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## The Role of Organizational Support and Problem Space Complexity on Organizational Performance – A Business Intelligence Perspective

Shin-Yuan Hung<sup>1</sup>, Kuanchin Chen<sup>2,\*</sup>

<sup>1</sup>National Chung Cheng University, Taiwan, ROC, [syhung@mis.ccu.edu.tw](mailto:syhung@mis.ccu.edu.tw)

<sup>2</sup>Western Michigan University, U.S.A., [kc.chen@wmich.edu](mailto:kc.chen@wmich.edu)

### Abstract

**Background:** *In today's business environment, BI systems are frequently bundled together or built with a good connection to existing ERP systems. Businesses implementing BI alone may not receive its full benefit if the necessary support structure and a fit of it to its problem domain are not in place.*

**Methods:** *In this study, we explored organizational support and problem space complexity in three models (base, direct-effect and moderation models) to study BI's effect on organizational performance.*

**Results:** *The moderation model explains the most variance of the dependent variable – organizational performance. Problem space complexity had both a direct effect on organizational performance and the relationship between BI implementation and this dependent variable. Organizational support along with its first-order factors did not have statistical significance on organizational performance.*

**Conclusions:** *The resulting moderation model provides the best explanation of organizational performance among the three models tested. The confirmed effects of problem space complexity show that matching BI implementation to the complexity of the problem in hand drives business performance. Organizational support may not be consistently required throughout all stages of BI adoption. As the BI literature has shown, the effect of organizational support on BI implementation could very much be on individuals in areas of affective commitment, extra-role performance and end-user satisfaction. Our work provides the beginning empirical evidence that such effects on individuals may not always result in business performance.*

**Keywords:** Business Intelligence Implementation, Business Intelligence Radicalness, Organizational Performance, Organizational Fit, Organizational Support.

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## Introduction

The business environment has transformed so rapidly that timely and effective business information is now critical to the survival of today's businesses (Lönnqvist & Pirttimäki, 2006). Analytical business intelligence (BI) techniques and visualization tools are on the rise to meet today's business demands (Ramakrishnan, Jones, & Sidorova, 2012; Howson, Richardson, Sallam & Kronz, 2019). This trend is evidenced in numerous reports and academic studies showing BI on the technology priority list of firms (Shariat & Hightower, 2007; Watson & Wixom, 2007; Yeoh & Koronios, 2010; UL-Ain et al., 2019). As BI relies on operational data collected and stored in a consistent manner (Saha, 2007) many ERP vendors are beginning to offer BI as an extension or an integral part of their systems. Examples include SAP's Business Objects BI Suite, IBM's Cognos BI, and Microsoft's SQL server and related services. Integration of BI with other systems is a highly desirable feature that can be done at the data, application, business process or user level (Isik et al., 2013).

Moreover, the empirical assessment of BI adds value to our understanding of how it relates to other individuals and organizational theories. Interest in its empirical research has gradually increased over the years. Jourdan et al. (Jourdan et al., 2008) reported in 2008 that BI research had been predominantly technical with only 3.59% (6 out of 167) articles being empirical studies. In 2014, Aruldoss et al. (2014) reported a list of "ongoing research" in BI compiled from the existing literature showing that the technical development of BI infrastructure (including systems, algorithms and techniques) still plays a major role in the current research (23.53%), while there is a growing interest in its role in business performance (15.69%). After years of refinement of the technical capabilities of BI, it is natural to see that the business focus has now shifted to how BI can be leveraged to improve organizational performance (Williams & Williams, 2003). As UL-Ain et al. (2019) work shows, the majority of BI studies adopted DeLone & McLean's IS Success Model, Technology Acceptance Model, and Diffusion of Innovation Theory, but little attention has been placed on other theoretical models or frameworks.

BI's application spans across functional areas, ranges of user base, and types of problems (Ahmed et al., 2019). As Ahmed et al. show, the applications of BI vary even across industries, but can still be broadly categorized into financial (e.g., reduce delivery time, track financial health, cost savings from supplier diversification, and benchmarking for pricing trends) and non-financial (e.g., visibility to customers, procurement performance, information availability & accessibility, and insights on consumer behavior). As BI systems require skills to excel and it impacts a range of users both individually and as a group, various forms of organizational support (such as resources for training, management endorsement, external consulting support) are critical to the success of BI implementations (Ali et al., 2018). Similarly, no single tool is best for all occasions. BI is not an exception. The complexity of the problem and the sheer amount & variety of information sources are strong reasons for BI adoption over simple technological tools. Therefore, organizational support, problem complexity and the nature of business data are all critical to the success of BI. Despite the value of the above theoretical trends in diffusion of innovation and the IS success model, the impact of BI on an organization goes beyond information & system quality, user adoption and technological diffusion. Here in this study we follow another line of research to study how organizational factors, problem complexity and information requirements help transform BI into business performance.

Recent BI studies on organizational performance have provided empirical insights into the effect of the business process performance (Elbashir et al., 2008), business process management (Vuksić et al., 2013), process effectiveness (Richards et al., 2017), innovativeness & network learning (Caseiro & Coelho, 2018) and absorptive capacity (Elbashir et al., 2011). Despite this recent effort, some key business factors (such as organizational support, problem space complexity, business process and characteristics of

information sources that have been of high interest in business disciplines) either have not entered the scene of BI research on organizational performance, or have just started to receive attention.

Despite technical soundness, BI implementation alone does not always lead to organizational performance without the necessary ingredients. In the present study, we are interested in how perceived organizational support, problem space complexity and other non-technical factors drive the success of BI and eventually affect business performance. As these organizational factors are frequently seen to be influential in some systems other than BI (such as ERP and Management Support Systems) as well, examining their effects on the BI-organizational performance relationship will help shed light on how well they play in the BI context.

Furthermore, both BI and ERP are major initiatives that could impact multiple functional areas of an organization during and after their implementation. Some common key requirements (such as top management support) are critical to the success of both systems. This is the reason common organizational support factors are cited in both the ERP and BI literature (Akkermans & Helden, 2002; Henderson & Venkatraman, 1993; Olszak & Ziemba, 2012). Despite the similarity in these success factors, the intended purposes of the two systems are quite different. The effectiveness of BI also depends on how its capabilities provide a good fit to the problem space environment as it becomes more complex, competitive and dynamic (Catellanos et al., 2012; Clark & Jones, 2008; Cooper et al., 2000). When the complexity of the problem space is low, BI may be considered an overkill. Simpler tools, such as Excel, are favored. This could be due to habitual use or other reasons. For example, Polites and Karahanna's work (Polites & Karahanna, 2012) found that habitual use of an existing system affects one's technological inertia, which in turn affects perceived ease of use, relative advantage and the intention to use a new system. However, ERP integrates business functions, embeds business processes into the system, and possibly replaces existing information systems that requires transformation of current business practices (Hawking & Sellitto, 2010), while BI is used to empower existing business practice or offer the necessary insights for business transformations (Chou et al., 2005). As a result of their requirement or even the degree of intrusiveness into the existing business practice, the success factors are likely to exert different effects on how the implementation of a system leads to business performance. Therefore, a study on the effects of organizational support factors and problem space complexity on the relationship between BI implementation and organizational performance will add insight to our understanding of how these external factors relate to BI's success. To date, there has been very little empirical research filling this gap.

Based on the above outline of current research gaps, the following research questions are devised to guide our approach to address these short comings.

*RQ1: what structure of managerial support and problem space best captures the effect of BI implementation on organizational performance?*

*RQ2: knowing that both ERP and BI require many common success factors, does the existing validated ERP model generalize well to BI?*

*RQ3: Do managerial support and problem space complexity factors affect organizational performance through the implementation of BI?*

## Background

### *BI Success Factors*

Identification of success factors can help shape the scope of requirements for initiation, implementation and the sustaining of benefits for information systems. In BI, critical success factors have been identified at multiple levels, including organization, process, technology, infrastructure, process, and management support (Isik, 2009; Yeoh & Koronios, 2010). Although not all studies agree on a common set of success factors for BI, Olszak and Ziemba's work shows that top management support, project management, resource availability and skilled staff are among the top success factors frequently mentioned in the majority of BI studies. Additionally, recent work (e.g., Isik et al., 2013) on success factors has started to focus on the role of the decision-making environment in BI success. The decision-making environment studied in Işık (Isik et al., 2013) is rooted in Munro and Davis (Munro & Davis, 1977) where decision type and information requirements were part of what Işık considered the decision-making environment. This view of success factors is quite different from past studies that primarily focused on financial, technological and organizational aspects. The rationale is that even when these aforementioned aspects are met, BI may still not be utilized for its intended purpose. Examples include using it to solve the wrong problem, or a type of decision for which it was not originally designed.

