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**Article**

## Data, attitudinal and organizational determinants of big data analytics systems use

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## OPERATIONS, INFORMATION & TECHNOLOGY | RESEARCH ARTICLE

# Data, attitudinal and organizational determinants of big data analytics systems use

Charlie Chen<sup>1</sup>, Hoon Seok Choi<sup>2</sup> and Peter Ractham<sup>2</sup>

**Abstract:** This study investigates influential factors on the use of Big Data Analytics (BDA) systems in terms of data quality, organizational support, and user satisfaction. We surveyed 236 actual users of BDA systems in different industries and used the PLS-SEM method to analyze the collected data. The empirical evidence shows that data integrity and data timeliness determine data connectivity of BDA systems, which affect user satisfaction along with relational knowledge of IT personnel. The findings also indicate that user satisfaction has a positive effect on BDA system use, whereas data connectivity does not. The findings imply that user experiences appear to have a significant influence on the intention of business practitioners to use BDA systems, but data connectivity does not. Based on the empirical findings, this study provides both theoretical and practical implications for the success of BDA systems use.

**Subjects:** Business, Management and Accounting; Industry & Industrial Studies; Information Technology

**Keywords:** big data analytics; user satisfaction; data connectivity

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### PUBLIC INTEREST STATEMENT

This study investigates influential factors on the use of Big Data Analytics systems in terms of data quality, organizational support, and user satisfaction. The empirical evidence shows that data integrity and data timeliness determine data connectivity of BDA systems, which affect user satisfaction along with relational knowledge of IT personnel. The findings imply that user experiences appear to have a significant influence on the intention of business practitioners to use Big Data Analytics systems, but data connectivity does not.

## 1. Introduction

Companies worldwide are facing fierce competition and high customer expectations. A growing number of companies are exploiting big data opportunities to achieve innovations and competitive advantages to sustain their profits (Chongthanavanit et al., 2020; Vassakis et al., 2018). Studies have shown that the use of BDA systems leads to improved business performance, competitiveness, and value (Gunasekaran et al., 2017). Based on an extensive interview from top executives in 330 public North American companies, a study investigated the relationship between data-driven decisions and financial and operational performance. It suggests that the top third of companies in their industry are 5% more productive and 6% more profitable than their competitors owing to the use of BDA, and more than 30% of the executives in the study expressed their concerns of relying too much on experience and intuition in their decision making (McAfee et al., 2012). Many business organizations have actively adopted BDA; the adoption rate has increased from 17% in 2015 to 59% in 2018 (Columbus, 2018), and the rate is still increasing. However, many business organizations are still struggling to implement and integrate the new trend successfully. Approximately 77% of major companies such as Ford and American Express reported BDA adoption is still a major challenge for the companies (Bean & Davenport, 2019).

Current studies show that many companies are still struggling with the successful adoption and use of BDA systems (Seth, 2018). While there are different obstacles, the major two obstacles are poor data quality and lack of or inadequate organizational support. The distributed big data, with its sheer magnitude size, security considerations, and possibly incompatible platforms, pose serious issues concerning data quality, discouraging the use of BDA (Kambatla et al., 2014). In addition, because of poor organizational support, many practitioners are reluctant to use BDA systems (Nemati & Udiavar, 2012) even after the adoption of BDA. To promote the use of BDA systems, an organization needs to address the challenges concerning data quality and organizational support, enabling the practitioners to access the right data and leading to efficient business decision making.

There have been studies investigating diverse issues on BDA, such as perception of business practitioners on BDA (Raguseo, 2018), perception difference on BDA by cultures (LaBrie et al., 2018), and most popularly, BDA adoption (Brock & Khan, 2017; Esteves & Curto, 2013; Shahbaz et al., 2019; Srivetbodee & Igel, 2021). However, to the best of our knowledge, little research focused on antecedents of the actual use of BDA even though the use remains a significant issue in the business organizations. The goal of this research is to understand how data quality and organizational support affect satisfaction with BDA systems and actual use of the systems. In particular, this study seeks to analyze how data integrity and data timeliness can contribute to IT connectivity for data and how organizational readiness and relational knowledge of data analytics personnel can contribute to user satisfaction and active use of BDA. The following discussion will be a thorough review of the literature related to the relationships between these constructs. The literature review will lead to a conceptual form of a research model and hypotheses. The research methodology section will explain how the data was collected and analyzed to validate our proposed hypotheses. Academic and practical implications will be discussed based on the hypothesis test results. Lastly, limitations and future research directions will be discussed to conclude this study.

## 2. Literature review

There has been a recent increase in the research literature on big data analytics because of the significant technological changes that has led to the ability to process and analyze large volumes of complex data for various applications. Big data is increasingly important for businesses but also for academics, policy-makers and governments (Chen & Zhang, 2014). Since data analytics has been a way for companies to increase business opportunities and strengthen market opportunities, especially for large corporations, it is of interest to these business organizations to adopt data analytics. The use of big data and analytics can also help firm performance in a variety of ways (Akter et al., 2016; Gunasekaran et al., 2017). The decision to use and adopt these systems appear to be motivated by varying factors and thus, it is important for researchers to investigate the important factors influencing companies to adopt big data.

