EXTENDING THE THEORY OF EFFECTIVE USE: THE IMPACT OF ENTERPRISE ARCHITECTURE MATURITY STAGES ON THE EFFECTIVE USE OF BUSINESS INTELLIGENCE SYSTEMS

Research-in-Progress

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Abstract

Business Intelligence (BI) has received wide recognition in IT, business and academia. Through the use of BI businesses are able to address ’big data’ related problems for better management decisions across all industries. However, few studies have clearly articulated a theoretically grounded model or provided empirical data to explain what factors influence the effective use of BI. Drawing on the theory of effective use (TEU) and literature on enterprise architecture, business intelligence and IT user performance, I developed a research model to examine the impact of different stages of enterprise architecture maturity on the representational fidelity of BI, which has been identified as one of the critical dimensions of effective use of BI influencing managers’ decision-making performance. The study will adopt a mixed methods approach combining qualitative and quantitative data collection from managers in BI-based organizations. This study makes an important theoretical contribution to the study of effective use of BI, and also makes a practical contribution by providing insights into the creation of environments to facilitate more effective BI use in the pursuit of better decision-making performance.

Keywords: Business Intelligence, Enterprise Architecture, Enterprise Architecture Maturity, Decision-Making Performance, Effective Use, Theory of Effective Use.
Introduction

Issues of data quality have become increasingly critical to organizations (Nord et al. 2005), especially in
the era of ‘big data’ (Chen et al. 2012). Business Intelligence (BI) has received wide recognition in the
business world as a tool to address ‘big data’ related problems in order to help managers to understand
their businesses and to assist them in making high quality, effective and timely decisions (Chen et al. 2012;
Shollo and Kautz 2010). However, to date there have been few studies which have clearly articulated a
theoretically grounded model that explains how the use of BI systems provides benefits to organizations
(Shanks et al. 2011) or explains what factors influence the effective use of BI (Clark et al. 2007;
Ramakrishnan et al. 2012). It is this need for a theoretically grounded explanation of the benefits and
effectiveness of BI use that has motivated the present study.

In order to achieve greater decision making performance, BI systems must be used effectively (Burton-
Jones & Grange, 2013). Because BI focuses on exploiting data and information sources to support
decision-making, one of the main factors that may impact the effective use of BI is data integration
(Sabherwal and Becerra-Fernandez 2011). Data integration helps to provide quality information for
decision-making (Reynolds et al. 2012), and only really occurs, according to Ross et al. (2006), once an
organization moves to higher stages of Enterprise Architecture (EA) maturity.

Tamm et al. (2011) argue that how EA maturity directly benefits businesses has been somewhat
overlooked in the literature because, although there are many claimed benefits of EA, such benefits are
often neither clearly explained nor supported by empirical evidence. Tamm et al. (2011) recommend
further empirical studies to test the extent to which different stages of EA maturity impact on decision-
making performance in order to develop a better understanding of both the potential value of transition
through stages of maturity and of how to maximize the likelihood of deriving these potential benefits.

This study responds to Tamm et al.’s call for empirical studies and aims to explore the relationship
between stages of EA maturity and the decision making performance of managers derived through the
effective use of BI. This will be done in order to develop a theoretically grounded explanation of: a) the
reasons why the certain stages of EA maturity are beneficial; b) how the use of BI systems can be
beneficial; and c) how BI-based organizations can enrich their understanding and improve their level of
effective use of BI systems. In order to achieve these objectives, this study will address the following
research question:

*How do the stages of IT enterprise architecture maturity of organizations influence the decision-making
performance of managers through their impact on the effective use of BI?*

Theoretical Foundation

**Business Intelligence and the Integrated Data Repository**

Business Intelligence is variously described as a process (Shollo and Kautz 2010) or concepts and methods
(Chen et al. 2010) used to support decision making with information systems. BI is defined as a process of
leveraging systems and tools to turn both internal and external data into meaningful information
throughout the organization (Ranjan 2008; Sabherwal and Becerra-Fernandez 2011). Sabherwal and
Becerra-Fernandez (2011 p.6) state that “BI enables decision makers to make better decisions by
providing them with the ability to formulate the necessary questions, direct access to the data and
information, and the tools needed to appropriately manipulate them in order to find the required
solutions”.