Although ERP and BI target different problem domains, there is a high degree of overlap of the factors that drive their success. This is because they both cut across borders of functional areas during and after their implementation, which require support from top management, training and other areas to be effective. Through Delphi studies, content analysis or other qualitative approaches, studies (Akkermans & Helden, 2002; Hawking & Sellitto, 2010; Yeoh et al., 2008; Yeoh & Koronios, 2010) have identified the success factors common between the two systems as top management support, project management, resource availability, organizational support, data quality and business processes. The literature has accumulated some empirical evidence as to how these factors contribute to organizational performance for ERP systems (e.g., Karimi et al., 2007), but little is known about whether these models also hold true for BI.

Additionally, the new trend of looking at the decision-making environment as a success factor needs more research. Isik et al. (2013) sets some very good ground work by assessing decision types and information processing needs (that were originally studied in Munro and Davis (Munro & Davis, 1977) as a way to look at the decision environment for BI. As Munro and Davis concluded in their study, characteristics of decisions, such as "the extent to which a decision is routine or non-routine, structured or unstructured, simple or complex" (p. 65) should be considered in determining what is needed to aid decision-making. Isik et al. (Isik, 2009) also alluded to the idea that factors other than the above are also part of a decision-making environment. In other words, it is quite a broad concept that requires a good match between a tool and the problem in hand. This is the reason that Clark, Jones and Armstrong (Clark et al., 2007) considered problem space complexity as also part of a decision-making environment. The need for a good match between the problem space complexity is more so for BI than ERP. Compared with ERP and operational information systems, BI users are generally more educated and information requirements are specific (e.g., data are less structured, methods are often ad-hoc, complex & research-oriented, and information relevance is focused), making a good fit between the problem at hand and BI essential (Grublješič & Jaklič, 2014). As a result, these user and information requirements have set BI apart from ERP, which makes findings from ERP not directly and readily applicable to BI without further examination. Additional research in this area for BI will add to our understanding of its success.

### ***A model of success factors***

In formulating a research model for BI's effect on organizational performance, it is useful to see how the common set of success or organizational support factors are modeled for other related systems such as ERP. Karimi et al.'s empirical validation of an ERP model provides many of these common success factors. In this model, the effect of ERP implementation on Business Process Outcomes is moderated by four success factors (top management support, project management resources, consultant resources, and training resources) and two complexity variables (process complexity and information intensity). It is worth noting that the two complexity variables characterize the requirement in the underlying decision environment that drives the adoption of the intended system. In Karimi et al.'s construction, the two complexity variables are collectively subsumed in a second-order variable called ERP Radicalness, which refers to "the extent to which an innovation represents technological changes and thus implies new behaviors for organizational subsystems or members" (p. 106).

### ***The research model for the present study***

Rather than starting anew, we adapted our model from Karimi et al.'s (Karimi et al., 2007) work on ERP implementation for several reasons. First, ERP and BI are initiatives that share a set of common requirements to be successful. As Yeoh and Koronios indicated, a BI system is similar to ERP in that it is "a complex undertaking requiring appropriate infrastructure and resources over a lengthy period". Adjustment in infrastructure, business process, behavior, training, resources and project management have been cited as success factors for both systems (e.g., Adamala & Cidrin, 2011) largely due to how they impact the organization as a whole and how they require changes that cut across functional areas. As BI systems benefit from data collected from ERP, several major ERP vendors (such as SAP, Oracle and Microsoft) have also incorporated BI as an extended offering.

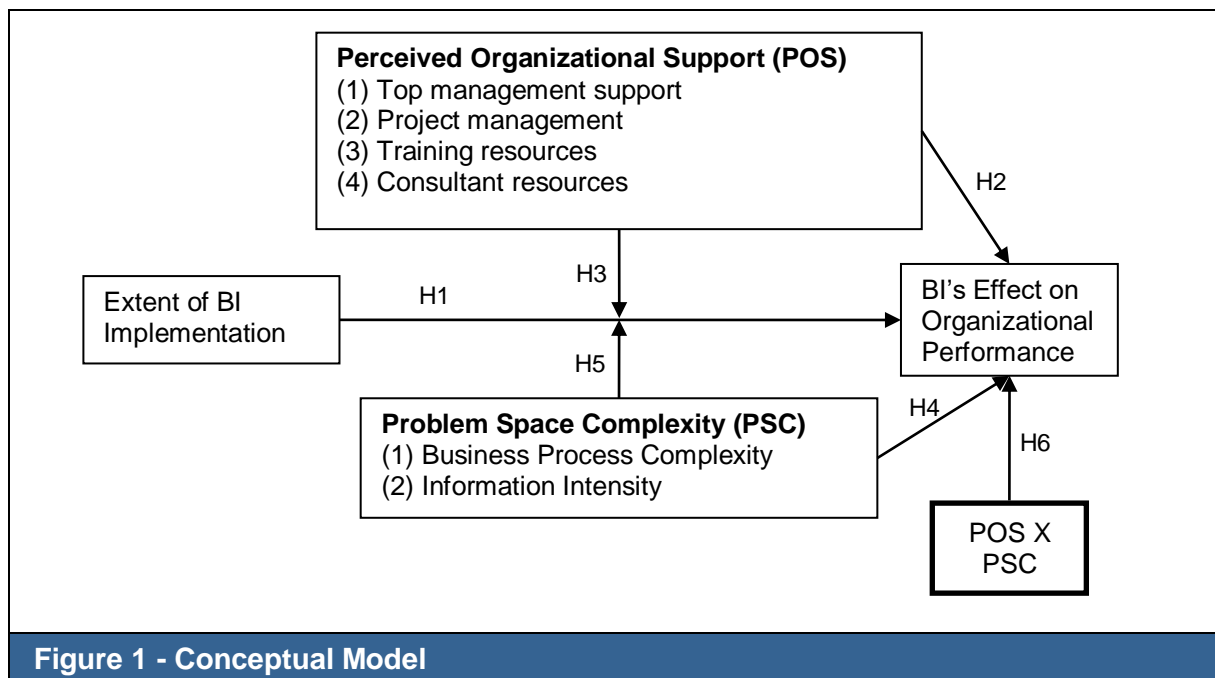
Despite the fact that the two systems share some common success factors and similarities in infrastructural requirements, the difference in intended purposes between the two systems likely affects how the success factors are utilized for organizational performance. Therefore, a model verified in ERP may not be readily applicable to provide empirical insights for BI. It does, however, provide a validated framework to start such a scholarly investigation.

Second, an empirically verified model, allows us to have a credible starting point to extend the generalizability of this line of research. Karami et al.'s model includes two key sets of variables on organizational support and decision environment, which are common success factors to both ERP and BI. The decision environment in the form of problem space complexity (Clark et al., 2007) is especially relevant to BI, as Isik et al.'s work highlights that the extent to which BI capabilities actualize BI success varies across decision environments. The literature also suggests that problem space complexity is related to task complexity, complexity in the business process and information processing requirements (Gill & Hicks, 2006; Gill & Murphy, 2011). As problem space is concerned with the context of the problem or situation in the decision environment, complexity in the problem space requires specialized tools and intellectual effort (Visinescu et al., 2017). As a result, the implementation of BI is often tied to how well it handles complexity in the problem space to support decisions (Gressner & Colonino, 2005). Karami et al.'s framework allows us to peek into the two forms of the complexity in business process and information requirements, which also

has theoretical backing from the BI literature (e.g., Lönnqvist & Pirttimäki, 2006; Popovič et al., 2012; Popovič et al., 2014).