The empirical literature has analyzed how data quality influences the usage of BDA. Data quality has several dimensions, and can be measured several ways, but the International Data Management Association uses the six quality dimensions of completeness, uniqueness, timeliness, validity, accuracy, and consistency (Lee et al., 2002). Data completeness measures the proportion of non-blank values against the stored data. The higher the proportion, the more complete the stored data is. Timeless is the time elapse or gap between the time an event occurs and the time the event is recorded. The higher the degree to which data represent reality, the more timeless the data is. Data duplication is an indicator of poor data quality. Uniqueness is to ensure that each data is not recorded more than once. Data have high validity if they conform to the syntax, metadata, format, range, and documentation rules. Data accuracy refers to the degree to which data can correctly describe the “real world” event or object. Data has high consistency when reference data are measured against counterparts in another data set and have the same data pattern and value frequency. Data integrity refers to the accuracy and consistency of the data in storage, and prior research has found that data quality is essential to businesses creating value from data and making decisions (Kwon et al., 2014). Data timeliness is also an important factor that is used as a measure of data quality (Cai & Zhu, 2015). In the literature, these two dimensions of data quality are helpful to generating business value (Ren et al., 2017).

In addition to the quality dimensions of the data, it is also important to the benefits of BDA that are derived from organizational and environmental factors contributing to the use of BDA. The literature has shown that there are benefits arising from organizational characteristics that can further motivate firms efforts and are crucial to the success and continued usage of BDA (Kwon et al., 2014). For organizations to be successful in their use of BDA through data-driven decisions, companies must have practices and managers to prioritize and ready to make decisions to prioritize the investment in BDA (Mikalef et al., 2018). A data-driven culture is thus an important driver of success for companies adopting BDA (Cao & Duan, 2014). Other organizational relationships that have an effect on promoting knowledge exchange that helps with the BDA process is discussed in papers by Brock and Khan (2017) and Ravichandran et al. (2005).

Big data adoption has several areas of related literature that have been analyzed. In these papers, the research models consider factors that increase the likelihood of BDA use and adoption, and include characteristics like perceived ease of use, managerial support, system quality, information quality, user satisfaction, organizational impact, and other related factors (Urbach et al., 2010). Brock and Khan (2017) discuss how the technology acceptance model has been used to provide empirical evidence on the relationship between usefulness, ease of use, perceived usefulness, and many other factors such as effectiveness, intrinsic motivation and organizational beliefs. There is a need for more empirical papers analyzing the relationship between factors underlying theoretical models that may have an influence on BDA use and adoption. We use the characteristics that have been used in theoretical and empirical models to find whether the empirical tests in this paper can provide further evidence on this topic.

### **3. Hypothesis development**

#### **3.1. The impact of data integrity on data connectivity**

Data integrity and timeliness are two important dimensions of data quality (Delone & McLean, 2003). Users are more motivated to use BDA systems when they know that the data available for analysis is of high quality, and accurate and current. The presence of quality data can help business practitioners ease the process of data integration (Kwon et al., 2014), thereby offering a global perspective and more insight. As such, users are more likely to continue to have a satisfactory experience when using the adopted BDA systems.

As data flourishes in volume, variety, veracity, and velocity, integrating data from different sources and ensuring their quality is challenging. Many companies recognize the growing

challenges and are promoting analytical culture and implementing data processing protocols to influence data quality (Cai & Zhu, 2015). Data quality is an input to the output of information used as the main source of decision making. Therefore, some scholars have strongly suggested that the Deming cycle for quality enhancement be adopted to improve each stage of the total data quality management (TDQM) cycle: define, measure, analyze and improve data quality (Wang, 1998). The enhancement of data quality is a multifaceted, cyclic concept. Data quality can be measured with its accuracy, timeliness, integrity, and readability. The benefits of using BDA systems can increase with higher levels of data quality. The improvement in any dimensions of data quality can potentially motivate users to adopt BDA systems (Kwon et al., 2014).

One of the important quality dimensions of data is data integrity. Data integrity refers to the overall accuracy, completeness, and consistency of data. Big data differs from traditional data integration because its data sources are volatile, dynamic, and heterogeneous (Dong & Srivastava, 2013) due to the volume, variety, veracity, and velocity of data. Low data integrity can result in low recoverability and poor traceability. As a result, business analytics results can be inaccurate, unreliable, and incomplete, no matter how much data is used if there is low integrity. Due to the quantity and diversity of sources, however, it is hard to maintain the integrity of big data, as it can be too large and unstructured to process and analyze.

IT connectivity is referred to as the technical ability to connect internal and external IT elements (Kim et al., 2012). Thus, the connectivity for data can refer to the ability to connect internal and external data sources effectively. As BDA systems often have multiple copies of a piece of data in multiple data centers, a firm's ability to maintain data integrity of all the distributed copies can enhance overall connectivity for data, thereby contributing to the success of data-related projects (Shen & Wang, 2014). For instance, when the users of BDA systems perceive a high level of integrity in their business information or data, they would likely consider that their organization has sufficient IT connectivity for their data to create more precise data analytics and predictive models (Soon et al., 2018). Thus, we propose:

**H1: Improving data integrity has a positive effect on data connectivity.**

### **3.2. The impact of data timeliness on data connectivity**

First mover advantage is critical for companies facing threats or having a chance to attack their competitors or to disrupt the existing industry structure (Bughin et al., 2011). Some companies also use the first-mover strategy to introduce new products, brands, or business models, thereby achieving long-term competitive advantages (Kerin et al., 1992). To support such business strategies, companies need timely data to make effective decisions on time.

