of consideration. In the simplest sense, it can be resulted that the main task of this category lies in the acceptance or rejection of claims (Jarupathirun and Zahedi, 2007). Zeleznikow and Nolan (2001) argued that the reasoning methodologies have the ability to render counsel or recommendations much like a professional by processing knowledge. Moreover, it can be more profitable by transforming data into operational knowledge. Actually, reasoning function could be used to diagnose problems and to manipulate knowledge in different decision situation (Özbayrak and Bell, 2003). By the same token, Gottschalk (2006) and Gao and Xu (2009) also stated that reasoning function in DS systems can be effective knowledge processing in order to provide facilities and ability enhancement for DM's. These previous studies showed that there is positive one-way relation between use of reasoning function and DS benefits in better knowledge processing. For this reason, in our model, better knowledge processing is driven by the reasoning function of BI. Thus, it is predicted that:

H5. The reasoning (REAS) function of BI positively affects the DS benefits in better knowledge processing.

In general, when organizations have to decide in real environment, some tools like risk simulation, prototyping models, optimization, and dashboards can provide instrumental aid in dynamic decision-making process (Bose, 2009; Evers, 2008; Gao and Xu, 2009; Shang *et al.*, 2008). According to Ghazanfari *et al.* (2011) classification, all aforementioned tools are grouped into ORM function. Indeed, the argument covers criteria and specifications which attempt to optimize decision-making results using optimization methods and simulation techniques. Furthermore, interactive optimization via dynamic and evolutionary prototyping is considered and base on them, recommendations to DM would be offered. Yigitbasioglu and Velcu (2012) determined that this function can decrease the time needed for task and decision making through dashboards by understanding a large amount of data in a minimum amount of time. In addition, optimization techniques and simulation models are able to decrease the alternatives of decisions and consequently decrease decision time through representing the possible result of situation (Power and Sharda, 2007; Shang *et al.*, 2008). In the area of dashboards, Williams and Williams (2010) argued that, enterprises are able to provide status information on key performance variables to present relevant and timely information in order to act promptly. Moreover, it can provide critical information using timely and relevant data which can be helpful in decision time reduction (Eckerson, 2010). Although, the relation between "ORM" function and reduced decision time have not been researched formerly, but to some degree these previous studies seem to be indicating that the ORM function have the ability to affect on reducing decision-making time. Therefore, we expect that this function positively affects the reduced decision time as DS benefit. Thus, this leads to *H6*:

H6. The ORM function of BI positively affect the DS benefits in reduced decision time.

According to the importance of acquiring environmental information and overall knowledge for adapting to current settings (March and Hevner, 2007), DS need to empower users by providing relevant information (Vahidov and Kersten, 2004). Therefore, to understand the entire business environment, managers require a kind of function that are mighty to provide a broad span of relevant information (Duan *et al.*, 2012). For this reason, Ghazanfari *et al.* (2011) introduced providing EEI function as one of the five core functions of BI. In here, DM's get support and assistance via importing explicit knowledge and documented experiments from business environments and providing them with groupware to decide by collective intelligence. The collective intelligence emerges from the collaboration, collective experiments and competition of many individuals and appears in consensus decision making. With regard to relation between EEI and reduced decision time, Özbayrak and Bell (2003) note that providing environmental information through importing data and exporting reports can be of assistance to DM's in reducing decision time. Similarly, this function can also have striking effect on decision-making time through problem clustering (Reich and Kapeliuk, 2005). In addition, managers with suitable access to environmental awareness and also using group decision making are able to adopt decisions in more quickly manner (Evers, 2008; Phillips-Wren *et al.*, 2004). To some degree, it is reasonable to expect that reduced decision time is driven by the providing EEI function of BI. Thus, it is predicted that:

H7. The providing EEI function of BI will be positively related to the DS benefits in reduced decision time.

Knowledge as a vital competency keeps DM's informed about what has happened, what is happening now, and what could happen. In fact, it helps the company to be ahead of its competitors by increasing decision-making abilities (Hua *et al.*, 2012). Further, in today's world data are so numerous that technology is needed to cope with this knowledge resource (Hua *et al.*, 2012). Thus, processing knowledge by employing specific DS function may actually be able to decrease the decision-making time reasonably. By the same token, providing a consolidated analysis of the data and integrated reporting functions will help users to make intelligent and correct decisions with more effective decision cost. Shim *et al.* (2002) argued that increasing in decision-making ability will lead to reduced decision costs. Finally, with respect to three stage of decision-making process include intelligence (problem findings activities), design (analyzing alternatives), and choice (selection), it is not surprising if we consider the positive relationship between reduced decision time and reduced decision cost. Thus, it is reasonable to anticipate that, when the time needed for each stage of decision-making process reduced, the cost required for problem searching, analyzing, and selecting an appropriate solution will naturally be reduced. Therefore, the following set of hypotheses is predicted as follows:

H8. The better knowledge processing of DS benefits positively affect reduced decision time.

H9. The better knowledge processing of DS benefits positively affect reduced decision cost.

H10. The reduced decision time of DS benefits positively affects reduced decision cost.

Many researchers have developed different scale for measuring the effectiveness of decision. For instance, Papamichail and French (2005) argued that effective decision can be measured through survey item such as reduction in decision time and costs. Moreover, the effectiveness of a decision-making activity considerably depends on usage on appropriate knowledge and its processing (Bolloju *et al.*, 2002). Bhatt and

Zaveri (2002) had explored that effective decisions are driven by enhancing the capabilities of DM's. In real, Effective decision making requires users to develop appropriate mental representations, where the mental processes that DM's use provide the link between representation and task (Yigitbasioglu and Velcu, 2012). Therefore, due to this fact that some information or knowledge is significantly more valuable than the others, Hill and Scott (2004) expressed that effective business decisions relies on the acquisition, processing, and utilization of relevant knowledge. In here, it can be concluded that better knowledge processing, reduced decision time, and reduced decision cost will lead to effective decisions as organizational benefit. Thus, the following set of hypotheses is presented as follows:

H11. The better knowledge processing of DS benefits positively affect organizational benefits in effective decisions.