The integrated data repository is the cornerstone of a BI system (Chen et al. 2012; Negash 2004; Turban
et al. 2011). In this repository, data is integrated from multiple organizational sources such as operational
databases, data archives, legacy data bases, and external data (Ramamurthy et al. 2008; Sabherwal and
Becerra-Fernandez 2011). Data integration brings benefits to organizations by improving managerial
information for organization-wide communication and also enhancing operational coordination between
interdependent parts of the organization (Goodhue et al. 1992). Data integration cuts through the obstacle
of multiple sources of data by accessing, integrating, and organizing operational data in a form that is consistent, reliable, timely, and readily available, wherever and whenever needed (Turban et al. 2011).

The integrated data repository is both a foundation and a prerequisite for BI as it enables the organization to obtain value from its data sources by preparing and storing current and historical organizational data into an organization-wide data repository designed to support decision making (Chen et al. 2012; Sabherwal and Becerra-Fernandez 2011; Turban et al. 2011). Therefore, the presence of a mature, consistent, and integrated data repository plays a crucial role in BI systems as it is an essential condition for information availability, information access, and information quality, all of which are critical for the effective use of BI.

**Stages of IT Enterprise Architecture Maturity**

According to Ross et al. (2006), EA maturity reflects the extent to which organizational data is shared and integrated. Organizations can enhance the quality of information and increase the benefits of IT by implementing more mature EA with increased standardization and integration (Venkatesh et al. 2007). Ross (2012) suggests that EA maturity progresses through the development of technology platforms, shared enterprise business processes and data, and reusable components. Prior studies have suggested that organizations should not skip any stage in this development because important lessons learned in each stage help prepare organizations for the next stage of development (Rai et al. 2010; Ross et al. 2006; Venkatesh et al. 2007). Ross et al. (2006) identify five stages of EA maturity as shown in Table 1.

<table>
<thead>
<tr>
<th>EA Maturity Stages</th>
<th>IT Capacity</th>
<th>Standardization and Integration</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Stage 1: Business Silos</strong></td>
<td>Local IT application</td>
<td>Business processes and applications not standardized or integrated. Multiple data sources.</td>
</tr>
<tr>
<td><strong>Stage 2: Standardized Technology</strong></td>
<td>Shared technical platforms</td>
<td>Standardization is introduced; however, transactional data is still often enclosed in individual applications.</td>
</tr>
<tr>
<td><strong>Stage 3: Optimized Core</strong></td>
<td>Building a platform. Companywide standardized processes and databases</td>
<td>Business processes and IT applications standardized if appropriate; transaction data is extracted and made available to all appropriate processes and across the organization.</td>
</tr>
<tr>
<td><strong>Stage 4: Business Modularity</strong></td>
<td>Reusing and leveraging a platform. Plug-and-play business process modules</td>
<td>Reusing and leveraging a platform of shared business processes and/or organization data (using and improving the platform). Both customized and industry-standard components are integrated achieving a “plug-and-play” capability integrating internal and external business processes.</td>
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<tr>
<td><strong>Stage 5: Dynamic Partnering</strong></td>
<td>Seamless merging with partners’ systems</td>
<td>Organizations which have progressed to dynamic partnering will provide business partners with selective access to their key data and business processes sharing an integrated data repository for their respective businesses.</td>
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As illustrated in Table 1, certain stages of EA maturity have specific IT capabilities which influence the extent to which data is integrated and shared across business units and organizations. The integration of data only really occurs, according to Ross et al. (2006), once an organization moves past the second standardized technology stage of maturity to at least the third ‘optimized core’ level. Therefore, this study argues that the EA maturity of an organization, defining the extent to which the data of the organization is integrated into a data repository, will impact on the degree to which the representational fidelity of BI systems can be obtained effectively given the aforementioned necessity of data integration to BI.