Third, BI implementation alone does not necessarily lead to the desired level of organizational performance. This is because many BI projects rely on data gathered from across multiple functional areas, collected from different sources and integrated from different formats. As a result, complexity arises that often surpasses the capabilities of the existing staff. Organizational support in the forms of training, capacity-building, project management, consulting, and others is a viable way to ensure BI success (Grublješič & Jaklič, 2014; Yeoh et al., 2008). With proper organizational support, the relationship between BI implementation and organizational performance will likely be stronger (Fink et al., 2017). This effect of organizational support has been reported to be influential in improving BI's post-adoptive behavior (Deng & Chi, 2012), extra-role performance (Chen et al., 2009), information culture (Grublješič & Jaklič, 2014) and organizational learning (Fink et al., 2017). Furthermore, the complexity of data and business processes from which the business data are collected can easily exceed the capabilities of basic analytic tools (such as Excel). As such, business intelligence tools outshine the basic analytical tools, but they also require the support structure to be in place. Therefore, proper organizational support and the complexity in problem space may both have a moderating effect on the relationship between BI and organizational performance.

Therefore, this paper focuses on the effects of the two groups of success factors (perceived organizational support and problem space complexity) on the relationship between BI implementation and its effect on organizational performance. Figure 1 shows the conceptual model.



## Hypotheses

### *Direct Effect*

#### **BI's Effect on Organizational performance as the dependent variable**

The dependent variable consists of three main areas (process efficiency, process effectiveness, and process flexibility) of organizational performance (Elbashir et al., 2008; Melville et al., 2004; Tallon et al., 2000). Studies (Heinrichs & Lim, 2003; March & Hevner, 2007) have shown that BI enhances organizational efficiency and effectiveness (Heinrichs & Lim, 2003; March & Hevner, 2007). Ou & Peng (2006) indicated that modern companies are increasingly process oriented, and that process-driven BI systems are emerging to help enterprises improve the efficiency and effectiveness of their business operations. Firms employ BI systems to improve tactical and operational processes, supply chain, production, and customer service (Elbashir & Williams, 2007; Williams & Williams, 2003). Therefore, the existing literature confirms that BI implementation has a positive effect on organizational performance.

*Hypothesis 1: Extent of BI implementation has a positive association with organizational performance*

### *Moderating Effects*

#### **Perceived Organizational support (POS)**

The implementation of a successful BI system is a complex assignment that requires securing a manifold of resources to meet both organizational and technological challenges (Williams & Williams, 2003; Yilmaz, 2007). A successful BI project requires that organizational support be aligned with the objectives of BI implementation (Saha, 2007; Watson et al., 2006; Yeoh & Koronios, 2010). In a meta study of the literature, Rhoades and Eisenberger (Rhoades & Eisenberger, 2002) found that perceived organizational support (POS) directly affects several outcome variables, including organizational performance, organizational commitment, job-related effects, job involvement and strains. As they pointed out, several of these above variables eventually also affect the overall performance of the organization.

In addition to treating POS as a direct antecedent of organizational performance, studies have also shown that it affects an outcome variable by way of a moderating role. For example, POS has been shown to have a moderating effect on the relationship between leader-member exchange and performance (Erdogan & Enders, 2007), and between organizational stressors and organizational citizenship behaviors (Jain et al., 2013). In the context of BI, a successful implementation is not simply a good installation of the software. It involves how the system can be used to fuller potential with supports across functional borders. Therefore, the relationship between BI implementation and organizational performance may operate conditionally in a way that higher organizational performance may be accomplished with better organizational support. Conversely, lower organizational support limits the impact of BI systems on organizational performance. Because of this, POS is hypothesized to directly impact organizational performance as well as be a moderator that influences the effect of BI implementation on organizational performance.

*Hypothesis 2: Perceived organizational support (POS) is positively associated with organizational performance.*

*Hypothesis 3: Perceived organizational support (POS) moderates the relationship between BI implementation and its effect on organizational performance.*

## **Problem Space Complexity (PSC)**

The lack of a match between an IT System and the intended problem space has been reported to cause users acceptance to drop (Clark, Jones & Armstrong, 2007; Clark & Jones, 2008). BI is no exception. Clark, Jones and Armstrong's work highlights the fact that a key reason that affects the BI to problem space match is the degree of complexity in the problem space, but the literature also suggests that problem space complexity is related to task complexity, complexity in the business process and information processing requirements (Gill & Hicks, 2006; Gill & Murphy, 2011). Problem space complexity in turn has an effect on management decision quality, level of system use, and perceived benefits (Clark, Jones & Armstrong, 2007). Gill (Gill, 2013) suggests that PSC requires a set of symbols and their operators to represent the problem space. Complexity in problem space arises when the symbolic representation of tasks and plans become difficult or laborious. Gill continues to indicate that PSC grows as people gain experience with a set of task contexts. As a result, the accumulated information needed to process and the number of symbols developed to represent the problem space may require specialized tools to manage. This is where people resort to specialty information systems for help.

Helquist et al. (Helquist, Deokar, Meservy & Kruse, 2011) indicated that the need to process and analyze the large amount of information needed for today's business problems adds to the complexity of business decisions. In addition to data volume, the complexity of business processes where the data comes from, the variety of data formats, and compliance/ privacy issues, all add an extra layer of difficulty to the business decision making environment. As a result, there is a renewed interest in the integration of BI, the business process and information sources (Isik, Jones & Sidorova, 2013; Marjanovic, 2009). As BI draws insights out of business data, the nature of data and the internal business processes that affect how data are generated greatly influence the success of BI. Therefore, we focus on two aspects of problem space complexity (business process complexity and information intensity) in the present study.

### Business Process Complexity (BPC)

Business process complexity (BPC) refers to the non-routineness, difficulty, uncertainty, and interdependence within a process (Setia et al., 2013). Previous research has shown that the complexity of business processes makes it difficult to establish procedures and rules (Mani, Barua & Whinston, 2010) define work flows (Sackmann, 2008), and standardize the process (Schäfermeyer & Rosenkranz, 2011). All this adds to the complexity of capturing, storing and analyzing the business data— an area where traditional information systems fall short, but BI may excel (Catellanos et al., 2010; Clark & Jones, 2008).

The complexity in business processes impacts on the effect of BI in several ways. First, BI relies on a substantial amount of data collected from business processes, especially operational processes (Sarma & Prasad, 2014). The findings derived from BI are fed back to support business processes and decisions across multiple functional areas (Zeng et al., 2012). Therefore, the two-way relationship between business processes and BI has created an integrated "system" that has the potential to impact organizational performance. Second, the increased complexity of business processes for today's business has created an extra layer of difficulty for traditional information systems in collecting, storing and analyzing the business data. When the complexity of business processes increases, a specialized tool, such as BI, will provide a better fit to solving the problem in hand.

### Information Intensity

Similarly, BI also has a better capability to handle activities that are information intensive. Porter and Millar (Porter & Millar, 1985) are among the first to coin the term Information Intensity, which refers to the amount of information processing required to acquire and process the product into the final form ready for the end-users. Firms with high information



intensity requirements in their value chains and products are more likely to benefit most from IT (Hu & Quan, 2003). Higher information intensity creates difficulties to integrate data collected from across multiple business processes. As a result, it creates opportunities for innovative applications of IT (Karimi et al., 2007), such as the application of BI and knowledge management systems (Shariat & Hightower, 2007). Compared to traditional information systems, BI provides a better fit to the decision-making environment when information intensity is high. The role that information intensity plays in this type of fit has an effect on corporate agility, which enables a firm to operate more successfully in changing and competitive environments (Mao et al., 2015). Therefore, the effect of BI implementation on business decisions and performance is better realized when this fit is matched.