H12. The reduced decision time of DS benefits positively affect organizational benefits in effective decisions.

H13. The reduced decision costs of DS benefits positively affect organizational benefits in effective decision.

Evidences indicate that making effective decisions are the most challenging mission that managers face in their managerial responsibilities. The outcome of Bose (2009) study, showed the fact that the organizational decision-making capability in an effective mode is known as a differentiator between successful and unsuccessful firms. According to March and Hevner (2007), managerial decision making must focus on leveraging organizational competencies in order to obtain competitive advantage for the enterprise. In other words, the ability to adopt convenient decisions is one of the primary factors that influence competitive strength of organization (Vercellis, 2009). Similarly, Duan *et al.* (2012) determined that the right handling of information in an effective decision making way permits organizations to take precedence from their competitors. Therefore, in order to stay competitive, organizations must be able to respond effectively to changes in their business settings (Bhatt and Zaveri, 2002; Rud, 2009). By the same token, Howson (2008) investigated that stakeholders' satisfaction is one of the basic expected benefits of BI which make it as a critical application. Rasmussen *et al.* (2002) argued that decision making based on fact-based information is the only way to promote satisfaction between stakeholders. Eckerson (2010) and Mora *et al.* (2003) also stated that taking effective decisions and strategies will lead to satisfactory solution and then satisfaction for all firm stakeholders. In addition, competitive advantage as one of the main results of suitable decision making provides greater satisfaction in both DS and organizational benefits (Holsapple and Sena, 2005) for stakeholders. Thus, it is reasonable to suppose that competitive advantage could be affective on providing more excellent satisfaction for entire stakeholders. Due to this fact, in our model, the competitive advantage and stakeholders' satisfaction are driven by effective decision. Furthermore, stakeholders' satisfaction can be a result of competitive advantage. Hence, the foregoing insight leads to the next set of hypotheses:

H14. The effective decision positively affects competitive advantage.

H15. The effective decision positively affects stakeholders' satisfaction. *H16*.

The competitive advantage positively affects stakeholders' satisfaction.

4. Research method

The research steps including research model and hypotheses formulation, instrument development, data collection, data analysis using PLS, and finally providing research discussion and implications are depicted in Figure 2 and more discussed in this section.

4.1 Instrument development

The questionnaire used for data collection contained scales to measure the various factors of the research model. In considering the acceptable level of error in 10 percent, to measure the constructs, we use a five-point Likert scale for all survey items ranging from "very low (1)" to "very high (5)". Face or content validity of the questionnaire is conducted through the literature review and experts judgment. Content validity refers to the extent to which the items on a test adequately reflect the domain of the content for which they were written. To ensure this, at first six BI systems implementation project managers of high academic levels and more than five-year experience reviewed the questionnaire. They had some comments on the length and the clarity of each question. Their suggestions were incorporated into the final version of the questionnaire. The content validity of the instrument was thereby addressed. Also, for evaluating the reliability of the questionnaire, test-retest method was used. Test-retest determines whether an instrument will produce the same scores from the subjects every time. For conducting test-retest method, authors asked 15 BI project managers in a 14-day interval to participate in the study. The resulted Cronbach's α estimated to be 0.87 (greater than 0.7) that implies good reliability of the instrument (see more information in Table AI).

4.2 Data collection

The research target were Middle East firms which have implemented and used BI system for at least one year time period. It is due to the fact that the results of some studies

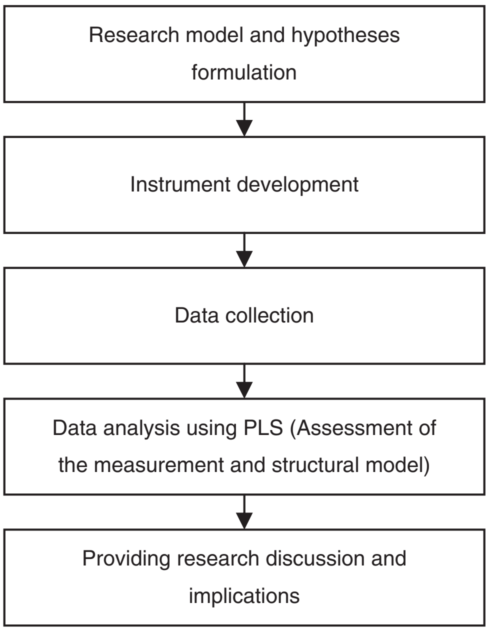


Figure 2. The research steps

suggest that the full effects of ISs for firms do not surface until after a considerable time-lag (Hunton *et al.*, 2002; Poston and Grabski, 2001; Rouhani and Zare Ravasan, 2013). From each of our research target, one Chief Information Officer (CIO) was selected as the key informant, because he/she is an executive-level manager who knows about the firms strategy, as well as IT issues (Chun and Mooney, 2009). The data for this study was collected by a survey sent out via mail and e-mail from April to July 2013. The survey questionnaire along with a cover letter was sent to the respondent of each firm. The letter served as a guide to fill out the questionnaire as well as to highlight the research rationale. About 750 surveys were sent to the firms. The returned questionnaires were 248, which showed the response rate of 33.06 percent. In total, 20 of the returned questionnaires were discarded because they were not completed, so the number of valid questionnaires reduced to 228; that is, the response rate reached 30.4 percent. The profile of the responding firms' demographic profile is shown in Table I.