Effective BDA systems adopt the holistic value chain concept to process data into useful information (Miller & Mork, 2013). Data from varying sources will need to first to be cleansed and filtered before they can be integrated for analysis. After the data is prepared, business analysts need to carefully select the right data sets for specific business inquiries and apply the right descriptive, predictive, or prescriptive analytics models to help make an effective business decision. The value chain is an iterative process. It involves many sequential steps, consisting of human collaboration, privacy and data ownership, data accuracy, data volume, and addressing data inconsistency and incompleteness (Jagadish et al., 2014). Each step in the big data life cycle entails complicated tasks and takes time to complete. Therefore, it is hard to maintain data timeliness, which indicates the degree to which the data reflects the current state of the phenomenon that it represents (Cai & Zhu, 2015).

In the BDA system, as data grows exponentially, the time lag gets longer between the time when data is captured and when the data can be used by different stakeholders to make timely

data-driven decisions (Janssen et al., 2017). The time delay also varies with stakeholders because they have varying capabilities to process the data. Therefore, as users perceive that information or data from the BDA system represent the current state of their business situation (i.e., data timeliness), they would believe the system to have an adequate capability to connect multiple data sources (i.e., data connectivity) to produce such timely data. Hence, we propose:

***H2: Improving data timeliness has a positive effect on data connectivity.***

### ***3.3. The impact of organizational readiness on user satisfaction***

Organizational readiness involves people, processes, systems, culture, and performance measurements that are synchronized and integrated for organization-wide use of BDA systems (Greeff & Ghoshal, 2004). Companies with a higher degree of organizational readiness often have a better return from their investment in BDA-enabled infrastructure (e.g., data warehouse, virtualization), hiring employees with requisite business analytics skills (Akter et al., 2016), and an established culture of analytics. Employees in such organizations often feel a higher satisfaction with the use of BDA systems because they are parts of the driver for BDA-enabled organizational competitiveness.

High data quality alone cannot ensure the success of BDA projects because they often involve people, processes, and other technologies. Organizational readiness is an important surrogate to measure whether an organization is ready for BDA-enabled changes. It is a multi-level, multi-faceted construct to assess the shared resolve and belief of organizational members to have the collective capability to implement a change (Weiner et al., 2008). People factors may include motivation and personality of program leaders and employees—process range from institutional resources to organizational climate. Readiness is an important organizational factor that is critical to the success of implementing new technologies (Lehman et al., 2002). Employees in an organization with high organizational readiness embrace new initiatives, exhibit greater persistence, and more cooperative behavior of implementing the new initiatives (Weiner, 2009). An organization needs to be flexible and creative to be constantly reacting to changes during the data analytics process. The BDA process often reveals new data management or organizational problems that were not discovered before. People in high organizational readiness can often take immediate action and resolve the detected problems, thereby achieving a higher rate of BDA project success.

***H3: Improving organizational readiness has a positive effect on user satisfaction.***

### ***3.4. The impact of relational knowledge on user satisfaction***

Relational knowledge indicates the IT personnel's capability for interpersonal communication and collaboration with business practitioners (Kim et al., 2012). It is known as an important capability of personnel to build business IT solutions and encourage users to use information technologies (Ravichandran et al., 2005).

Relational knowledge can be essential for the success of BDA systems because the users of the systems need to communicate with the IT personnel to deal with diverse technical issues. For example, the data are often stored in a silo and not integrated for the discovery of new insights. To effectively use BDA systems, support of IT personnel is highly important. If personnel do not have effective communication and collaboration skills to resolve the issues, additional problems can be introduced in the problem-solving process (e.g., delayed work process, inaccurate data manipulation, etc.) and thus, the users would be dissatisfied with the systems. Hence, we propose:

***H4: Improving relational knowledge has a positive effect on user satisfaction.***

### **3.5. The impact of data connectivity on user satisfaction**

Ad hoc queries and connectivity to multiple data sources can affect the application, business process, and user satisfaction (Isik et al., 2011). BDA system effectiveness relies on the successful execution of all these factors at the data, application, process, and user levels. Ensuring a high level of data connectivity can be a part of data preparation for business analytics (Stodder & Matters, 2016). The high connectivity of BDA systems can help business analysts exploit big data analytics to improve user satisfaction (Zeydan et al., 2016). Hence, we propose:

**H5: Improving data connectivity has a positive effect on user satisfaction.**

### **3.6. The impact of data connectivity on BDA system usage**

The adoption of big data analytics (BDA) capabilities as an important source of organizational competitiveness often goes through three sequential phases: acceptance, routinization, and assimilation (Wu & Chen, 2014). In the adoption process, IT connectivity and information sharing are critical to BDA success and have a positive influence on BDA acceptance (Gunasekaran et al., 2017). Since data is a core element of BDA systems, the users should consider data connectivity, which represents the ability to connect multiple business sectors to deliver integrated, timely information and data, before deciding to use the systems. As the systems have more data connectivity, the users should be more likely to use them to improve their job performance and efficiency. This discussion leads to the following hypothesis:

**H6: Improving data connectivity has a positive effect on BDA system use.**

### **3.7. The impact of user satisfaction on BDA system usage**

User satisfaction and system use are two important measures of information systems success (Delone & McLean, 2003). When users are satisfied with the use of BDA systems, they are more likely to engage in the use of the systems. As BDA systems are involved with different capabilities and require different skills, it is important to continuously evaluate the dynamic relationship between user satisfaction and system use in the context of BDA systems (Sharma et al., 2010). User satisfaction can help predict users' continued intention to use an information system. Therefore, it is important to increase user satisfaction with the use of BDA systems to improve the intention of users to continue adopting the systems. Hence, we propose:

**H7: Improving user satisfaction has a positive effect on BDA system use.**

Figure 1 is a research model to summarize the relationship between seven constructs pertinent to BDA system use:

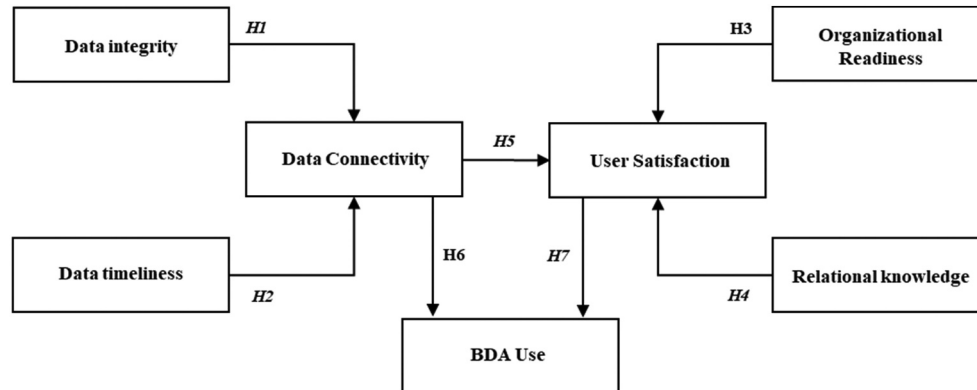
## **4. Research methodology**

We adopted a survey method to test the proposed hypotheses. The survey method is beneficial to answering research questions of this study because our findings can be generalized to other BDA users who have already adopted BDA applications. Also, the research method is cost-effective and reliable, given the limited research budget available for this research project. We also addressed the weaknesses of the inflexibility and validity of the survey method by selecting our subjects discreetly and improve the validity of our survey questionnaire based on previously validated items and feedback from experts in the BDA field (Table 1).

After completing the original survey instrument design, we conducted a pilot study with IS faculty, graduate students, and 5 actual BDA users and solicited their feedback to improve the



Figure 1. Research model.



content validity and reliability. Their feedback included issues, such as some constructs having too many items, which could have affected the response rate; several items having word ambiguity; some items not reflecting the context of the study. After the content reliability and validity were improved in the pre-test, 21 executive MBA students were invited to participate in a pilot test with 21 executive MBA students. These students were representatives of target BDA users for the full-scale survey. The participants in the pilot recommended some more changes and helped further ensure that all the survey questions properly reflected real-life situations. After the pilot test, we finalized and distributed our online survey to actual users of BDA systems. All constructs were measured on the five-point Likert scale, from one = “strongly disagree” to five = “strongly agree.”

### 5. Demographics of respondents

We conducted a two-step approach to identify subjects for our survey. First, we identified the top 1000 companies listed by the two leading recruiting firms, “104” and “1111” in Taiwan. Second, we contacted employees who are currently working for one of the top 1000 companies. Each employee was asked to help collect 5 to 10 questionnaires from the company and other companies in the top 1,000 list. All potential subjects answered the first question of whether their companies have adopted a BDA application or in the testing or evaluation stage to adopt BDA. If the answer is “NO,” the subject was directed to the end of the survey. This prevented unqualified respondents from completing the survey and confounding the findings of the study.

We collected a total of 236 valid responses for testing the proposed hypotheses. In the survey, 71% of companies have adopted BDA applications and 29% of companies are in the adoption stage, indicating that the respondents have been exposed to BDA (Table 2). Most respondents are in the age group between 20 and 29 (47.5%) and between 30 and 39 (35.6%) years old. Concerning the gender of respondents, male and female subjects account for 72% and 28%, indicating that most respondents are males. In terms of education level, the majority have degrees higher than a bachelor’s degree (97%). The largest number of respondents are from large companies with more than 500 (64.8%). IT, R&D, and sales accounted for 74.15% of the business domains of survey respondents.