In summary, both business process complexity and information intensity contribute to the complexity of problem space. When the complexity of problem space increases, simple tools may fall short in their capability to process different forms of data, integrate data from multiple sources and create aggregated analytics. BI is more likely to excel in these areas. Based on the above discussion and the literature (Karimi et al., 2007; Setia, Venkatesh & Joglekar, 2013), problem space complexity is proposed as a second-order factor with business process complexity and information intensity as the first-order factor. When problem space complexity is higher, businesses are more likely to benefit from BI tools. As a result, it helps foster a better business performance. Based on this discussion, the following hypotheses are postulated to test the direct effect of problem space complexity (PSC) on business performance and its moderating effect on the relationship between BI implementation and business performance:

*Hypothesis 4: Problem space complexity (PSC) is positively associated with organizational performance.*

*Hypothesis 5: Problem space complexity (PSC) moderates the relationship between BI implementation and its effect on organizational performance.*

The complexity of problem space creates a need for sophisticated information systems, such as BI, but such a system can be crippled when the support structure is not in place. This is the reason that the information systems literature is full of studies stressing the importance of organizational support (e.g., (Rai & Bajwa, 1997)). The effect of support continues to be influential on corporate performance and earnings during post-implementation of a system (Galy & Saucedo, 2014). However, the need for organizational support is lessened if the tasks at hand are self-sustained and thus do not require the full capability of BI. Therefore, the following hypothesis is designed to study the interaction between perceived organizational support (POS) and problem space complexity (PSC):

*Hypothesis 6: Greater perceived organizational support (POS) in conjunction with greater problem space complexity (PSC) is positively associated with higher organizational performance.*

## Research methodology

### Measurement

The survey instrument contains a five-part questionnaire (see Appendix A). The first part captures the demographic background of the respondents. Parts two and five use a summative scale, and the remainder uses a 5-point Likert's scale anchored by "strongly disagree" and "strongly agree".

## **Extent of BI implementation**

Previous research on IT implementation advises that measures used to operationalize the extent of the implementation of an initiative can vary depending on the objectives of the research and the nature of the innovation (Karimi et al., 2007). Therefore, our instrument for the extent of BI implementation was adapted from the existing literature. It is defined in the present study as the functional, organizational and geographic scope of BI. BI functional scope was measured as the range of the implementation and a summation of the number of the business functions covered by the BI implementation. BI organizational scope measures the number of locations (departments, divisions, entire company, multiple companies, etc.) targeted for BI implementation. BI geographic scope measures the geographic reach of the BI implementation (i.e., single site, multiple sites, national, or worldwide).

## **BI to Problem Space Match**

BI to problem space match is a second-order construct that comprises business process complexity (BPC) and information intensity (II) (Karimi et al., 2007). There are four items for BPC (the degree of non-routineness, interdependence, complexity, and uncertainty in business processes) and four items for II (the number of steps in production or service processes, the extent of information use, the updated frequency, and accuracy) that were adapted from Karimi et al.

## **Organizational support**

Organizational support is defined as the degree to which organizations assimilate IT innovations, and is one of the key success factors for BI implementation. This is a second order construct with four first-order constructs adapted from Karimi et al. Each of the first order constructs includes three questions as follows: top management support (enthusiasm and interest, degree of support, and involvement in the project), project management resources (tools and techniques were employed for this project, and a realistic schedule), training resources (investment in training, adequate training, and provision of training to employees), consultant resources (consultants provided guidance, were experienced, and brought expertise and experience to the project).

## **BI's Effect on Organizational Performance**

Organizational performance includes process efficiency, effectiveness, and the flexibility of the organization (Karimi et al., 2007). Process efficiency is the extent to which the implementation of BI has improved the operating efficiency, reduced operational costs and decreased data entry errors. Process effectiveness refers to the extent to which BI implementation has provided better functionality, added value to operations, and enhanced the quality of work. Process flexibility is the extent to which BI implementation has provided firms with more flexibility to respond to changing business environments by providing new ways to customize their processes and become more agile.

## **Data collection**

The survey questionnaire was carefully reviewed by two professors and 12 doctoral students to ensure an accurate representation of the intended constructs. The questionnaire was also administered to twenty-eight EMBA students in a pretest, where the majority of the respondents were business executives or IT managers. Further minor improvements were made to the questionnaire. Some fundamental evidence of content validity was achieved through the above procedure.

A study sample, comprised of the Top 500 firms ranked by the Common Wealth Magazine (a popular commercial magazine in Taiwan), was selected for the mail survey. The majority of

these companies were IT manufacturers and/or service companies from which middle and top IT managers were surveyed because of their wider responsibilities that could encompass a broad spectrum of operations and strategy formulations. This is important since BI is often implemented to support analytical and managerial activities. Additionally, to improve the survey return rate, a follow-up phone call or reminder letter was sent out targeting the non-respondents 2-3 weeks after the initial mailing.

The questionnaire yielded 171 responses, three of which were incomplete and thus deleted. The remaining 168 responses represent a 33.6% response rate. Table 1 lists the sample demographics. The seemingly low response rate raises concerns regarding a non-response bias. To check for this, the sample was divided into two subsamples, that is, early and late subsamples containing 70 and 98 respondents respectively. The two groups were compared in terms of various demographic characteristics for their correlation using the t-test, including annual revenue, IS department budget, number of IS employees, and IS department history. The respondent groups exhibited no significant differences at the .05 level in these areas ( $t$  value = .74, .41, .79, .67), indicating no systematic non-response bias for the responding sample. Accordingly, we could infer that the responding sample effectively represents the sample frame. The final sample of 168 included 92 firms that have implemented BI projects.

<b>Table 1 - Demographics</b>		
Characteristics	Frequency	Percent (%)
<b>Industry Type</b>		
Manufacturing	107	63.69
Service	61	36.31
<b>Annual Revenue (NT \$ Billion)</b>		
≤9.9	41	24.40
10~19	62	36.90
20~29	17	10.12
30~39	13	7.74
40~49	4	2.38
≥50	31	18.45
<b>IS Department Budget (NT \$ Million)</b>		
≤19	71	42.26
20~39	28	16.67
40~59	15	8.93
60~79	6	3.57
80~99	6	3.57
≥100	34	20.24
Missing	8	
<b>Number of IS Employees</b>		
≤19	75	44.46
20~39	40	23.81
40~59	13	7.74
60~79	10	5.95
80~99	2	1.19
≥100	25	14.88
Missing	3	
<b>History of IS Department (Year)</b>		
≤9	15	8.93
10~19	60	35.71
20~29	51	30.36
30~39	23	13.69
≥40	15	8.93
Missing	4	
<b>Have Implemented BI Project</b>		
Yes	92	54.76
No	76	45.24

Note: The monetary unit is NT dollars; 1US\$ = 31NT\$

## Reliability and validity

In order to examine the issue of common method bias, Harman's single-factor test is one of the most widely used techniques (Rhoades & Eisenberger, 2002). We used this technique to load all variables into an exploratory factor analysis (EFA) and examined the unrotated factor solution to determine the number of factors that were necessary to account for the variance in the variables. The results supported multiple factors with a variance of the first principal component to be 29.64%. The low to moderate level of variance explained by the first factor and more than one other factor suggested by EFA, together provided some evidence of no substantial common method bias.

The EFA with an oblique rotation suggested eight factors (See Table 2). Most factor loadings were .700 or above, except the first item of the Extent of BI Implementation (EX) factor. Construct reliability measured in Cronbach's alpha is reported in the bottom half of Table 2. As this table shows, Cronbach's alpha is larger than the generally accepted threshold of .70 for all constructs except for the Extent of BI Implementation (EX). Although not meeting the minimum, the Cronbach's alpha of this variable is nonetheless very close (alpha = .691). Additionally, the composite reliability measured by Dillon-Goldstein' rho shows that all constructs exceeded the cut-off of 0.7. Therefore, EX is retained for further analyses. Table 3 shows the correlation between the constructs.

Convergent validity is supported in part by the high factor loadings shown in Table 2 for each construct. The results also showed acceptable levels of AVEs for the constructs according to Fornell & Larcker's (1981) recommendations (> 0.5), thus providing yet some evidence for convergent validity. Discriminant validity is confirmed when the squared root of AVE for each construct exceeds the correlation between the construct and others in the model. As shown in the diagonal line of Table 3, all AVEs are substantially higher than the construct correlations. The results confirmed good discriminant validity among constructs.