5. Data analysis

To validate our hypotheses we utilized the structural equation modeling (SEM) for data analysis. We used the PLS technique of SEM that utilizes a variance-based approach for estimation. The specific tool used was SmartPLS 2.0, which was created by Ringle *et al.* (2005). Unlike the covariance-based packages, i.e., LISREL that employs χ^2

Category	Percent of respondents
Industry type	
Automobile dealership	6.2
Bank, insurance, investment	8.2
Chemical and pharmaceuticals	5.8
Dairy, food, and meat products	6.3
Electrical and electronics	4.2
Medical and healthcare	2.5
Information technology (IT)	2.3
Manufacturing	25.1
Retail/wholesale/distribution	14.2
Telecommunications	3.2
Transportation, logistics, and courier	7.3
Construction	2.7
Other	12.0
Revenue ($ millions)	
Over 1,000	22.0
501-1,000	10.0
251-500	17.0
101-250	16.0
Less than 100	32.0
Missing data	3.0
Number of company employees	
Less than 50 employees	21.0
51-100 employees	10.0
101-500 employees	20.0
501-1,000 employees	17.0
1,001-10,000 employees	23.0

Note: Number of organizations = 228

Table I. The demographics of the firms statistics, PLS uses R^2 statistics and does not place strict demands on sample size and data normality. In general, the PLS approach is suitable for predicting the validity of models (Chin, 1998). Two assessments are supported by PLS: the measurement model assessment – here item reliability, convergent and discriminant validities of the measurement scales are examined; and the structural model assessment – this aspect presents information related to the strength of paths in models. The path significance levels using *t*-values are estimated by the bootstrap method.

5.1 Assessment of the measurement model

Internal consistency is demonstrated when the reliability of each measure in a scale is above 0.7. The results for two-item reliability indicators, i.e., the Cronbach's α and composite reliability are shown in the Table II. All of the scales had Cronbach's α and composite reliability exceeding the recommended value of 0.70 indicating adequate internal consistency. Convergent validity is adequate if each of the constructs in the model has an average variance expected (AVE) of least 0.50 (Fornell and Larcker, 1981). AVE measures the percentage of overall variance for indicators represented in a latent construct through the ratio of the sum of the captured variance and the measurement error. The resulted value for AVEs is depicted in the Table II. It is further recommended that the factor loadings of all items should be above 0.60 for convergent validity to be demonstrated (Hair Jr *et al.*, 1995). The factor loadings are presented in Table AII.

Fornell and Larcker (1981) recommend that the following three conditions be met for adequate discriminant validity to be assured: the square root of AVE of all constructs should be larger than all other cross-correlations; all AVEs should have values above 0.5; the principal component factor analysis should have item loadings greater than 0.6 on their respective constructs, and no item should load highly on any other construct(s). The results in Table III indicate that in no case was any correlation between the constructs greater than the squared root of AVE (the principal diagonal element); and all the AVEs were above the 0.5 threshold. The AVEs ranged from 0.51 to 0.78. As well, the SmartPLS confirmatory analysis results showed that all items loaded on the construct for which they were designed to measure. On the whole, our results showed the variance shared between each construct and its indicators are distinct and unidimensional. Thus, the discriminant validity of the scales used for this study is adequate.

Construct	No. of items	AVE	Composite reliability	Cronbach's α
1. Analytical and intelligent decision support	11	0.58	0.94	0.93
2. Enhanced decision-making tools	2	0.78	0.88	0.72
3. Reasoning	3	0.77	0.91	0.85
4. Optimization and recommended model	7	0.62	0.92	0.90
5. Providing experiments and environmental information	9	0.60	0.93	0.91
6. Better knowledge processing	3	0.66	0.85	0.74
7. Reduced decision time	3	0.60	0.82	0.76
8. Reduced decision cost	3	0.56	0.79	0.76
9. Effective decision	3	0.51	0.81	0.78
10. Competitive advantage	3	0.62	0.82	0.77
11. Stakeholders' satisfaction	2	0.67	0.80	0.75

Table II. AVE, composite reliability, and Cronbach's α

Table III. Discriminate validity of the constructs (square root of the AVE and correlations)

Dimension	1	2	3	4	5	6	7	8	9	10	11
1. AIDS	*0.76*										
2. EDMT	0.24	*0.88*									
3. REAS	0.23	0.27	*0.88*								
4. ORM	0.31	0.33	0.30	*0.79*							
5. EEI	0.26	0.11	0.17	0.31	*0.77*						
6. BKNP	0.40	0.19	0.49	0.21	0.19	*0.81*					
7. RDT	0.52	0.19	0.05	0.22	0.35	0.36	*0.77*				
8. RDC	0.33	0.12	0.19	0.12	0.08	0.51	0.52	*0.75*			
9. ED	0.26	0.18	0.20	0.06	0.11	0.51	0.50	*0.57*	*0.71*		
10. CA	0.18	0.11	0.16	0.03	0.06	0.37	0.34	0.38	0.57	*0.79*	
11. SS	0.22	0.11	0.16	0.15	0.19	0.38	0.38	0.38	0.52	0.50	*0.82*

Notes: The italic fonts in the leading diagonals are the square root of AVEs; off-diagonal elements are correlations among constructs

The survey data for this study were collected from a single respondent. Therefore the results being driven by common method bias may be a source of concern. However, multiple reasons associated with this study mitigated any potential effects of method bias. First, we surveyed the CIO of each firm that was knowledgeable about their IT as well as business operations. Such high-level managers are recognized to be reliable sources of information in order to respond at the firm level hence minimizing any issue of common method bias (Narayanan *et al.*, 2011). Furthermore, following Podsakoff *et al.* (2003), we enforced the procedural remedy through counter balancing question order, and improving scale items, such as providing examples to help the respondents understand the unfamiliar concepts. In addition, statistical assessments were performed with multiple methods. Then, all items were put together to perform a Harman's single-factor test. Results show that single-factor model did not well match the sample data, while the multi-factor model matched the sample data with significant improvement. Thus, it seems no common factor exists. In addition, it has been suggested that the problem of common method bias can be less serious for research with a moderation effect (Dong *et al.*, 2009). Therefore, we conclude that common method bias may not be a serious concern in this research.

