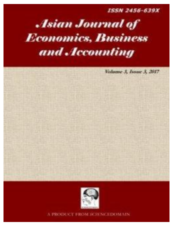

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User Satisfaction and Work Impact of Using Business Intelligence Systems

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Authors' contributions

This work was carried out in collaboration between all authors. Author SMP designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors KCL and CYL managed the analyses of the study. Author KCL managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

With the maturity of the enterprise information environment and the complexity of the enterprise information application, the business intelligence becomes important in the corporate decision-making support context. The purpose of this paper is to explore the user's assessment of the business intelligence systems. In this paper, we adopt quantitative approaches and use the survey as the data collection method. We conducted a questionnaire survey through the Internet, and 115 valid respondents were collected and analyzed. The results show that satisfaction with data quality and user interface of business intelligence systems will affect the user decision support satisfaction. These factors will also affect the task support satisfaction, and thereby affecting the short-term and long-term cognitive outcome of the work.

Keywords: Business intelligence systems; decision support; user satisfaction; work impact.

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1. INTRODUCTION

With the rapid changes in the business environment, it makes the decision makers have the urgent need to get useful information from data. Because of this, many companies paid great attention to manage data flow and to keep track of their data. They tend to spend a lot of time going through multiple reports and documents without getting a good and concrete overview. This is the reason why business intelligence (BI) systems increasing attention. BI systems provide the ability to analyze business information in order to support and improve management decision making across a broad range of business activities [1]. As the decision support features of BI systems, it gets the attention of the enterprises and organizations.

Gangadharan and Swami [2] also point out that managing an organization requires access to information in order to monitor activities and assess performance. Trying to understand what information an organization has can be challenging because the information systems collect and process a vast amount of data in various forms. To flow in the running stream of rapidly changing, increasingly competitive global market scenario and increasingly volatile consumer and market behavior and rapidly shortening product life cycles, enterprises today are necessary to analyze accurate and timely information about financial operations, customers, and products using familiar business terms, in order to gain analytical insight into business problems and opportunities. Enterprises are building BI systems that support business analysis and decision making to help them better understand their operations and compete in the marketplace. In this trend, so that companies must begin to assess the effectiveness of BI Systems.

About the effectiveness of BI systems, Li, Hsieh and Rai [3] based on data from 193 employees using a BI system at one of the largest telecom service companies in China, their findings provide insights on the effectiveness of BI systems. Isik, Jones and Sidorova [4] also examines the role of the decision environment in how well BI capabilities are leveraged to achieve BI success. They examine the decision environment in terms of the types of decisions made and the information processing needs of the organization. Their findings suggest that technological capabilities such as data quality, user access and the integration of BI with other systems are necessary for BI success, regardless of the decision environment. However, the decision environment does influence the relationship between BI success and capabilities, such as the extent to which BI supports flexibility and risk in decision making. Moreau [5] analyzes the impacts of intelligent decision support systems (IDSS) on intellectual task, the main findings of this study are that intellectual workers who are satisfied with IDSS user-friendliness perceive their tasks as being more enriched and the systems themselves as being more useful. In addition, if these users perceive a good job outcome with IDSS, then it may lead to the successful performance of the user's task.

Based on the previous studies, most of them addressed only users' satisfaction but not the decision support satisfaction of BI systems. In this paper, the objective of this research is to understand the decision support effectiveness of the BI systems. There are three research questions: (1) What are the factors influence decision support satisfaction of BI systems? (2) What are the factors influence task support satisfaction of BI systems? (3) What is the work impact of BI systems?

2. LITERATURE REVIEW

According to Reinschmidt and Francoise [6], a BI system is "an integrated set of tools, technologies and programmed products that are used to collect, integrate, analyze and make data available". It means the main tasks of a BI system include "intelligent exploration, integration, aggregation and a multidimensional analysis of data originating from various information resources" [7]. Yeoh and Koronios [8] also have addressed that implementation of BI systems is a complex undertaking requiring considerable resource. Yet there is a limited authoritative set of critical success factors (CSFs) for management reference because the BI market has been driven mainly by the IT industry and vendors. A cross-case analysis of finding the most crucial role in determining the success of a BI system implementation indicates that non-technical factors, including organizational and process-related factors, are more influential and important than technological and data-related factors [9].