Table 2 - Factor Analysis and Reliability								
Factor Analysis								
Items	1	2	3	4	5	6	7	8
EX1	0.302	0.094	0.680	0.082	-0.043	0.164	0.161	<b>0.591</b>
EX2	0.141	-0.008	0.273	0.008	0.070	0.162	0.171	<b>0.837</b>
EX3	0.363	0.065	0.337	0.265	0.124	0.054	0.086	<b>0.837</b>
TM1	0.259	0.369	0.129	<b>0.937</b>	0.384	0.516	0.240	0.117
TM2	0.341	0.244	0.244	<b>0.930</b>	0.422	0.516	0.263	0.109
TM3	0.235	0.366	0.104	<b>0.874</b>	0.392	0.570	0.280	0.187
PM1	0.054	0.408	0.051	0.521	0.456	<b>0.866</b>	0.127	0.065
PM2	0.217	0.296	0.173	0.577	0.508	<b>0.875</b>	0.336	0.120
PM3	0.101	0.253	0.213	0.446	0.432	<b>0.809</b>	0.077	0.163
TR1	0.099	0.384	0.134	0.520	<b>0.850</b>	0.592	0.268	0.108
TR2	0.323	0.216	0.267	0.357	<b>0.917</b>	0.399	0.319	0.096
TR3	0.192	0.342	0.266	0.431	<b>0.879</b>	0.534	0.315	0.132
CR1	0.001	<b>0.898</b>	0.191	0.305	0.355	0.324	0.224	-0.026
CR2	0.036	<b>0.924</b>	0.039	0.249	0.189	0.290	0.224	-0.023
CR3	0.084	<b>0.947</b>	0.125	0.367	0.289	0.422	0.241	0.121
II1	<b>0.832</b>	-0.043	0.240	0.351	0.154	0.096	0.311	0.322
II2	<b>0.912</b>	0.111	0.373	0.309	0.218	0.174	0.382	0.210
II3	<b>0.871</b>	0.068	0.443	0.153	0.215	0.037	0.467	0.130
II4	<b>0.884</b>	0.043	0.322	0.256	0.181	0.168	0.378	0.256
PC2	0.342	0.088	0.264	0.184	0.284	-0.003	<b>0.843</b>	0.115
PC3	0.370	0.284	0.320	0.258	0.287	0.284	<b>0.912</b>	0.141
PC4	0.513	0.294	0.340	0.265	0.186	0.279	<b>0.808</b>	0.115
OP1	0.281	0.056	<b>0.806</b>	0.145	0.347	0.035	0.257	0.163

OP2	0.355	0.151	<b>0.890</b>	0.210	0.207	0.213	0.251	0.349
OP3	0.377	0.153	<b>0.869</b>	0.126	0.141	0.230	0.424	0.272
Note: Principal component analysis; Promax rotation with Kaiser normalization. EX: Extent of BI implementation; TM: Top management support; PM: Project management resources; TR: Training resources; CR: Consultant resources; II: Information intensity; PC: Process complexity; OP: BI's effect on Organizational performance. Item removed from analysis: PC1.								
Reliability Analysis								
Variable	Mean	S.D.	Cronbach's $\alpha$	DG rho*	AVE			
Extent of BI Implementation	3.00	1.09	0.691	0.829	0.602			
Process Complexity	3.87	0.74	0.826	0.896	0.742			
Information Intensity	4.26	0.55	0.900	0.931	0.771			
Top Management Support	3.88	0.80	0.912	0.945	0.850			
Project Management Resources	3.80	0.66	0.840	0.903	0.758			
Training Resources	3.84	0.65	0.888	0.931	0.817			
Consultant Resources	3.37	0.88	0.917	0.947	0.858			
BI's Effect on Organizational Performance	2.05	0.94	0.840	0.904	0.758			
Extent of BI Implementation	3.00	1.09	0.691	0.829	0.602			
* Dillon-Goldstein's rho								

**Table 3 - Correlation matrix of variables**

Variables	EX	TM	PM	TR	CR	II	PC	OP
EX	<b>.776</b>							
TM	.153	<b>.922</b>						
PM	.126	.623**	<b>.871</b>					
TR	.133	.492**	.615**	<b>.904</b>				
CR	.059	.355**	.366**	.352**	<b>.926</b>			
II	.336**	.307**	.155	.245*	.048	<b>.878</b>		
PC	.217*	.301**	.210*	.338**	.256*	.469**	<b>.861</b>	
OP	.535**	.206*	.201	.277**	.144	.392**	.362**	<b>.871</b>

Note: \*  $p < .05$ , \*\*  $p < .01$

EX: Extent of BI implementation; TM: Top management support; PM: Project management resources; TR: Training resources; CR: Consultant resources; II: Information intensity; PC: Process complexity; OP: BI's effect on Organizational performance.

Diagonal line shows the squared root of AVEs. Off diagonal values are construct correlations.

## Analysis and results

The results of the three research models (base, direct-effect, and moderation models) are reported in this section. The statistical significance of each model was obtained by running a bootstrapping resampling technique with 500 samples. The base model is the baseline benchmark of comparison for the other two models. Only the extent of BI implementation and its effect on organizational performance were included in the base model. Perceived organizational support (POS) and problem space complexity (PSC) were included in the moderation model as the moderators, while the two variables were studied as the direct antecedents of organizational performance in the direct-effect model.

### Base model

In this base model, the effect of BI implementation on organizational performance was tested. As Figure 2 shows, the direct effect of the extent of BI implementation on organizational performance was quite strong. However, the R squared value for the dependent variable was only .284, indicating that the independent variable alone did not explain much of the variance of the dependent variable.

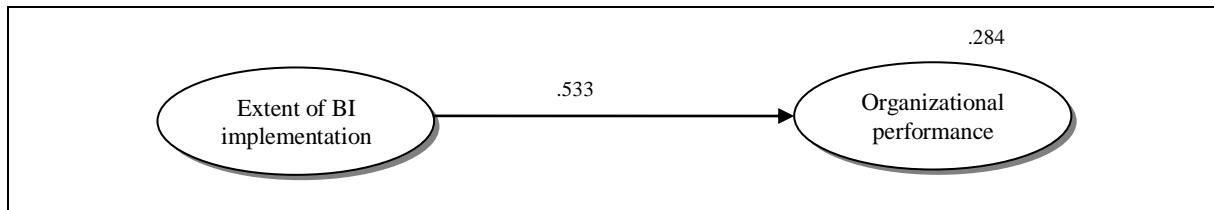


Figure 2 - The Base Model

### Direct-effect model

In this extended version of the base model, Perceived Organizational Support (POS) and Problem Space Complexity (PSC) were added in addition to BI Implementation to study the direct effects of the three antecedent variables on organizational performance. Both POS and PSC were second-order constructs; each was composed of several lower-order latent variables. Figure 3 shows that the effect of BI implementation was still statistically significant after POS and PSC were added to the model. POS' effect on organizational performance was quite weak ( $p > 0.05$ ). PSC did have a statistically significant effect on organizational performance ( $p < 0.01$ ). The R squared value for this second model improved to .377 from the base model, indicating that more variance of the dependent variable was explained in this model.