5.2 Assessment of the structural model

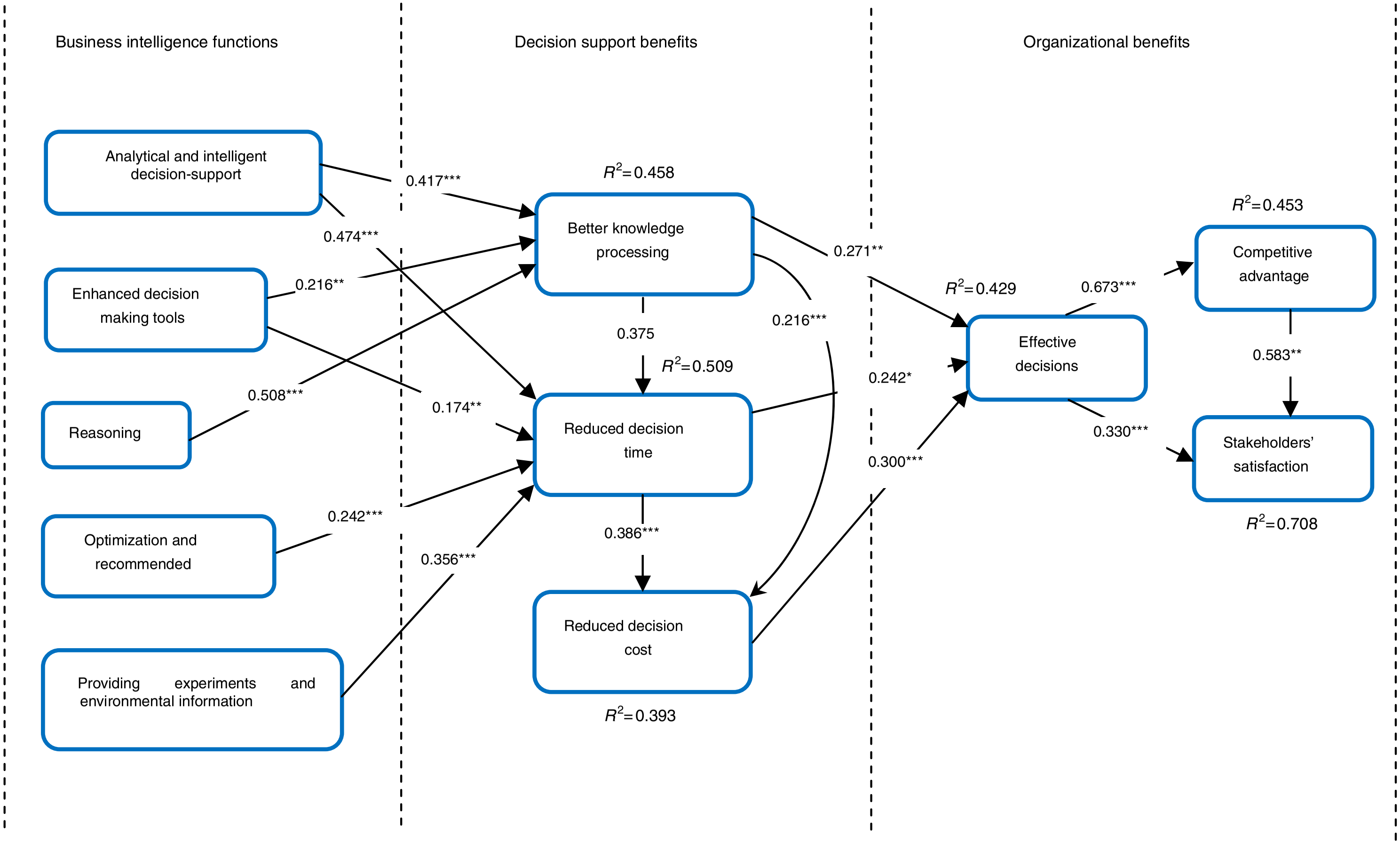
SmartPLS 2.0 provided the squared multiple correlations (R^2) for each construct in the model and the path coefficients (β) with other constructs also given. The R^2 indicates the percentage of a construct's variance in the model, while the path coefficient indicates the strength of relationship between constructs (Chin, 1998). Unlike other SEM such as LISREL, SmartPLS 2.0 does not generate a single goodness-of-fit metric for the entire model. Both the β and the R^2 are sufficient for analysis. The SmartPLS 2.0 results for the βs and the R^2s are shown in Figure 3. Also, the summary of the results is provided in Table IV. All but one of the 16 hypotheses were supported. Contrary to our prediction, *H8* was not supported by the data. That is, better knowledge processing was not found to have a significant, positive association with reduced decision time ($\beta = 0.375$, $t = 1.84$).

The hypothesized path (*H1*) between AIDS and better knowledge processing ($\beta = 0.417$, $t = 6.84$) was confirmed. The data supported *H3*, which predicted a significant, positive relationship between EDMT and better knowledge processing ($\beta = 0.216$, $t = 2.83$). Also, the data supported *H5* indicating that reasoning and EDMT are positively related ($\beta = 0.508$, $t = 8.81$). The three constructs jointly explained 46 percent of the variance in the better knowledge processing construct.