**The Theory of Effective Use (TEU)**

Understanding the effective use of information systems is “critically important” (Straub and Giudice 2012 p. iii) as the fact of system use alone is not sufficient to ensure organization goals are achieved (Seddon
Knowledge Management and Business Intelligence

To achieve their designed goals and benefits, systems must be used effectively (Burton-Jones & Grange 2013). System use, according to Burton-Jones and Straub (2006 p. 231), is defined as an activity that involves a user, a system and a task, with task defined as a “goal-directed activity”. Effective use at an individual level, therefore, is defined as “using a system in a way that helps attain the goals for using the system” (Burton-Jones & Grange 2013 p. 4). In their Theory of Effective Use (TEU), Burton-Jones and Grange (2013) propose two levels of effective use which focus firstly on the nature of effective use and its impact on performance, and secondly on drivers of effective use.

As shown in Figure 1, Burton-Jones and Grange (2013) present transparent interaction, representational fidelity and informed actions as three dimensions of effective use that impact on performance. Additionally adaptation actions and learning actions are identified as the major antecedents of effective use.

Although Burton-Jones and Grange’s TEU suggests two dimensions of actions that drive effective use, in this study I focus solely on investigating the impact of learning factors for reasons of scope as well as the significance of learning actions. According to Burton-Jones and Grange (2013), learning actions refer to any action a user takes to learn: 1) the system with its representations, or its surface or physical structure; 2) the domain it represents; 3) the extent to which it faithfully represents the domain (fidelity); or 4) how to leverage representations obtained from the system (how to engage in more informed actions). Learning
actions are critical to the effective use of systems since they not only impact the linkages between dimensions of effective use but also moderate the linkages between adaptation actions and dimensions of effective use.

Burton-Jones and Grange additionally define dimensions of effective use as follows. First, transparent interaction “refers to the extent to which a user is accessing the system’s representations unimpeded by the system’s surface and physical structures” (Burton-Jones and Grange 2013 p.11). When using BI, an effective user is able to seamlessly access the BI system’s representations; for example, she/he can easily query and analyze the data needed. Second, representational fidelity refers to “the extent to which a user is obtaining representations from the system that faithfully reflects the domain being represented by its surface and physical structures” (Burton-Jones and Grange 2013 p.11). Effective BI users are therefore able to obtain content from the system which is sufficiently complete, clear, correct and meaningful since representation fidelity can be measured based on consideration of user’s needs (Burton-Jones and Grange 2013). Third, informed action refers to “the extent to which a user acts upon the faithful representations he or she obtains from the system to improve his or her state” (Burton-Jones and Grange 2013 p.11). When a BI user obtains information from the system that faithfully presents a complete picture of the domain it describes, she/he is able to act upon the information to make better business decisions.

This study draws on and adapts the TEU to further understand the relationships between drivers and dimensions of effective BI use and managers’ decision-making performance. When BI transparent interaction incorporates knowledge of fidelity then the linkage between BI transparent interaction and BI representational fidelity becomes more certain as users know what to look for and how to access BI representational fidelity. As it is learning actions that enhance knowledge of fidelity, learning what to access (learning fidelity) and how to access BI representations (learning systems) are very important actions that drive the effective use of BI. In addition, BI representational fidelity is not sufficient on its own to take informed action (informed decision), it is only when the BI representation fidelity is coupled with knowledge of how to leverage the BI representation (learning to leverage) that users are more likely to take informed action (informed decision).

**Research Model and Hypotheses**

Referring to the aforementioned literature on BI, data integration, EA maturity, and effective use, I propose that having mature EA development is a key factor influencing BI representation fidelity, one of the dimensions of effective BI use. Further, I suggest that operational and managerial decision-making task performance will be enhanced and optimized resulting from effective use of BI.
Derived from the TEU, this study also argues that learning factors influence and moderate the linkages between dimensions of effective use of BI. Upon identifying the implications of dimensions in the TEU to effective BI use, I set out to identify a framework that could reflect these dimensions in the BI context. As shown the research model in Figure 2 above, I identify BI interaction transparency as transparent interaction, BI representational fidelity as representational fidelity, informed decision as informed action, and decision-making effectiveness and decision-making efficiency as two dimensions of decision-making performance. I have also adopted learning dimensions to be drivers of effective use of BI.