### 6. Validity and reliability

We performed several tests to ensure the validity and reliability of the constructs. Cronbach’s  $\alpha$  coefficients for the measurement were higher than the acceptable cut-off value of 0.7 (Chin, 2010; Hair et al., 2012), suggesting internal consistency reliability. Convergent validity was examined with composite reliability, and average variance extracted (AVE) and all of the values for composite reliability exceeded the recommended threshold of 0.7 (Fornell & Larcker, 1981), with the smallest AVE being 0.64, which is larger than the cut-off of 0.5 (Fornell & Larcker, 1981; Hulland, 1999). Also, the square root of the construct’s AVE was greater than the correlations with other constructs,

**Table 1. Survey items**

Construct	Item	Reference
Data Connectivity (DC)	<ul style="list-style-type: none"> <li>• Compared with our competitors in the same industry, our company's IT and BDA systems have better connectivity (DC1).</li> <li>• Our company has a central control system, which connects all functions, equipment, and the BDA system (DC2).</li> <li>• Our company utilizes open systems network mechanisms to boost the connectivity (DC3).</li> </ul>	Kim et al. (2012)
Data Integrity (DI)	<ul style="list-style-type: none"> <li>• The data used by the BDA system is in a clear format and conforms to library standards (DI1).</li> <li>• The information used by the BDA system is consistent with structural integrity (DI2).</li> <li>• The data used by the BDA system is consistent with the content (DI3).</li> </ul>	Cai and Zhu (2015)
Data Timeliness (DT)	<ul style="list-style-type: none"> <li>• The information used by the BDA system can be transmitted within a given time (DT1).</li> <li>• The BDA system will update the database regularly (DT2).</li> <li>• The data used by the BDA system conforms to the data used by the pre-system from the time of collection, processing, and release (DT3).</li> </ul>	Cai and Zhu (2015)
Organizational Readiness (OR)	<ul style="list-style-type: none"> <li>• Lack of funding or financial resources will prevent companies from using BDA (OR1).</li> <li>• Lack of necessary IT infrastructure will hinder companies from using BDA systems (OR2).</li> <li>• Lack of analytical capabilities will hinder companies from using the BDA system (OR3).</li> </ul>	Chen et al. (2015)
Relational Knowledge (RK)	<ul style="list-style-type: none"> <li>• Our company's BDA personnel can plan, organize, and lead the project (RK1).</li> <li>• Our company's BDA personnel can plan and execute work in a group environment (RK2).</li> <li>• Our company's BDA personnel can teach others (RK3).</li> <li>• Our company's BDA personnel work closely with customers and maintain good relationships (RK4).</li> </ul>	Kim et al. (2012)

(Continued)

Satisfaction (SAT)	<ul style="list-style-type: none"> <li>• The BDA system was very helpful for me to complete my work and responsibilities (SAT1).</li> <li>• The BDA system greatly helped me work efficiently (SAT2).</li> <li>• The BDA system is effective for my work (SAT3).</li> </ul>	Urbach et al. (2010)
BDA Usage (BU)	<ul style="list-style-type: none"> <li>• The frequency of using the BDA system (BU1)                             <ul style="list-style-type: none"> <li>○ The weekly duration of using the BDA system (BU2)</li> </ul> </li> </ul>	Urbach et al. (2010)

**Table 2. Demographical analysis**

Categories	Variables	Frequency (%)
<b>Age</b>	20–29 years old	112 (47.5)
	30–39 years old	84 (35.6)
	40–49 years old	32 (13.6)
	50–59 years old	7 (2.9)
	60 years old and above	1(0.4)
<b>Gender</b>	Female	67 (28.3)
	Male	169 (71.7)
<b>Education</b>	High school	4 (1.7)
	Vocational school	3 (1.3)
	Bachelor	66(28.0)
	Graduate degree	153(64.8)
	Doctorate	10(4.2)
<b>Business Domain</b>	IT	104 (44.1)
	R&D	47 (19.9)
	Sales	24 (10.2)
	Manufacturing	22 (9.3)
	Marketing	15 (6.4)
	HR	5 (2.1)
	Finance	3 (1.3)
	Purchasing	2 (0.8)
	Others	14 (5.9)
<b>Company Size</b>	More than 500	153 (64.8)
	200–499	25 (10.6)
	50–199	27 (11.4)
	30–49	17 (7.2)
	Fewer than 29	14 (5.9)
<b>BDA Stage in Company</b>	Adopted	168 (71.1)
	In the adoption process	68 (18.9)

ensuring the discriminant validity of the measurement (Chin, 2010), and no significant multicollinearity in the model. Table 3 summarizes the model quality indicators discussed. We also performed a PLS confirmatory analysis to assure convergent and discriminant validity (Appendix). The results show that items have higher self-loadings than cross-loadings, confirming the validity (Gefen et al., 2000).

We employed Structural Equation Modeling (SEM) with Partial Least Squares (PLS) to test the proposed hypotheses. SEM is a reliable technique to test multiple causal relationships (Henseler et al., 2009), and is not sensitive to the issues about population, the scale of measurement, and residual distribution (Chin, 1998; Fornell & Bookstein, 1982). Partial least squares (PLS) regression was the statistical technique used for data analysis. The major benefit of PLS regression is that it does not require data to be normally distributed, and it supports a smaller sample size for the analysis (Gefen et al., 2000). In particular, PLS regression is appropriate for this study because the Jarque-Bera test of normality was performed before data analysis. It indicated that all key variables in the hypotheses were not normally distributed, thereby making PLS provide more reliable results than other covariance-based structural equation modeling techniques. Table 4 and Figure 2 summarize the results of the hypothesis tests.