The hypothesized paths (*H2*, *H4*, *H6*, and *H7*) from AIDS ($\beta = 0.474$, $t = 6.42$), EDMT ($\beta = 0.174$, $t = 2.67$), ORM ($\beta = 0.242$, $t = 3.44$), and providing EEI ($\beta = 0.356$, $t = 5.53$), to reduced decision time were all confirmed which jointly explained 51 percent of the variance in the reduced decision time construct.

Reduced decision time has a significant, positive relationship with reduced decision cost ($\beta = 0.386$, $t = 4.75$) to provide support for *H9*. Also, the data supported *H10* indicating that better knowledge processing and reduced decision cost are positively related ($\beta = 0.216$, $t = 4.74$). Better knowledge processing and reduced decision time with all the preceding BI functions layer constructs, jointly explained 39 percent of the variance in the reduced decision cost construct.

Our data found support for the existence of a positive association between better knowledge processing ($\beta = 0.271$, $t = 3.09$), reduced decision time ($\beta = 0.242$, $t = 2.53$), and reduced decision cost ($\beta = 0.300$, $t = 3.32$) and the dependent construct; effective decision to support *H11*, *H12*, and *H13*, respectively. These three constructs, jointly explained 43 percent of the variance in the effective decision construct.



Notes: $*p<0.05$; $**p<0.01$; $***p<0.001$

Figure 3. Results of PLS analysis

Hypothesis	Path coefficient	t-value	Result
H1: analytical and intelligent decision support → better knowledge processing	0.417***	6.84	Supported
H2: analytical and intelligent decision support → reduced decision time	0.474***	6.42	Supported
H3: enhanced decision-making tools → better knowledge processing	0.216**	2.83	Supported
H4: enhanced decision-making tools → reduced decision time	0.174**	2.67	Supported
H5: reasoning → better knowledge processing	0.508***	8.81	Supported
H6: optimization and recommended model → reduced decision time	0.242***	3.44	Supported
H7: providing experiments and environmental information → reduced decision time	0.356***	5.53	Supported
H8: better knowledge processing → reduced decision time	0.375	1.84	Not supported
H9: better knowledge processing → reduced decision cost	0.386***	4.75	Supported
H10: reduced decision time → reduced decision cost	0.216***	4.74	Supported
H11: better knowledge processing → effective decision	0.271**	3.09	Supported
H12: reduced decision time → effective decision	0.242*	2.53	Supported
H13: reduced decision cost → effective decision	0.300***	3.32	Supported
H14: effective decision → competitive advantage	0.673***	13.47	Supported
H15: effective decision → stakeholders' satisfaction	0.330***	4.73	Supported
H16: competitive advantage → stakeholders' satisfaction	0.583***	9.03	Supported

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Table IV. Summary of the results

The predictions related to the positive relationships (*H14*) between effective decision and competitive advantage ($\beta = 0.673$, $t = 13.47$) was significantly supported by the data as well which explained 45 percent of the variance in the competitive advantage construct.

The result also demonstrated a statistical support for hypotheses *H15* and *H16*, which predicted a significant positive relationship between effective decision and stakeholders' satisfaction ($\beta = 0.330$, $t = 4.73$) and between competitive advantage and stakeholders' satisfaction ($\beta = 0.583$, $t = 9.03$). All the preceding constructs totally explained 71 percent of the variance in the dependent construct; stakeholders' satisfaction.

As seen in Figure 3, the relationship with the largest path coefficient is that between effective decision and competitive advantage ($\beta = 0.673$). The least significant path coefficient values are seen for the relationships between EDMT and reduced decision time ($\beta = 0.174$). Further discussion is presented in the next section.

6. Discussion

In response to the challenges of decision-making environment, organizations require to resolve their problems by using various BI functions. In this regard, it is crucial for firms to be aware of the main benefits of each BI function to employ an appropriate functions that fits to their business requirements and follow the strategic and empirical pattern. Therefore, developing a conceptual model for organizations as BI function adoption pattern toward strategic decision making is needed. Hence, the main objective of this study is to investigate the relationship between BI functions, DS benefits, and organizational benefits. The findings empirically display this fact that how BI functions impact on various DS benefits. Similarly, it shows the impact of DS benefits on organizational benefits. Based on research findings, some interesting propositions are exhibited.

As mentioned before in introduction, we had two fundamental research questions. We shall answer the first research question:

RQ1. What is the relationship between different BI functions and DS benefits?

Regarding resulted path coefficients, there are significant relationships among BI functions and different DS benefits. We also shall answer second research question:

RQ2. What is the relationship between different DS benefits and organizational benefits?

To this aim, in DS benefits and organizational benefits layers of our research model, we have examined hypothesized relationship and have proved that these DS benefits have major effects on achieving organizational benefits.

6.1 Discussion on RQ1

The *H1* and *H2* are strongly supported, suggesting that DS benefits on better knowledge processing and reduced decision time are positively impacted by usage of AIDS function in organizations. The main goal of this function is to prepare a DS environment for managers by providing some special analytical report that could be of value in decision-making process. Moreover, this function helps in exploiting the available data to retrieve information and knowledge which is useful in supporting complicated decision-making process. This result can be interpreted that for instance data mining as one of the elements of this function provides valuable and insightful information for DM's through knowledge discovery process, which enhance DM's decision-making abilities and also shortening the decision time. By the same token, some works (Delen and Pratt, 2006; Lee *et al.*, 2009; Negash, 2004) confirmed our prediction before.

H3 argued that using EDMT positively influences better knowledge processing. This issue reveals the fact that managers require a holistic approach to consider different aspect of a decision. At the same time, information as a central item in decision-making process is related to complexity and uncertainty which means that DM's requires a suitable DS with fuzzy functions to cope with ambiguity of problems and finally processing knowledge into desired way (Zack, 2007).