**Business Intelligence Interaction Transparency**

Adapting the definition of transparent interaction (Burton-Jones and Grange 2013), I define BI interaction transparency as the extent to which a user has seamless access to the content (data and information) contained in the BI system.

Learning system refers to any actions that users take to gain knowledge about a system’s representations or how to access and interact with these representations (Burton-Jones and Grange 2013). IT users acquire knowledge of transparent system interaction through their learning process and repeated performances (Aral and Weill 2007). Because users interact with information systems for particular purposes, they learn, build skills, and develop competence toward effective use (Aral and Weill 2007). In order to use BI systems effectively, users need to learn how to use the system, how to access the data repository, and how to use the analytic tools of BI systems in order to get quality information that will assist them in decision-making tasks. This study argues that learning the system influences the degree to which BI users achieve interaction transparency. Therefore, this study hypothesizes that:

**Hypothesis H1:** There is a positive relationship between a higher level of learning system and a higher level of BI interaction transparency.

**BI Representational Fidelity**

The TEU posits that when using a system such as BI, people seek faithful representations (Burton-Jones and Grange 2013). Adapting the definition of representation fidelity (Burton-Jones and Grange 2013), this study defines BI representation fidelity as the extent to which a BI user is obtaining content from the BI system that faithfully reflects the domain being represented. Since BI relies on data and information as inputs, the quality of this data and information is critical for the BI to generate faithful representations (e.g. reports that sufficiently present a complete picture of the domain they describe) as an output to facilitate decision-making. Therefore, if a user is able to interact with a BI system seamlessly (i.e. unimpeded by the surface structure or physical structure of the system), he/she is more likely to be able to obtain representational fidelity from the BI system. Following this line of argument, this study hypothesizes as follows:

**Hypothesis H2:** There is a positive relationship between a higher level of BI interaction transparency and a higher level of BI representational fidelity.

**Learning fidelity** plays an important role in supporting the positive effect of transparent interaction on representational fidelity (Burton-Jones and Grange 2013). Based on TEU, I define learning fidelity in a BI use context as any actions that users take to gain knowledge about the extent to which the information provided by the system faithfully represents the domain. In order to identify BI representational fidelity, a BI user must have learned how to evaluate if the content generated by the system is compete, clear, correct and meaningful or not. From that, users can take action to improve the fidelity of BI systems’ representations if it is suboptimal, such as asking people involved in the issue to check or correct the data source or analysis rule. The TEU notes that when transparent interaction is coupled with knowledge of fidelity, the link between transparent interaction and representational fidelity becomes more certain. Following this line of argument, I propose the following hypothesis:

**Hypothesis H2a:** Learning fidelity will amplify the positive effect of BI interaction transparency on BI representational fidelity.

In addition, as the representation fidelity produced by BI is queried from the integrated data repository, and as the integration of data within organizations only really occurs once organizations reach or exceed
the third level of EA maturity (Ross et al., 2006), this study further argues that data integration defined by EA maturity stages influences the degree to which a user can obtain BI representations faithfully. This gives rise to the following hypothesis:

Hypothesis H2b: Data integration defined in level 3 or above of EA maturity will lead to higher levels of BI representational fidelity.

Informed Decision

Although information is widely recognized as a valuable asset, it will not generate benefits if it is not used for making decisions and informing action (Popović et al. 2012). Adapting Burton-Jones and Grange’s (2013) definition of informed action and learning to leverage in a BI system use context, this study identifies informed decision as an informed action that a BI user makes based on the BI generated information (Leonard-Barton and Deschamps 1988; Popović et al. 2012). In addition, learning to leverage (learning to leverage information) refers to any action that a BI user takes to further improve his/her ability to take high-quality decisions.

Brodbeck et al. (2007) claim that the best informed decision is the correct decision. Informed decision processes require both appropriate decision making tools and information quality (Remus and Kotteman 1986). However, having quality information is not sufficient alone to guarantee an informed decision. Users must also have the knowledge and experience of how to interact and to leverage information in order to be more likely to make better informed decisions (Ayres 2008)

This study therefore argues that actions based upon BI representational fidelity (i.e. sufficient and quality information generated from BI) will help decision-makers generate informed decisions, and that learning to leverage quality information moderates the impact of information quality and informed decision.