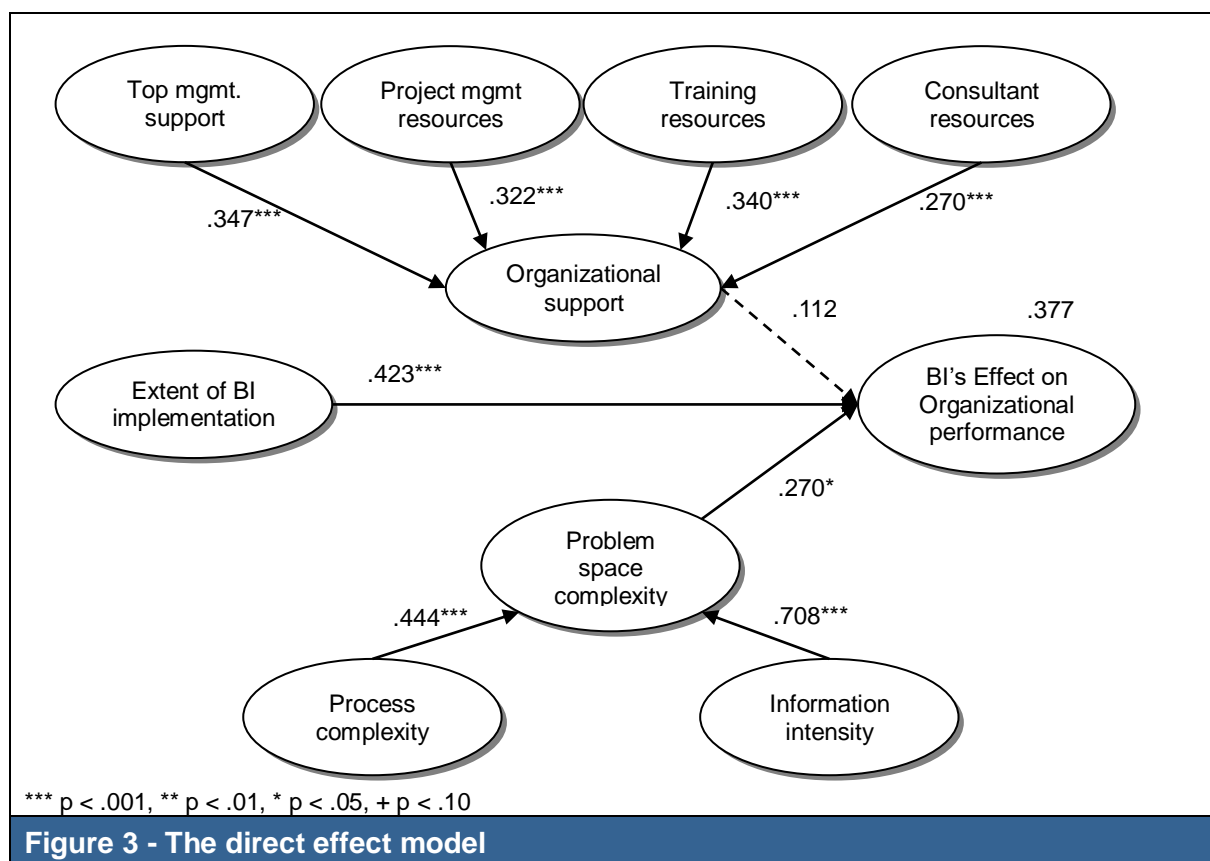
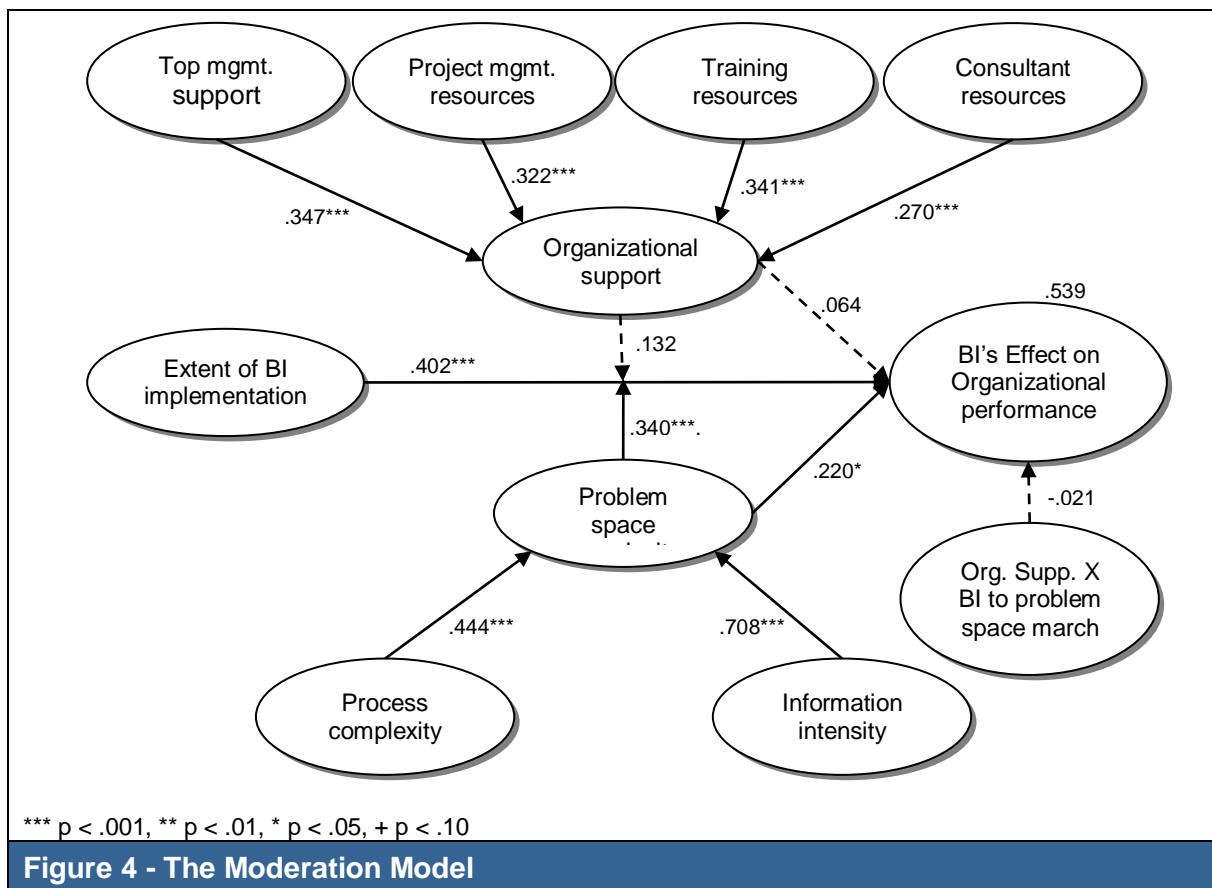


Figure 3 - The direct effect model

### The Moderation Model

In this model, POS and PSC were added to the direct-effect model as moderators for the relationship between the extent of BI implementation and organizational performance. Additionally the interaction term (POS \* PSC) was also included to study their interaction effect. The results of the PLS analysis after the bootstrapping procedure are in Figure 4. The two main moderators were measured as second-order reflective factors, while the interaction moderator (POS \* PSC) was produced by the standardized product term of indicators from the two main moderators. The first-order factors for POS were all statistically significant. The same is true for the first-order factors of PSC. It had a statistically significant moderating effect ( $\beta = .270, p < .001$ ), but the moderating role of the other two moderators (POS and the interaction moderator) was quite weak. We then conducted a pseudo F test (Chin, 2010) for the difference of R squared values between the direct effect model and the moderation model. In our case, the results show that the pseudo-F = 9.957,  $p < 0.01$ . Therefore, the improvement of the moderation model over the direct effect model was statistically significant.



In all three models, the direct effect of BI implementation on Organizational Performance was statistically significant. Therefore, hypothesis one purporting this direct relationship is not rejected. POS was hypothesized to have a direct effect (hypothesis 2) on organizational performance, and a moderating effect (hypothesis 3). Both hypotheses are rejected because of a very low statistical significance. Similarly, hypotheses 4 and 5 were designed to study the direct and moderating effect of PSC. As Figure 4 shows, both the direct effect (hypothesis 4) and moderating effect (hypothesis 5) cannot be rejected. The interaction term (POS \* PSC) as postulated in hypothesis 6 did not have a statistical significance on organizational performance.

## Discussion

In recent years, ERP vendors have started adding BI capabilities to their offerings. From the technical standpoint, BI relies on good consistent data collected, processed and stored – an area where ERP excels. Adding BI to ERP makes good business sense. Both systems share a common set of success factors such as organizational support, training, project management, resource availability, etc., but the effects of these factors vary due to the difference in expectations of user, information and methodology requirements (Grublješič & Jaklič, 2014).

Our first research question concerns the model that best explains how organizational support and problem space complexity affect the relationship between BI and organizational performance. In the present study, the effects of these success factors are examined in three models: the base model, the direct-effect model and the moderation model. In the base model, only the direct effect of BI implementation on organizational performance was studied. BI implementation only explained 28.40% of the variance of organizational performance, suggesting that there are other relevant variables also affecting performance. In the direct-effect model, both the POS and PSC were added in conjunction with BI Implementation to study their direct influence on organizational performance. All but POS had an effect on organizational performance. The variance explained increased to 37.70%. The moderation model explains 53.90% of the variance, even higher than similar models for ERP (Karimi et al., 2007) and banking (Setia et al., 2013). It is also an improvement over the base model that explains only a mere 28.40% of the variance for the dependent variable.