Although, the path coefficient for *H4* is the least between the others, it is supported, which indicates that this function can be effective on reducing decision time. In the simplest sense, this function combines MCDM approach and fuzzy inferences to improve managerial capacity for analyzing and comparing alternatives with higher level of accuracy in a timely manner. Other researchers like Liu and Stewart (2004) and Wadhwa *et al.* (2009) noticed that this function can play an undeniable role in decreasing the decision time.

H5 argues that reasoning function positively influenced better knowledge processing. Reasoning function supports the needs of background logic for each decision making, so in this hypothesis better knowledge processing as a part of decision making, is influenced by this background logic. Consistent with previous research, this function have the ability to propose some useful recommendation in regard to different problem situation by processing knowledge like a professional. Also, it can be effective for managers by preparing special facilitation arguments. This issue has also been discussed in Gao and Xu (2009).

The results for *H6* confirmed a positive relationship between ORM function and reduced decision time. This result shows that optimization techniques are able to decrease decision alternatives and also provide timely and the most relevant information to take decision in the shortest possible time. For instance, dashboards/recommender function as a visual display would improve firm's decision-making process by preparing the most important information at a glance for managers, and consequently limit the alternatives by eliminating unsuitable solution (Howson, 2008). To some degree, our findings were approved in Williams and Williams (2010) and Yigitbasioglu and Velcu (2012).

H7 indicates that providing EEI function positively influenced reduced decision time. In organizational problem solving, the facts and information resources are not limited to internal context and they need to utilize business and external information. In this proved hypothesis this function helps to make decision in the shortest possible time. Some special functions like acquiring environmental information, providing relevant knowledge and also using collective intelligence may be helpful for managers to reduce the decision time. This could be like "absorptive capacity" that represents the ability to exploit outside knowledge, assimilate, and apply it to gain productive ends (Cohen and Levinthal, 1990). Based on Cohen and Levinthal (1990) definition, absorptive capacity within organization attempts to identify, and apply external knowledge from certain areas. In other words, it brings value for organizations through preparing new knowledge received from external sources such as customers, suppliers, or competitors (Liu *et al.*, 2013). In here, this function intends to develop firms' absorptive capacity that would increase decision-making time by excavating higher usable amount of information. To some degree, this result is consistent with prior research (Duan *et al.*, 2012; Evers, 2008; Reich and Kapeliuk, 2005).

The results of survey shows that *H8* which supposes better knowledge processing impacts on reducing decision time, has not been proven. This fact has root in executing issues of better knowledge processing. In precise knowledge discovery process, we need parallel paths to validate extracted knowledge. As a result, better knowledge processing usually needs more mechanism and consequently window time. Insufficient resources and mechanisms cause prolongation of analytical process and accordingly increase of decision time. In fact, the main objective in adopting BI technology by firm is to achieve special capacity in processing knowledge much better. However, applying such technology provides advanced technical solution to improve the achieved quality of data sources. But it should be considered that employing different types of analysis on information would increase analysis latency which cause to decision latency (Watson *et al.*, 2006). Thus, it can be inferred that beyond all benefits of knowledge processing for organizational decision making, it also have negative impact on decision-making process in terms of the decision time. From Figure 3, as expected, we found that both better knowledge processing and reduced decision time exert a significant influence on reduced decision costs which was not surprising. It is necessary to declare that processing organizational information results to cost effectiveness about data gathering and analytics in the process of decision making by eliminating redundant data. Further, consistent with rational, the data were obtained in regard to *H10*, confirmed the fact that cost reduction in decision-making process is driven by reducing the decision time. Thus, we concluded that there is a significant positive relationship between decision time and decision cost.

6.2 Discussion on RQ2

In response to environmental challenges, managers need to access relevant and useful information by considering both time and cost factors. Therefore, it is reasonable to expect that effective decision are driven by *H11*, *H12*, and *H13*. Thus, as predicted by our hypotheses, better knowledge processing, reduced decision time, and reduced decision cost positively affect organizational benefits in effective decisions. These findings are consistent with previous research results (e.g. Bolloju *et al.*, 2002; Hill and Scott, 2004; Papamichail and French, 2005; Yigitbasioglu and Velcu, 2012). In making effective decision, we must consider three main aspects which includes the time and cost of decision making and also processing knowledge to represent more valuable information for DM's.

The *H14* and *H15* are also strongly supported, indicating this fact that both organizational benefits on competitive advantage and stakeholders' satisfaction are positively influenced by taking effective decisions. Therefore, it is suggesting that higher level of effectiveness in the decision-making process provides more competitive advantage for organizations and also more satisfaction for stakeholders. These hypotheses which confirmed by the data provide support to prior works (Eckerson, 2010; Howson, 2008; March and Hevner, 2007). Similarly, the last prediction (*H16*) is approved to posit there is a strong, significant, and positive relationship between competitive advantage and stakeholders' satisfaction. Somewhat the relationship between competitive advantage and stakeholders' satisfaction was explored before; this finding shows that our logical reasoning about the mentioned relationship is supported by the data. Although respondents were not representing the entire stakeholders, but it should be noticed that CIOs society are the best and qualified person to judge the stockholders satisfaction in this field.

In summary, our findings prepare a reliable model to determine the impact of BI functions on DS and organizational benefits. In this study, all hypotheses except one are consistent with our prediction. Based on our results, organizations are able to pick out more apt function by considering their requirements and also decision-making environment.

7. Implications for research and practice

Since, there are few studies assesseing the main benefits of BI function in detail, our findings could provide several insightful implications for both academicians and practitioners as follows.