Hypothesis H3: There is a positive relationship between a higher level of BI representational fidelity and a higher level of informed decision.

Hypothesis H3a: Learning to leverage information quality will amplify the positive effect of BI representational fidelity on informed decision.

Decision Making Effectiveness

The quality of decisions can be assessed according to the quality of the process by which decisions were made (Davern et al. 2008; Keren and De Bruin 2004). Decisions that are made from data and high-quality information are more likely to be good decisions (Ayres 2008; Raghunathan 1999). In this study, the quality of decisions is reflected through the level of informed decision. Because the outcome of one’s task performance can be assessed in terms of effectiveness (Burton-Jones and Grange 2013; Campbell 1990), in this study decision-making effectiveness is defined as one dimension of decision-making performance. Decision-making effectiveness is assessed through the outcome of the goal attainment (i.e. the outcome of decisions). If the decision is good, then the outcome of decision is good (Davern et al. 2008). Again, adapting the TEU, a high level of informed decision (informed action) primarily enhances decision-making effectiveness by improving one’s state in the domain; alternatively, a low level of informed decision decreases effectiveness by damaging one’s state. Following this line of argument, this study hypothesizes that:

H4: There is a positive relationship between a higher level of informed decision and a higher level of decision-making effectiveness.

Decision Making Efficiency

The outcome of one’s task performance can be assessed in terms of efficiency (Beal et al. 2003). Adopting Burton-Jones and Grange’s (2013) definition, in this study decision-making efficiency refers to the extent of goal attainment (decision making) for a given level of input (such as effort or time). Burton-Jones and Grange (2013) argue that for any system usage, transparent interaction enhances task performance by increasing task efficiency (saving users’ time when working on the system). In other cases, a lack of
transparent interaction could increase the time users spend on checking and performing the task (reducing task efficiency). Therefore, when working on the BI system, a high level on BI interaction transparency will save the time and effort spent on interacting and finding the features necessary to conduct the task. Following this line of argument, this study proposes that:

**H5:** There is a positive relationship between a higher level of BI interaction transparency and a higher level of decision-making efficiency.

Additionally, information quality is identified as an important factor that could improve performance (Raghunathan 1999) and task efficiency (Gattiker and Goodhue 2005). The TEU posits that when representational fidelity is high, task efficiency is increased because the system user can save time otherwise spent on checking and verifying fidelity (Burton-Jones and Grange 2013). Therefore, when users gain high quality information the decision-making task efficiency is increased. Following this line of argument, this study proposes that the higher the level of information quality the BI system provides to the user, the higher level of decision-making efficiency they will achieve:

**H6:** There is a positive relationship between a higher level of BI representational fidelity and a higher level of decision-making efficiency.

**Methodology**

To answer the research question and to test the validity of the research model this study will adopt a mixed methods approach combining qualitative and quantitative research. Moreover, this study will adopt a two-phased approach in which the researcher will conduct a qualitative phase of study (exploratory interviews) followed by a quantitative phase (survey study) (Tashakkori and Teddlie 1998 p.18).

The exploratory interview phase will comprise of semi-structured in-depth questions with selected participants. The interviews will be conducted in order to gain a sense of the completeness of the research model and to gather descriptive information of the phenomena being investigated. The information gained from these interviews will be incorporated with the theoretical information gained during the literature review to help refine the model, the variables, and to develop the survey instruments for the main survey (MacKenzie et al. 2011). Participants will be selected following the key informant selection method suggested by Phillips (1981). This study will select junior and senior managers as participants because they possess a special qualification of interest, that being their decision-making experience. The study will invite fifteen to twenty junior and senior managers in Australia who have knowledge and experience in using BI to support their decision-making tasks and are able and willing to share their experiences (Campbell 1955). The selection of both junior and seniors managers in the study is to prevent the issue of “elite bias” (Myers and Newman 2007 p.5). This study will follow a template approach to analyze qualitative data obtained from the interview. This approach involves preparing a set of codes or categories based on theoretical perspectives used in this study. Then I will apply the codes or categories to organize the interview data to identify major themes within the data (Silverman 2011).