Olszak and Ziemba [10] thinks that there are important factors for SMEs, from organization perspective, it includes adequate budget, competent BI project manager (leadership) and skilled (qualified) sufficient staff/team/managers, experience and cooperation with a BI supplier; from process perspective, it includes well-defined users' expectations (information requirements) and adjusting the BI solution to users' business expectations (requirements); and from technology perspective, it includes integration between BI system and other systems (e.g., ERP), appropriate technology and tools and "user friendly" (usability) BI system.

The information systems literature has long emphasized the positive impact of information provided by BI systems for decision-making, particularly when organizations operate in highly competitive environments. Evaluating the effectiveness of BI systems is vital to our understanding of the value and efficacy of management actions and investments. Yet, while IS success has been well-researched, our understanding of how BI systems dimensions are interrelated and how they affect BI systems use is limited. Popovič, Hackney, Coelho, and Jaklič [11] conduct a quantitative survey-based study to examine the relationships between maturity, information quality, analytical decision-making culture, and the use of information for decision-making as significant elements of the success of BI systems. Empirical results link BI systems maturity to two segments of information quality, namely content and access quality. They, therefore, propose a model that contributes to an understanding of the interrelationships between BI systems success dimensions. Specifically, they find that BI systems maturity has a stronger impact on information access quality. In addition, only information content quality is relevant for the use of information while the impact of the information access quality is non-significant. They find that an analytical decision-making culture necessarily improves the use of information, but it may suppress the direct impact of the quality of the information content.

Shollo and Galliers [12] propose an evidence of the performative outcome of BI systems from the perspective of data quality and selection. Chen, Chiang, and Storey [13] find that business intelligence and analytics (BI&A) has emerged as an important area of study for both practitioners and researchers, reflecting the magnitude and impact of data-related problems to be solved in contemporary business organizations. This introduction to the MIS Quarterly Special Issue on Business Intelligence Research first provides a framework that identifies the evolution, applications and emerging research areas of BI & A. BI & A 1.0, BI&A 2.0, and BI&A 3.0 are defined and described in terms of their key characteristics and capabilities. Current research in BI&A is analyzed and challenges and opportunities associated with BI&A research and education are identified. We also report a bibliometric study of critical BI&A publications, researchers, and research topics based on more than a decade of related academic and industry publications. Finally, the six articles that comprise this special issue are introduced and characterized in terms of the proposed BI&A research framework.

Vukšić, Bach, and Stjepić [14] proposed a technology–organizational–environment framework to verify the success factors of adopting BI systems. Hou [15] pointed out that to enhance their management decision-making capability, many organizations have made significant investments in BI systems. The realization of business benefits from BI investments depends on supporting effective use of BI systems and satisfying their end user requirements. Even though a lot of attention has been paid to the decision-making benefits of BI systems in practice, there is still a limited amount of empirical research that explores the nature of end-user satisfaction with BI systems. End-user satisfaction and system usage have been recognized by many researchers as critical determinants of the success of information systems. As an increasing number of companies have adopted BI systems, there is a need to understand their impact on an individual end-user's performance. In recent years, researchers have considered assessing individual performance effects from IS used as a key area of concern. Therefore, this study aims to empirically test a framework identifying the relationships between end-user computing satisfaction (EUCS), system usage, and individual performance. The results indicate that higher levels of EUCS can lead to increased BI system usage and improved individual performance and that higher levels of BI system usage will lead to higher levels of individual performance. In addition, this study's findings, consistent with DeLone and McLean's IS success model, confirm that there exists a significant positive relationship between EUCS and system usage.

Similar to BI systems, users' satisfaction with intelligent decision support systems (IDSS) leads to a good job performance. Factors such as the decision characteristics, decision process, information used in decision making, and decision quality are studied to determine the effectiveness of the IDSS [16]. Boukhayma and Elmanouar [17] extend DSS behavioral/cognitive effects on users and DSS evaluation. Researches lead to using the decision outcomes to evaluate the effectiveness of the systems. Moreau [5] evaluated the impact of IDSS based on task success. Results showed that user friendliness and data quality were significantly linked to work design and then to perceived job outcome. Based on the previous studies, this study proposed a research model include the crucial factors to understand the decision support effectiveness of the BI systems.

3. RESEARCH METHODOLOGY

In this study, we based on the information system success model of DeLone and McLean, and refer intellectual task success model of IDSS from Moreau [5] to explore user satisfaction of BI systems; include satisfaction with data quality, satisfaction with interface quality, decision support satisfaction, and task support satisfaction. About work impact, we divided into short-term and long-term work impact. Thus, this study proposes the following research framework and hypothesis shown in Fig. 1.