First, it contributes to the IS adoption literature by empirically preparing a holistic model. Although this research considers the critical issues in terms of BI and DS concept, sufficient explanations in order to justifying the impact of each BI function and also helpfulness for managerial decision making are still lacking. Thus, future research could follow up and use the developed framework into an specific industry to make a new contribution in this line.

Second, the conceptual model is based on an extensive review of literature without considering an specific type of industry. It is encouraged that future research attempt to find other potential factors and investigate the new relationships and make a comparative study to find the main defect of the current paper. Moreover, it would be intresting to refine or change BI functions with another generic classification to demonstrate the results from distinct viewpoint. Third, it should be considered that several legal issue and policies within the industries, could provide different results. In addition, it is recommended for future research to note the importance of moderator variables such as market turbulance and its impact on the achieved results. Actually, considering the effect of such variables in this issue provide an insightful outcome through considering environmental issue on the way that firms could be competitive.

For managers and DM's, the outcome of this study revealed that not all functions of BI technology necessarily accelerate decision-making process. In here, we found that using BI functions prepare a context in which the achieved information could be processed with highly sophisticated methodology to reach competitive knowledge. For this reason, the required time to analyze the achieved information cause to increase analysis latency which also appeared in decision latency. On this basis, it is worth bearing in mind that managers should be aware about the needed time for analysis and focus on the quality of decision making at first, then attempt to find an appropriate solution to decrease the level of decision latency.

In our conceptual model, the competitive advantage is shown as the outcome of effective decision. Hence, it recommended for managers to do their best in the decision-making process by hiring proper function and also create a balance between DS benefits to obtain new pattern from existing knowledge in one hand, and foster the decision-making cycle on the other hand. Besides, the results of this study implied that using "EDMT" function could be beneficial for managers to support decision-making process with decreasing related-time to decision and also processing knowledge more efficiently. Employing fuzzy concept by firms prepare a decision environment with less vagueness of human thought and help DM's to deal with uncertainty. Moreover, using multi-criteria decision-making methods enable them to take more effective action into account by contrasting and analyzing the information from each solution and select the best in this way. Furthermore, managers need higher amount of information to process and reach realistic view from the surrounding environment. So, the growing trend of external information must be considered by managers for gaining the desired goal. In this line, they need using highly sophisticated and complex systems in their firms to process the achieved information and generate higher-value knowledge for increasing decision effectiveness. In here, managers should be noticed that using reasoning function would enable them for processing and analyzing the knowledge in an effective manner.

In terms of EEI function, our finding revealed that this function prepare an insightful fact that companies must pay more attention than before to cope with a large volume of data set and improve their capacity in using external source of data.

Finally, in response to growing interest in using advanced analytics, our findings have remarkable value for enterprises to achieve the promised benefits of BI systems at work based on their business requirements. In this sense, the current study strengthens our understanding about the impact of BI functions on the desired benefits, by presenting a conceptual model as a road map for managers to determine what they precisely need within their firms to reach competitive advantage.

8. Limitation and future research

This study has five main limitations. First, we focussed on a limited number of benefits in terms of DS environment. Although these are known as the most famous benefits, other benefits such as greater reliability, better communication and coordination could also be considered. Second, our research does not have a strong theoretical background in some parts of the relationships between BI function and DS benefits. Although our research model and hypotheses were established through logical reasoning on BI function associated with DS benefits, we did not provide certain robust theoretical background for our model in mentioned sections. Third, there are several different approaches to describe BI, which unconsciously affect and also create bias on participants' responses in here. We tried to minimize this bias by giving a standard and spectrum definition of BI in the questionnaire. Forth, while making generalizations from the research sample, the context of Middle East has to be taken into consideration. It is difficult to establish the validity of findings on the basis of a single study. Further testing of the proposed model should seek to establish its validity in other contexts. Last but not least research limitation, is the choice not to use control variables, such as industry type, organization size or management support, that could potentially influence the dependent variables. We did not include these additional control variables in the model because of our relatively small sample size. Based on mentioned limitations, and in considering the results obtained in the study, it is possible to make some insightful recommendations for future research. First, it is difficult to establish the validity of findings on the basis of a single study. Second, using a broad span of benefits in both DS and organizational context might present more valuable knowledge for organizations. Finally, it is recommended to consider the aforementioned control variables on the model behavior and also mapping the relationships based on decision environment.

9. Conclusion

In this paper, a model for examining the relationship between BI functions and the desired decisional and organizational benefits is presented. This study provide a conceptual framework comprising three major layers: "BI function," "DS benefits," and "organizational benefits" to determine the direct impact of BI functions on both DS and organizational benefits and also shed light on to adopt more appropriate function in regard to firms' requirements. Based on the literature, 11 components such as AIDS, EDMT, reasoning, providing experiments and environmental environments, ORM, better knowledge processing, reduced decision time, reduced decision cost, effective decision, competitive advantage, and stakeholders' satisfaction were identified as the constitutes of those model layers. After finalizing the components of conceptual model, based on literature, our model was designed and the expected relationships were confirmed. The findings of this research, demonstrate that among all the 16 hypotheses only the relationship between better knowledge processing and reduced decision time are not supported. With respect to our results, some respectful and applicable suggestion can be presented as follows: first, due to the relationship between the three layers, we can decide on the precedence of each function than others by considering the degree of importance. Second, determining the most needed functions by considering business requirements and making bridge between them are required, therefore the organizations have a roadmap to implement the right BI functions and evaluate their impacts in an evaluation system based on the research model and findings of this research. Current research provides an insightful understanding about which functions of BI have strongest impact on the outcome benefits. Also, the results can provide effective and useful insights for investors and business owners to utilize more appropriate BI tools and functions to reach more idealistic organizational advantages.