Data integrity (DI) explained 38.7% of the variance in data connectivity (DC). DI had a positive influence on DC at the 99% confidence level ( $\beta = 0.38.7$ ;  $t = 3.646$ ), supporting Hypothesis 1. Hypothesis 2 was supported at the 99% level ( $\beta = 0.231$ ;  $t = 2.388$ ), suggesting a positive impact of data timeliness (DT) on DC. DI and DT together explained 32.7% of the variance in DC ( $R^2 = 0.327$ ). Hypothesis 3 was not supported at the 90% level ( $\beta = 0.079$ ;  $t = 0.967$ ), suggesting that organizational readiness (OR) had no effect on user satisfaction (SAT). Hypothesis 4 was supported at the 99% level ( $\beta = 0.367$ ;  $t = 4.306$ ), indicating a positive effect of relational knowledge (RK) on SAT to use BDA systems. Hypothesis 5 was supported at the 99% level ( $\beta = 0.230$ ;  $t = 2.609$ ). This suggests that DC had a positive effect on the SAT. OR, RK, and DC together explained 30.4% of the variance in SAT ( $R^2 = 0.304$ ).

Hypothesis 6 was not supported at the 90% level ( $\beta = 0.01$ ;  $t = 0.233$ ), suggesting no significant impact of DC on BDA system usage (USE). Hypothesis 7 was supported at the 99% level ( $\beta = 0.539$ ;  $t = 10.261$ ), suggesting a positive impact of the SAT on USE. DC and SAT together explained 29.7% of the variance in USE ( $R^2 = 0.297$ ).

### 7. Discussion

The goal of this study is to examine the influence of data quality and satisfactory user experience on continuous BDA use. Data quality metrics measured in this study consist of data integrity, data timeliness, and data connectivity. The former two quality measures are important antecedents for

**Table 3. Quality indicators and correlations with square root of AVE on the diagonal**

Const.	CA	AVE	CR	DC	DI	DT	OR	RK	SAT	USE
DC	0.784	0.700	0.860	0.837						
DI	0.913	0.850	0.934	0.547**	0.922					
DT	0.752	0.669	0.928	0.500**	0.695**	0.818				
OR	0.829	0.654	0.878	-0.031	0.137	0.145	0.809			
RK	0.809	0.638	0.871	0.568**	0.628**	0.556**	0.224**	0.799		
SAT	0.912	0.793	0.934	0.441**	0.503**	0.588**	0.169*	0.516**	0.890	
USE	0.830	0.853	0.946	0.252**	0.298**	0.353**	0.188*	0.369**	0.5458**	0.923**

※CA: Cronbach's  $\alpha$ , CR: Composite Reliability, AVE: Average Variance Extracted, Square of AVE on the diagonal, \*\*  $p < 0.01$ , \* $p < 0.05$

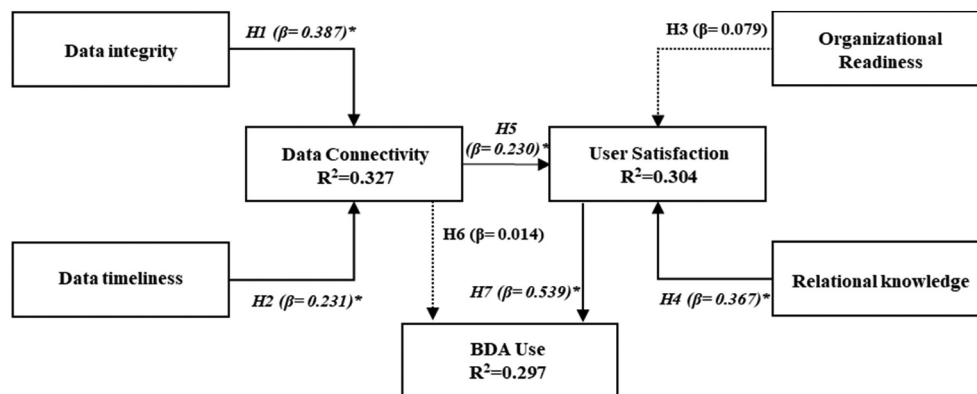
**Table 4. Results of hypothesis testing**

Hypothesized Path	Path Coefficient	T-statistics	Hypothesis Test Results
H1: DI → DC	0.386556	3.646**	Supported
H2: DT → DC	0.231516	2.388**	Supported
H3: OR → SAT	0.079100	0.967	Not Supported
H4: RK → SAT	0.367273	4.306**	Supported
H5: DC → SAT	0.230214	2.609**	Supported
H6: DC → USE	0.014014	0.233	Not Supported
H7: SAT → USE	0.538953	10.261**	Supported

※ Significance: \*p < 0.01

**Figure 2. Theoretical model with results of hypothesis testing.**

※ Significance: \*p < 0.01



the improvement of data connectivity. As predicted in Hypothesis 1 and 2, we found that there is a significant relationship between both data integrity and data timeliness with data connectivity. This result is consistent with other literature findings that the quality dimensions of data are influential to the BDA process (Kwon et al., 2014; Ren et al., 2017).