Fig. 1 shows our research model with seven hypotheses. The research model aims to identify user satisfaction and work impact of using BI systems. User satisfaction include satisfaction with data quality, satisfaction with interface quality, decision support satisfaction, and task support satisfaction; work impacts include short-term and long-term work impact. Table 1 lists the definitions of constructs used in this study. To test the proposed research model, we conducted a questionnaire survey through the Internet for data collection and examined the proposed hypotheses using partial least squares (PLSs).

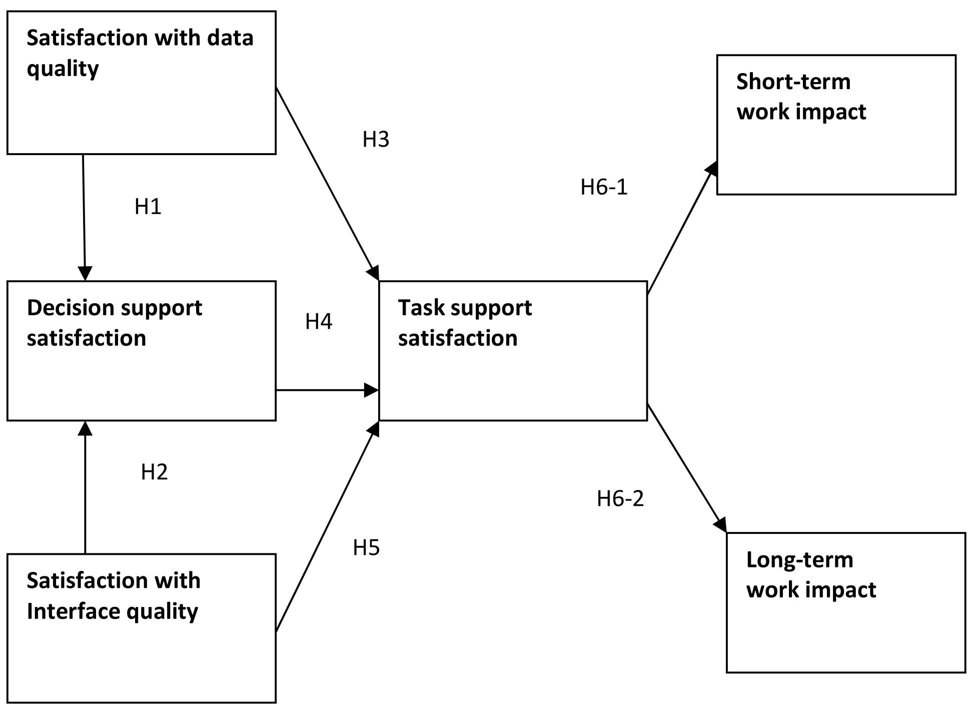

Fig. 1. Research model

H1. The more positive data quality is, the greater decision support quality will be.
H2. The more positive interface quality is, the greater decision support quality will be.
H3. The more positive data quality is, the greater task support quality will be.
H4. The more positive decision support quality is, the greater task support quality will be.
H5. The more positive interface quality is, the greater task support quality will be.
H6-1. The more positive task support quality is the greater short-term work impact.
H6-2. The more positive task support quality is the greater long-term work impact.

Table 1. Operational definition of variables in research model

Variable	Variable definition
Satisfaction with data quality	The degree of the individual's perception of report through using BI systems
Satisfaction with interface quality	The degree of the individual's perception of operation through using BI systems
Decision support satisfaction	The degree of the individual's perception of supporting decision and solving problems through using BI systems
Task support satisfaction	The degree of the individual's perception of completing the work and meeting task requirements through using BI systems
Short-term work impact	The degree of the individual's perception of promoting personal work performance through using BI systems
Long-term work impact	The degree of the individual's perception of increasing opportunities for meaningful work through using BI systems

4. DATA ANALYSIS

The survey was conducted over the Internet and social networks. The respondents were limited to having the experience of BI systems. We collected 115 valid responses, 53.9% was from male and 46.1% was from female. The mode of age category was 20-29 and 30-39. The two categories consisted of 92.2% of valid sample size. In terms of level of education, the largest group completing the survey was college and university (56.5% of valid sample size). Table 2 also summarizes the demographic information and BI system's usage frequency of the respondents. More than 50% of respondents have the experiences regarding data warehousing, OLAP, reporting tools and statistical analysis.