Appendix

Please indicate the level of utilization for each below business intelligence function in your organization
"In this survey BI functions are considered as spectrum from infrastructure to interface which can be useful by providing special outcomes to enhance decision making abilities of decision makers. These functions cover a wide range of tools, techniques and technologies that are used to gather, provide access to, analyze data from the different sources and optimize results to help decision makers in taking more effective managerial and operational decisions"

Label	Items	VL	L	M	H	VH
AIDS1	Visual graphs	1	2	3	4	5
AIDS2	Alarms and warnings	1	2	3	4	5
AIDS3	OLAP	1	2	3	4	5
AIDS4	Data mining techniques	1	2	3	4	5
AIDS5	Data warehouses	1	2	3	4	5
AIDS6	Web channel	1	2	3	4	5
AIDS7	Mobile channel	1	2	3	4	5
AIDS8	E-mail channel	1	2	3	4	5
AIDS9	Intelligent agent	1	2	3	4	5
AIDS10	Multi agent	1	2	3	4	5
AIDS11	Summarization	1	2	3	4	5
EEI1	Group sorting tools and methodology (groupware)	1	2	3	4	5
EEI2	Flexible models	1	2	3	4	5
EEI3	Problem clustering	1	2	3	4	5
EEI4	Import data from other systems	1	2	3	4	5
EEI5	Export reports to other systems	1	2	3	4	5
EEI6	Combination of experiments	1	2	3	4	5
EEI7	Situation awareness modeling	1	2	3	4	5
EEI8	Group decision making	1	2	3	4	5
EEI9	Environment awareness	1	2	3	4	5
ORM1	Optimization technique	1	2	3	4	5
ORM2	Learning technique	1	2	3	4	5
ORM3	Simulation models	1	2	3	4	5
ORM4	Risk simulation	1	2	3	4	5
ORM5	Evolutionary prototyping model	1	2	3	4	5
ORM6	Dynamic model prototyping	1	2	3	4	5
ORM7	Dashboard/recommender	1	2	3	4	5
REAS1	Financial analyses tools	1	2	3	4	5
REAS2	Backward and forward reasoning	1	2	3	4	5
REAS3	Knowledge reasoning	1	2	3	4	5
EDMT1	Fuzzy decision making	1	2	3	4	5
EDMT2	MCDM tools	1	2	3	4	5

Please indicate the achieved level of each below decision support benefits in different decision-making stages in your organization

Label	Benefits	VL	L	M	H	VH
	Better knowledge processing					
BKNP1	In intelligence stage	1	2	3	4	5
BKNP2	In design stage	1	2	3	4	5
BKNP3	In choice stage	1	2	3	4	5
	Reduced decision time					
RDT1	In intelligence stage	1	2	3	4	5
RDT2	In design stage	1	2	3	4	5

Table AI. Questionnaire items (*continued*)

RDT3	In choice stage	1	2	3	4	5
	Reduced decision cost					
RDC1	In intelligence stage	1	2	3	4	5
RDC2	In design stage	1	2	3	4	5
RDC3	In choice stage	1	2	3	4	5
Please indicate the achieved level of each below organizational benefits in your organization						
Label	Benefits	VL	L	M	H	VH
	Effective decisions					
ED1	Clear and specified conclusion	1	2	3	4	5
ED2	Right feeling about your decisions	1	2	3	4	5
ED3	Timely decisions process	1	2	3	4	5
	Competitive advantage					
CA1	Suitable extraction ability from wide range of data	1	2	3	4	5
CA2	Suitable ability to act instantly to environmental challenges	1	2	3	4	5
CA3	Suitable access to entire overview of critical information at all times	1	2	3	4	5
	Stakeholders' satisfaction					
SS1	Acceptable satisfaction between stakeholders'	1	2	3	4	5
SS2	Acceptable level of reliability and accuracy of analysis	1	2	3	4	5

Notes: VL, very low; L, low; M, medium; H, high; VH, very high. Intelligence stage: problem finding activities related to searching of the environment for identifying conditions; design stage: inventing, developing, and analyzing alternatives of action to the problem situation; choice stage: selection of a specific alternative or course of action

Table AI.

	AIDS	EDMT	REAS	ORM	EEI	BKNP	RDT	RDC	ED	CA	SS
AIDS1	0.74										
AIDS2	0.76										
AIDS3	0.75										
AIDS4	0.75						0.41				
AIDS5	0.74						0.41				
AIDS6	0.97						0.50				
AIDS7	0.72										
AIDS8	0.75										
AIDS9	0.72										
AIDS10	0.75						0.41				
AIDS11	0.73										
EDMT1		0.89									
EDMT2		0.87									
REAS1			0.94			0.48					
REAS2			0.85			0.42					
REAS3			0.84								
ORM1				0.75							
ORM2				0.76							
ORM3				0.77							
ORM4				0.95							
ORM5				0.78							
ORM6				0.76							
ORM7				0.78							
EEI1					0.96						
EEI2					0.76						
EEI3					0.75						
EEI4					0.74						
EEI5					0.75						
EEI6					0.75						
EEI7					0.71						
EEI8					0.74						
EEI9					0.76						
BNKP1						0.80					
BNKP2						0.82		0.44	0.45		
BNKP3			0.45			0.82		0.42	0.41		
RDT1	0.45						0.76	0.41			
RDT2	0.44						0.79	0.41			
RDT3							0.76				
RDC1								0.65			
RDC2						0.43	0.40	0.87	0.43		
RDC3								0.71	0.43		
ED1									0.81		0.42
ED2									0.78		
ED3									0.88		
CA1										0.91	
CA2										0.60	
CA3										0.82	
SS1										0.45	0.88
SS2											0.75

Table AII.
Cross-loading values for measurement items

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