Following the exploratory interview phase, I will conduct a survey to test the proposed model and the hypotheses derived from the literature and from the key findings of the exploratory interview phase. The confirmatory survey aims to further validate the model and instrument derived from the literature and enhanced by the results of the exploratory phase, as well as to reconfirm the model and measures using quantitative data. The survey will involve undertaking a cross-sectional, self-administered, and non-experimental field survey. The survey will target management members who have used or are using BI systems within Australian organizations. This study will use panel providers to select and ensure the suitability of participants for the study. The use of perceptual data from management members has been widely used in previous IS research (see Tallon et al. 2000). The survey process will involve survey instrument development, a pre-test and pilot test. To begin with, this study will follow the processes suggested by MacKenzie et al., (2011) to develop and validate a survey instrument for the research model. The processes involve reviewing extant literature to identify existing survey instruments which could be suitable for this study. If there are no existing adaptable survey instruments, the literature will be used to identify and develop appropriate survey items (also called scale) for this study. After generating the survey instrument, a pre-test of the survey instrument will be conducted. In order to reduce common method bias, this study will use an objective scale for task performance. Independent coders (i.e.
managers/supervisors of participants) will rate participants’ performance using the scale. The survey instrument’s content validity will be assessed through expert panel reviews. This test is intended to acquire empirical feedback from expert participants to assess the appropriateness of the original survey instrument (Lewis et al. 2005). The last step in the survey development process is performing a pilot test. A pilot test will be conducted to assess and test the feasibility of the survey and to identify any possible ambiguities or lack of clarity in the survey questions. Structure Equation Modeling (SEM) will be used to assess the measurement model and to test the structural model. The use of SEM helps to create more robust analysis since SEM takes into account the random measurement errors that are inherent in behavioral studies (Blanthorne et al. 2006).

**Conclusion**

This research study is motivated by the research gaps identified in prior literature (Clark et al. 2007; Shanks et al. 2011; Tamm et al. 2011) and the opportunity for a significant practical and theoretical contribution. The research proposes that having mature EA development is a critical factor influencing BI representation fidelity which is a key dimension of effective BI use, and which ultimately contributes to improved decision-making performance. The potential findings of this study can contribute to both the IS and BI theoretical base as well as to practical BI adoption and use.

**Potential Theoretical Contribution**

This study makes several potential theoretical contributions. First, this study builds a theoretical underpinning with tenets from the literature on BI, EA maturity and TEU to investigate the impact of EA maturity stages on effective use of BI, and on the decision-making performance of managers. This is critical because the body of literature on BI use tends to lack theoretical depth (Shanks et al. 2011). By providing value-laden arguments with a strong theoretical basis, this study adds great value to the literature on BI. Second, most previous research has investigated benefit gains from the successful use of BI systems but paid little attention to factors that influence the effective use of BI (Ramakrishnan et al. 2012). This research takes an initial step to systematically explore the black box of effective BI use by sharpening our understanding of the complexity of effective use of BI and the factors that impact on it. To our best knowledge, this is the first study to examine the impact of stages of EA maturity on the effective use of BI. Third, by drawing on the TEU, this study identifies dimensions of effective use of BI. By doing so, this study stimulates a platform for research on what factors influence the effectiveness of BI use, and how BI systems are and need to be used to attain desired outcomes.

**Potential Practical Contribution**

This study also has important potential practical implications. Firstly, this study may help organizations improve their level of effective BI use by providing a better understanding of the factors that drive the effective use of BI. Secondly, this study may also provide insights into how to improve the decision-making performance of managers by adopting BI and using BI effectively. Thirdly, this study provides BI-based organizations with insights to create an environment that facilitates and motivates BI users to more effectively use BI in the pursuit of better decision-making performance. Finally, the research will help organizations to recognize of the potential value of transition through the stages of EA maturity and demonstrate how organizations can maximize the likelihood of deriving potential benefits from different EA stages.

**References**