4.1 Measurement Model Analysis

We accessed content validity, convergent validity, and discriminant validity to validate our measurement model. Content validity was done by interviewing two domain experts and pilot-testing the survey instrument by 15 users. We followed the thresholds suggested in the literature to access convergent validity. First, all factor loadings should exceed 0.5 [18]. Second, the average variance extracted (AVE) by each construct should exceed 0.5 [19]. Third, composite reliability (CR) should exceed 0.7 [20]. Composite reliability and Cronbach's α can also be used to access model's internal consistency. Cronbach's α should exceed 0.7 [21]. In discriminant validity, Fornell and Larcker [19] recommended that the square root of the AVE for each construct should exceed other correlation coefficient of the construct. The results are prepared in a cross-loading matrix.

Table 3 summaries the convergent validity and reliability analysis. The loadings ranged from 0.769 to 0.915 exceed the recommended 0.5 threshold. The AVEs ranged from 0.687 to 0.781 exceed the suggested 0.5 threshold. Also, CRs ranged from 0.945 to 0.966 exceed the commonly used 0.7. Hence, all three criteria of convergent validity were met. In addition, Cronbach's a ranged from 0.931 to 0.962 exceeds 0.7. The model's internal consistency

Table 2. Demographic information and BI system's usage frequency of respondents

Measure	Category	Frequency	Percent (%)
Gender	Male	62	53.9
	Female	53	46.1
Age	20-29	57	49.6
	30-39	49	42.6
	Above 40	9	7.8
Education	High school	8	7.0
	College and university	65	56.5
	Graduate school	42	36.5
Tools of BIS	Data warehousing	78	67.8
	OLAP	64	55.7
	Data mining	35	30.4
	Dashboard	36	31.3
	Reporting tools	79	68.7
	Statistical analysis	70	60.9

was acceptable. Moreover, the square root of the AVE of each construct (numbers in the diagonal of the cross-loading matrix in Table 4) exceeds other correlation coefficient of the construct (off-diagonal numbers in the corresponding rows and columns), demonstrating discriminant validity.

4.2 Structural Model Analysis

Since PLS does not provide overall model fit, it is required to use R^2 to determine the explanatory power of the model. The path coefficient shows the strength and direction of the relationship between two constructs. R^2 represents the percentage of explained variability. Thus, larger R^2 provides better explanatory power [22]. The bootstrapping method can be used to determine the significance of model path coefficients when testing hypotheses in the structural model. In this study, we built the PLS structural model based on seven proposed constructs, using path coefficients and R^2 to test our hypotheses and the explanatory power of the model.

In order to determine the significance of the path coefficient, bootstrapping method in PLS was used to compute test statistic t value. The significance of coefficient can be reached in different levels with different t values ($p < 0.05$ when $t > 1.96$; $p < 0.01$ when $t > 2.58$; $p < 0.001$ when $t > 3.29$). Fig. 2 summarizes the results of the analysis with significance level highlighted next to the coefficient of paths. We found significant support between Data Quality and Decision Support Quality ($b = 0.648$, $t = 6.252$, $p < 0.001$), between Interface Quality and Decision Support Quality ($b = 0.23$, $t = 2.137$, $p < 0.01$), between Decision Support Quality and Task Support Quality ($b = 0.23$, $t = 2.337$, $p < 0.01$), between Interface Quality and Task Support Quality ($b = 0.576$, $t = 6.355$, $p < 0.001$), between Task Support Quality and Short-term Work Impact ($b = 0.849$, $t = 28.904$, $p < 0.001$), between Task Support Quality and Long-term Work Impact ($b = 0.8$, $t = 20.262$, $p < 0.001$). The R^2 of the constructs ranged from 64.0% to72.1%, suggests the good explanatory power of our research model. Fig. 2 summarizes the results of path coefficient analysis. All hypotheses were supported except H3.