Although the first-order variables for perceived organizational support (POS) were all statistically significant, it did not turn out to be a moderator for the relationship between BI implementation and organizational performance. Nor did POS have a direct effect on organizational performance, despite numerous studies on its role in the adoption or pre-adoption stage. This finding between POS and organizational performance is quite interesting. The literature shows five possible sources of this discrepancy. First, the effect of organizational support may stay at changing an individual's perception on usefulness and ease of use, but it stops short of affecting the actual use due to factors, such as self-efficacy (Delice, 2009; Chen et al., 2011). Second, organizational performance measured at the coarse or overall level may not pinpoint the actual effect of organizational support. Rhoades and Eisenberger (Rhoades & Eisenberger, 2002) indicated that most organizational support studies assume that its effect on organizational performance holds, which is true if it is measured as the "overall performance". They found that POS relates more to extra-role performance (e.g., aiding fellow employees, offering constructive suggestions and taking actions that protect the organization from risks), but less on in-role performance. It is this in-role performance that is more likely to be monitored and reported in the literature than the extra-role performance. Although BI may be used to advance performance in both in-role and extra-role activities, it is the extra-role performance that requires an individual to go the extra mile on something not required by their jobs. The motive to do so is likely to be affected by other factors. Third, when resistance to use is in effect, more organizational support does not always translate into positive results. Organizational support may exacerbate resistance to use and can be viewed by users who are less willing to use the system as an unwanted intrusion (Veiga et al., 2014). Fourth, organizational support is concerned not only about extrinsic elements of adoption, but intrinsic factors are also relevant in realizing the full range of system benefits. Similarly, organizational support reduces transition costs, which is only one part of switching costs, but it does not affect other components, such as sunk costs (Kim & Kankanhalli, 2009). Another possible reason is that BI is frequently packaged in a way friendly to users (such as dashboards). Fifth, ongoing resource needs are likely to be less than what was initially invested as a company progresses through the six-stages of IS implementation, namely initiation, adoption, adaptation, acceptance, routinization and infusion (Cooper & Zmud, 1990). Factors intrinsic to an individual drive the last three phases



(Hsieh & Zmud, 2006). As a result, the need for organizational support varies. For example, training resources as one of the organizational support components is less demanded/needed after the initial series of training. Similarly, the need for consultant's assistance also gradually decreases as an individual's mastery of the BI system becomes productive. All of this translates to less need for organizational support during the later phases of the usage life cycle.

Problem Space Complexity (PSC) had a moderate level of moderation effect (coefficient = .340,  $p < 0.001$ ). Between the two first-order factors of PSC, information intensity ( $\beta = .708$ ,  $p < 0.001$ ) contributed more to it than did business process complexity ( $\beta = .444$ ,  $p < 0.001$ ). This is consistent with our expectation. As today's business environment grows more complex, businesses are relying on more sophisticated tools to "provide actionable information delivered at the right time, at the right location, and in the right form to assist decision makers" (Negash, 2004). This is an area where BI shines by offering a capability to better meet today's problem space – something that general-purpose tools (such as Excel) or traditional information systems fall short in. Our work shows this match is in the form of a moderating effect and to a lesser extent a direct effect ( $\beta = .220$ ,  $p < .05$ ) for PSC. Additionally, the interaction effect between the two proposed moderators (POS and BI to problem space match) was not statistically significant.

Although our present work builds on Karimi, Somers and Bhattacharjee's work and the two systems (ERP versus BI) are fundamentally different, a comparison between our findings and theirs serves the purpose of a reference, rather than a direct extension of the ERP literature. Two key areas are fundamentally interesting. First, our results show that BI relies more on a good fit of the problem space. Not only that the problem space complexity had a larger moderation effect in our case, the two first-order variables also had stronger strengths to explain problem space complexity. Second, organizational support for post-adoption as in our study was not statistically significant, while it was the second strongest moderator in their study. As we explored in the preceding paragraphs, this shows that other factors may be in effect for BI (such as less demand for organizational support after post-adoption, resistance and other intrinsic factors that affect individuals outlined in the post-adoption stages of the Cooper & Zmud's model). Additionally, the structure of the model and the constructs as proposed in Karimi et al. explained the dependent variable slightly better in our study as the proportion of variance explained was 0.539 versus 0.490 in theirs. In all, ERP and BI share many common success factors, but our work highlights that such success factors may be manifested in different forms, and required to different degrees at different adoption stages.

Several forms of theoretical and practical contributions are present in our work. First, our initial research question asks about the structure of organizational support and problem space complexity that best explains the relationship between BI implementation and organizational performance. Our findings show that the moderation model outperforms the base and direct-effect models by explaining a larger proportion of the dependent variable. The confirmation of the moderation model adds value to formulate strategies to enhance the effect of BI on organizational performance. Second, the support for the moderation model for BI offers empirical evidence for the generalizability of Karimi et al.'s work. As we expounded on the nature between ERP and BI in previous sections, the two systems share a common set of success factors and yet aim to provide solutions to different problem domains. Little will be known of the applicability of the moderation model for BI until it is empirically verified. Our work shows that Karimi et al.'s model generalizes well into BI for the most part, but we also observe interesting differences that highlight the specific requirements of BI as compared to ERP.

Third, the third research question asks if the key second-order constructs are still as statistically significant as we postulated. The measurement model was quite valid between Karimi et al.'s findings and ours, since all first-order constructs and their relationships with the

second-order constructs were empirically validated in both studies. Different from Karimi et al.'s findings, POS's role as a moderator was nearly non-existent in the present study. This shows that the need for POS may vary between the two systems. In BI, the pre-implementation phase may very likely require more organizational support than the post-implementation phase, since most BI tools today are built with ease of use in mind and require a flatter learning curve. Once mastery of the tool is attained, little organizational support (such as consulting and training resources) is required.

Fourth, our work also adds additional insights to the concept of the decision-making environment in BI. Munro & Davis and Isik et al. pioneered the assessment of the decision-making environment by focusing on two aspects of it (decision type and information need). This provides a good view into the decision-making environment from the standpoint of decision and information requirements, but as to how the tool fits into the problem domain is yet to be explored. In fact, Clark, Jones and Armstrong (Clark, Jones, & Armstrong, 2007) have suggested that problem space complexity (PSC) can be considered part of a decision environment. We approached PSC by looking at business process complexity and information intensity. The results offer initial evidence of how a match of tool in problem space complexity helps actualization of BI on organizational performance. A summary of the contributions is listed in Table 4.

Table 4 - Key highlights of contributions	
Number	Highlight
1	The moderation model outperformed the direct effect and base models in explaining the variance of the dependent variable – organizational performance for BI.
2	ERP and BI shared many common success factors. A validated ERP model generalized to BI reasonably well, but construct relationships and weights vary between the two systems due to specific requirements between the two systems.
3	The construction of second-order constructs is quite valid as evidenced in the solid measurement model validated in both studies. Perceived organizational support, however, has less implication in our study during post-adoption stage of BI implementation.
4	Our work adds to the line of research of decision environment by empirically validating the addition of problem space complexity to it, thus enriching the scope of decision environment to analytical systems.

## Conclusion

BI has become an increasingly strong strategic tool to enhance an organization's competitive advantage (Watson & Wixom, 2007). Our work tests three models treating POS and PSC as direct antecedents, moderators, and non-existent from the model (i.e., the base model). The moderation model explained more variance of organizational performance than the other two models. The implications for researchers derived from our work are discussed below. First, although BI in business is becoming more widely accepted, few studies have looked directly at how organizational support and problem space complexity moderates the effect of BI implementation. The assumption that a mere implementation of BI will add value to an organization may fall short if the required conditions are not in place. Our work was designed to fill this gap.

Second, the empirical support for the moderation model validates the generalizability of Karimi et al.'s model, which can be used as a foundation for others to look into variables beyond POS and PSC. Although it is not the focus of the present study, the vast number of existing BI studies on technical soundness (such as information quality, visualizations and the ability to encompass a variety of data structures) may be integrated into our work to offer possible additional insights. In our study, the lack of the statistical significance of POS as a

moderator and a direct antecedent to organizational performance may indicate that there may not be a constant need for organizational support across all phases of BI implementation. In fact, Cooper and Zmud's six stages of IS implementation shows that as a company progresses into the latter stages of IS implementation, factors relevant to individuals become more salient than organizational factors for companies to capitalize on the IS investment. Our work primarily focuses on the success factors common to ERP and BI, but a possible direction for future research would be to also look at the success factors unique to BI.