Concerning organizational support, relational knowledge of BDA personnel has a significant impact on the satisfactory experiences of using BDA systems, as Hypothesis 4 shows a significant relationship with satisfaction. This is consistent with the findings in Kim et al. (2012) that use relational knowledge as one of the factors in IT capability. However, in Hypothesis 3, organizational readiness is found to have no significant relationship with satisfaction, as the test result indicates. This finding is somewhat inconsistent with some of the literature that has found organizational readiness is positively related to BDA use (Chen et al., 2015).

We also found that data connectivity is significant concerning the satisfaction with BDA systems use. This result is consistent with Gunasekaran et al. (2017) paper finding that connectivity has a significant influence on big data acceptance. It appears that the relational knowledge and data connectivity are both important to improve user satisfaction with the systems. To promote the use of BDA systems, the users' satisfactory experiences exhibit a significant impact, but data connectivity does not. This finding indicates that the data connectivity of BDA systems alone may not be enough to motivate more use of BDA systems. Rather, the satisfactory experience, which can be created by communicable and collaborative BDA personnel, can be more critical in encouraging the actual use of BDA systems. As discussed in Delone and McLean (2003) and Urbach et al. (2010),

user satisfaction is one of the most important factors in IT success, as further supported by our findings in Hypothesis 7.

### **8. Theoretical implications**

The findings of this study provide several theoretical implications. First, it suggests a research framework for BDA studies. Different from the previous study primarily investigating BDA adoption from organizational perspectives (Schryen, 2013), our study offers a more comprehensive perspective on the use of BDA systems. BDA adoption is prone to failure because the issues faced by BDA users are complex and multidisciplinary (Sheng et al., 2017). This study suggests three critical dimensions of BDA use, such as data quality, organizational support, and user satisfaction. Data dimension includes data integrity, data timeliness, and data connectivity. Organizational dimension includes organizational readiness and relational knowledge. The user dimension consists of user satisfaction with BDA systems. In particular, it suggests that user satisfaction has the highest impact on the decision of business analysts to embrace the use of BDA systems. Relational knowledge and data quality, consisting of data integrity, timeliness, and data connectivity, have a similar influence on the satisfaction with BDA systems. These findings show that user satisfaction can directly lead to the active use of BDA systems, but data connectivity alone does not directly affect it. Users are more motivated to engage in the use of BDA systems when they are satisfied with data connectivity. Second, our finding suggests that organizational readiness may not be a critical factor to affect user satisfaction with BDA systems. This is somewhat interesting because it does not correspond to the extant literature (Lehman et al., 2002). This unexpected finding can be explained by fully established organizational support after the adoption of BDA systems. The average scores of the three items for Organizational Readiness are approximately 4.2 out of 5.0 (4.119, 4.174, and 4.169 respectively), indicating that the survey respondents have high level of organizational support. Therefore, the readiness has little impact on their satisfaction with BDA systems. This implies that although the readiness can be important in the adoption of BDA systems, it may not be when business practitioners are using it after the adoption. Rather, cooperative attitude of IT personnel for BDA systems (i.e., relational knowledge) is more important to increase satisfaction. This also implies that the interpersonal relationships of users with IT personnel should be considered as a critical factor in understanding the user's satisfaction. Our findings reveal that data integrity and data timeliness determine perceived data connectivity, which refers to an organization's ability to connect various data sources. Lastly, this indicates that perceived IT system quality concerning data processing is determined by how well data output is integrated across multiple business functions and how timely data output is provided to the users.

### **9. Practical implications**

This study offers some suggestions to cultivate a business analytical culture and environment to promote the active use of BDA systems within an organization, focusing on three areas: data, organizational, and user. First, user satisfaction with BDA systems depends on the establishment of sound data connectivity, which can be improved by data integrity and data timeliness. Maintaining data integrity throughout the data analytics life cycle is challenging (Zhang et al., 2017) because different stakeholders have different interests in using the stored datasets and perform uncoordinated actions, such as modifying data models, updating datasets, and aggregating analytics results. Consequently, data integrity could be easily or accidentally compromised. Low data integrity can lead to the decreased trust of users and the ability to interpret the data scientifically (Wallis et al., 2007). As a result, users become reluctant to using BDA systems embedded with low data integrity. In the face of companies embracing IoT and cloud computing to generate, distribute, store and analyze the data, data integrity can be the first and foremost issue that has to be properly addressed to drive the smart decision-making processes (Kumarage et al., 2016). Data quality has also been shown to increase the competitive advantage for a business (Corte-Real et al., 2020). Our findings further affirm the importance of data integrity for business analysts when considering to be actively involved in the use of BDA systems across industries.

An effective BDA system can not only process big data efficiently, but also, more importantly, help various stakeholders arrive at timely conclusions (Al-Jaroodi et al., 2017). With a shortening product life cycle, some retail businesses even consider recent data as “good data,” but old data as “bad data” (Bradlow et al., 2017). Without timely data, managers’ ability to make good decisions may be hampered. Predictive analytics requires more recent data to maximize the predictive accuracy of some machine learning models (Dietterich, 1995). Our finding also confirms that timely data is indispensable for BDA system users.