Table 3. Convergent validity and reliability analysis

Construct	Item	Average	Standard deviation	Factor loading	t value	Composite reliability	Average variance extracted	Cronbach's α
DQ	DQ_1	4.983	0.053	0.798	15.188	0.956	0.704	0.961
	DQ_2	5.104	0.066	0.809	12.349			
	DQ_3	5.174	0.027	0.902	13.824			
DSS	DSS_1	5.113	0.027	0.885	13.436	0.945	0.711	0.931
	DSS_2	5.070	0.030	0.869	19.122			
	DSS_3	5.157	0.053	0.809	15.320			
UIS	UIS_1	4.930	0.050	0.769	15.316	0.966	0.687	0.962
	UIS_2	4.991	0.026	0.852	13.447			
	UIS_3	5.000	0.034	0.793	13.043			
TSS	TSS_1	5.009	0.045	0.846	18.928	0.955	0.781	0.943
	TSS_2	5.035	0.017	0.908	12.082			
	TSS_3	5.017	0.017	0.915	13.373			
STW	STW_1	4.991	0.040	0.874	11.923	0.947	0.749	0.933
	STW_2	5.052	0.044	0.871	19.874			
	STW_3	5.035	0.025	0.895	15.901			
LTW	LTW_1	4.826	0.044	0.822	18.726	0.947	0.717	0.934
	LTW_2	4.843	0.032	0.824	15.441			
	LTW_3	4.765	0.023	0.882	17.928			

Table 4. Correlation between constructs

Construct	DQ	DSS	UIS	TSS	STW	LTW
DQ	0.839					
DSS	0.817	0.843				
UIS	0.732	0.705	0.829			
TSS	0.712	0.719	0.813	0.884		
STW	0.743	0.788	0.750	0.849	0.865	
LTW	0.618	0.618	0.748	0.800	0.764	0.847

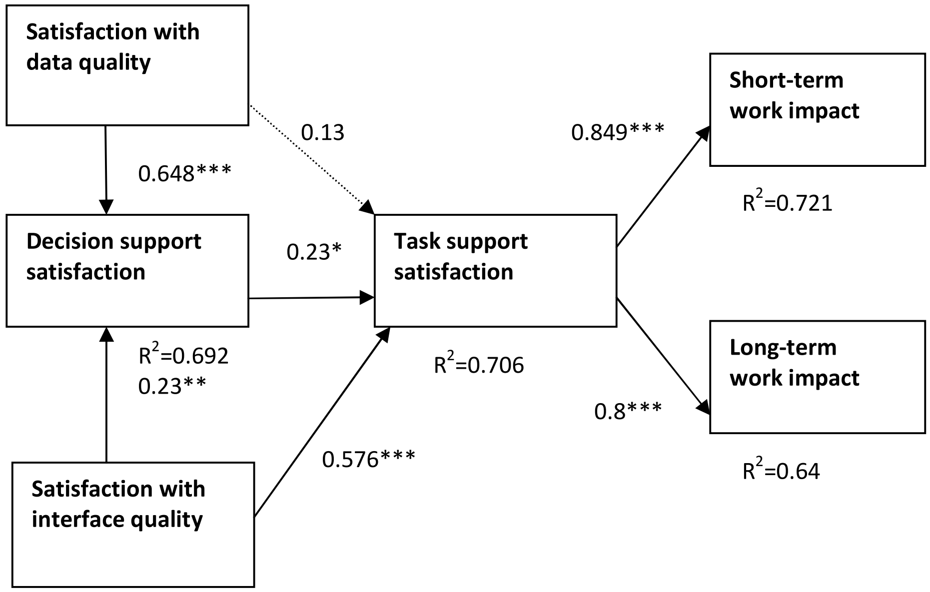

Fig. 2. Results of structural model analysis

5. CONCLUSIONS

In the past, academic research on the issue of information systems success is quite rich. Many researchers adopt user satisfaction as a predictive factor for information system success. Other than user satisfaction, task satisfaction and work impact should be more interested in the enterprises adopting BI systems. In order to evaluate the effectiveness of BI systems, this study focuses on the decision-making capacity and support of business intelligence system. In this paper, we define variables based on IS success and DSS success and propose our research model. We use data quality satisfaction, interface satisfaction, decision support satisfaction, and task support satisfaction as the measurement of satisfaction of BIS. The research finding indicated that data quality directly influences decision support satisfaction, and indirectly influences task support satisfaction. Besides, task support satisfaction significantly influences short-term and long-term work impact. Results showed that decision support satisfaction plays the key role in the proposed model. To increase the effectiveness of the BI system, the systems have to provide the satisfying decision supports which partially come from the accurate data and the satisfying interface quality. The representativeness of the samples may not be strong; it is suggested to adopt a different sampling approach to obtain samples more normally distributed. Although the proposed hypotheses were tested through statistical quantitative analysis, it is suggested to analyze the research questions qualitatively through in-depth interviews. Future studies may focus on these limitations, and be able to conduct a more comprehensive analysis of the BI Systems.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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