Third, the support of the moderation model, especially the confirmation of PSC's moderating effect, offers some basic evidence that there is a need for a fit between the tool itself and the problem domain. The more the tool fits solving the problem on hand, the better the utilization of the tool will be. Although our work does not directly assess the concept of fit, it is useful to point out that the organizational and strategic fit literature has suggested the concept of fit does not always entail a direct correlation between the variables. For example, Venkatraman (Venkatraman, 1989) classified six forms of fit into criterion fit (fit as moderation, fit as mediation, and fit as profile deviation) and criterion-free fit (fit as matching, fit as co-variation and fit as gestalts). Not all types of fit will be present at the same time or for a system. Therefore, there may be different fit requirements across the Cooper and Zmud's six stages of implementation. It will be interesting in future studies to report the types of fit that BI provides to enhance organizational performance.

The implications for practitioners include the empirical evidence of antecedents of organizational performance in the context of BI. With the confirmation of PSC and its first-order factors, managers are advised to identify areas that match these variables (e.g., processes or activities that heavily depend on information being collected, analyzed and stored) to actualize the benefits of BI. As the direct effect of BI implementation on organizational performance was confirmed for all three models, making BI available to employees may still have its benefits.

Our findings show that both information intensity and process complexity are key drivers to organizational performance through the second-order construct of PSC. They are more so for BI than for ERP. This presents BI managers and developers with a direction of where to put BI to its best use. As for organizational support, it should still be considered for BI initiatives, knowing that its effect is more on the individual level that motivates individual performance through affective commitment (Eisenberger & Stinglhamber, 2011), extra-role performance (such as helping peers, offering constructive suggestions and gaining knowledge beneficial to the company) (Chen et al., 2009) and end-user satisfaction (Hung et al., 2016). Despite these benefits at the individual level, our present work shows organizational support may not always affect how BI implementation is translated into corporate performance. This offers an area of possible future expansion in that studies may focus on the needs for organizational support at different stages of BI implementation to examine how they jointly affect organizational performance.

Managers may want to start with the following ideas: First, the most influential component of problem space complexity is information intensity. This indicates that a good fit of the volume, variety and structure of the business data to the tool adopted is of most importance to the success of an IS implementation. As Rienzo & Chen (2018) indicated, a successful analytical implementation requires mapping of three components of the problem space, namely process, tool and technique. Therefore, a fit of BI's problem space requires a fit of the tool, available techniques, and analytical process to the business problems. Second, after a fit is perceived and understood, it still does not necessarily entail continued adoption, especially when other factors, such as self-efficacy and ability, are sub-par leading to under-utilization or even early abandonment of the IS implementation. One key is to establish a shared norm where colleagues or friends continue to sustain the benefits of immersing oneself in the tool despite difficulties along the path (Chen et al., 2011) for both mandatory and voluntary IS

usage (Rezvani et al., 2017). Another possibility is to work with users to instill the BI tool, technique and process work to the existing routines to minimize transition costs (Ye & Potter, 2011). For example, training or other system encounters can emphasize how BI connects well to existing tools. If Excel is part of the habitual routine for analytics, pulling BI data into Excel or Excel plug-ins to access the extended capabilities of BI will expand additional possibilities to the old tool.

No research is without its limitations. Our work is no exception as it captures a snapshot view of BI implementation, rather than all stages of an IS implementation life cycle. Although this allows us to examine the relationships among variables and establish generalizability between ERP and BI, it should not be taken that the construct relationships will always stay constant across all stages of the IS life cycle. For example, the key components of organizational support (such as training resources and consulting resources) are more likely to be needed in the early stages of IS, since users are still familiarizing themselves with the tool and its capabilities. As users progress into the later stages, such as Cooper & Zmud's adaption, acceptance and routinization stages of IS implementation, support in the form of training and consulting is less needed. Therefore, the strength of organizational support on how BI implementation actualizes business performance gradually decreases, while the importance of other factors is more pronounced. In our study, these other factors are the two key components of problem space complexity.

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## Appendix A. Questionnaire

### Part 1: Basic information

1. Industry type: \_\_\_\_\_
2. Annual revenue (NT\$ billion):  ≤9.9  10~19  20~29  30~39  40~49  ≥50
3. IS department budget (NT\$ million):  ≤19  20~39  40~59  60~79  80~99  ≥100
4. Number of IS employees:  ≤19  20~39  40~59  60~79  80~99  ≥100
5. History of IS department (Year):  ≤9  10~19  20~29  30~39  ≥40
6. Have implemented BI project:  Yes  No

### Part 2: Extent of BI implementation

1. Functional scope of implementation of your selected BI (select all that apply):  
Accounting/Finance | Manufacturing | Planning/Scheduling | Human Resources |  
Sales/Distribution | Logistics/Inventory Control | Other (please specify): \_\_\_\_\_
2. Scope of implementation of your selected BI:  
Department | Division | Entire company | Multiple companies | Other: \_\_\_\_\_
3. Geographical extent of implementation:  
Single site | Multiple sites | National | Worldwide

### Part 3: Problem Space Complexity

#### Process complexity

1. The business processes we deal with often cut across multiple functional areas.
2. We frequently deal with ad hoc, non-routine business processes.
3. We generally have a high degree of uncertainty in our business processes.
4. A majority of our business processes are quite complex.

#### Information intensity

1. Our production/service operations require a significant amount of information processing.
2. There are many steps in our value chain that require frequent use of information.
3. Information used in our production/services operations needs frequent updating.
4. Information constitutes a large component of our product/service to customers.

### Part 4: Organizational support

#### Top management support

1. Senior executives demonstrated a lot of enthusiasm and interest throughout the project.
2. The overall level of management support in this project was quite high.
3. Upper-level managers were personally involved in the project.

#### Project management resources

1. Formal project management tools and techniques were employed for this project.

2. Project managers in charge of the project were highly capable and experienced.
3. The implementation schedule was realistic.

#### **Training resources**

1. Significant time and resources were invested in training employees on using the new system.
2. Adequate on-the-job training was provided to internal user groups to use the new system.
3. Both technology and process training were provided to employees using the system.

#### **Consultant resources**

1. Experienced consultants guided us throughout the course of the project.
2. External consultants were experienced in our business processes.
3. External consultants brought considerable expertise and experience to our project.

#### **Part 5: BI's Effect on Organizational performance (select all that agree)**

##### **Process efficiency**

1. BI implementation has improved our efficiency of operations.
2. BI implementation has lowered our cost of operations.
3. BI implementation has reduced the amount of rework needed for data entry errors.

##### **Process effectiveness**

1. Data provided by BI add value to our operations.
2. BI implementation has improved timely access to corporate data.
3. The BI provides a high level of enterprise-wide data integration.
4. BI implementation helps us make better sales forecasts than before.
5. The functionalities of BI adequately meet the requirements of our jobs.
6. BI implementation has improved our quality of operations.

##### **Process flexibility**

1. BI implementation has given us more ways to customize our processes.
2. BI implementation has made our company more agile.
3. BI implementation has made us more adaptive to the changing business environment.
4. BI implementation has improved the flexibility of our operations.

## About the Authors

**Shin-Yuan Hung** is an Information Systems Professor at National Chung Cheng University in Taiwan. Also, he is currently the provost of the same university. He was a visiting scholar of the MIS Department at the University of Arizona during summer 2007-spring 2008. Dr. Hung received his bachelor degree in Statistics from National Chung Hsing University and his master and doctoral degrees in Information Systems from National Sun Yat-sen University. His current research interests include decision support systems, knowledge management, electronic commerce, and big data analysis. He has published papers in *Decision Support Systems*, *Information & Management*, *International Journal of Human-Computer Studies*, *Journal of the Association for Information Science and Technology*, *Information Technology & People*, *Communications of the AIS*, *Government Information Quarterly*, among others. Currently, he serves as an Associate Editor of *Information & Management* and an Area Editor of *Journal of Information Management*.

**Kuanchin Chen** is a Professor of Computer Information Systems and John W. Snyder Faculty Fellow at Western Michigan University. He is a co-director of WMU's Center for Business Analytics. His research interests include electronic business, analytics, social networking, project management, privacy & security, online behavioral issues, data mining and human computer interactions. He has published in journals, such as *Information Systems Journal*, *Decision Support Systems*, *Information & Management*, *IEEE Transactions on Systems, Man, and Cybernetics*, *International Journal of Information Management*, *Journal of Database Management*, *Internet Research*, *Communications of the Association for Information Systems*, *DATA BASE for Advances in Information Systems*, and many others. He has frequently been invited to give research talks at universities, government agencies and other institutions.