Organizational readiness ranges from the financial resources, IT infrastructure, analytics capability, skilled resources to agile project management culture. This study found that organizational readiness has no significant effect on user satisfaction. Contrary to the previous study, users do not correlate their satisfactory experiences of using BDA systems with complementary assets while relational knowledge exhibits a strong effect on user satisfaction with BDA system use. Therefore, business organizations may want to emphasize the relationship between IT personnel for BDA systems and the users, particularly after the adoption of BDA, to promote actual use of the system.

### 10. Limitations and future research

Although this study is one of the first attempts to investigate the use of BDA systems, it has several limitations, as others do. First, survey data to test hypotheses were collected randomly from BDA users of the Top 1000 companies in Taiwan to get a good representation of the BDA user population. A reference system was adopted to increase the participation rate. We first asked a group of executive MBA students to help distribute the survey to friends who are holding BDA related positions in their social networks. The prescreening process may limit the data collected from the easily accessible and available group. Therefore, the findings warrant careful interpretations and can best represent the viewpoints of BDA users of the Top 1000 companies in Taiwan. Future research may test the hypotheses using data collected from different locations and industry domains.

Second, although this study offers a balanced framework to understand user, organizational, and data-related factors, the research model can only explain 29.7% of BDA use. Future studies can try to add additional dimensions to our research model because they may be able to significantly increase the use of BDA systems within an organization (Delone & McLean, 2003). Data connectivity does not have a direct effect on BDA system use. Scholars interested in understanding other dimensions of data quality, such as data accuracy, timeliness, integrity, and readability, could extend the study and assess whether they have a direct influence on BDA system use. Researchers interested in expanding our research model can consider other key factors that can also potentially promote the active use of BDA systems, such as user, organizational, technical, managerial, process, and data related factors (Greeff & Ghoshal, 2004). For example, as the capabilities of BDA systems continue to advance, a dynamic approach can be adopted to assess various factors to encourage BDA use, such as organization-wide capabilities and contribution to work performance (Sharma et al.). The organizational policy concerning IS use can also influence how an information system is adopted and use within an organization (Hossain & Quaddus, 2014). Researchers who are interested in understanding the impact of system environment on BDA use can consider whether BDA system use is mandatory or voluntary across various business functions. The previous study shows that in the early adoption stage, IS managers can use a mandatory use environment to influence end-user dissonance levels to promote high compliance and use according to dissonance theory (Rawstorne et al., 1998). Future research may consider these policy factors to have a more comprehensive understanding of the use of BDA systems.

Lastly, although organizational readiness is found to have no significant influence on BDA use, future studies may want to test the relationship of satisfaction with BDA system with more specific constructs concerning readiness, rather than a single measure. For instance, measures of readiness might be divided into technical and non-technical supports to verify which aspects of

readiness might affect overall satisfaction of BDA users, and perhaps future research can help with the implications of other related constructs on BDA use.

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**Appendix: Cross Loadings of Construct Indicators**

Items	Mean	S.D.	DCON	DI	DT	OR	RK	SAT	BU
<b>DCON1</b>	3.606	0.059	<b>0.607</b>	0.280	0.107	0.013	0.223	0.233	-0.077
<b>DCON2</b>	3.708	0.066	<b>0.714</b>	0.243	0.106	-0.011	0.114	0.183	0.146
<b>DCON3</b>	3.593	0.072	<b>0.575</b>	0.294	-0.033	-0.124	0.167	0.135	0.134
<b>DI1</b>	3.919	0.052	0.347	<b>0.733</b>	0.174	0.058	0.189	0.158	0.195
<b>DI2</b>	3.903	0.052	0.119	<b>0.854</b>	0.032	0.046	0.125	0.220	0.047
<b>DI3</b>	3.826	0.054	0.097	<b>0.862</b>	0.032	0.033	0.160	0.218	0.015
<b>DT1</b>	3.979	0.048	0.213	0.424	<b>0.481</b>	0.091	0.128	0.327	0.099
<b>DT2</b>	3.881	0.051	0.232	0.450	<b>0.452</b>	-0.023	0.036	0.329	0.118
<b>OR1</b>	4.119	0.057	0.112	0.119	-0.106	<b>0.735</b>	0.050	-0.011	0.023
<b>OR2</b>	4.174	0.051	-0.120	0.080	0.098	<b>0.729</b>	0.023	0.119	0.049
<b>OR3</b>	4.169	0.052	-0.034	-0.037	0.041	<b>0.788</b>	0.068	0.104	0.052
<b>RK1</b>	3.792	0.053	0.235	0.326	-0.010	0.038	<b>0.616</b>	0.259	-0.032
<b>RK2</b>	3.987	0.046	0.132	0.370	0.026	0.134	<b>0.630</b>	0.201	0.134
<b>RK3</b>	3.996	0.051	0.243	0.291	0.213	0.099	<b>0.500</b>	0.266	0.210
<b>SAT1</b>	4.047	0.050	0.103	0.204	0.069	0.092	0.152	<b>0.833</b>	0.154
<b>SAT2</b>	4.021	0.051	0.127	0.246	0.119	0.054	0.120	<b>0.768</b>	0.234
<b>SAT3</b>	4.038	0.051	0.145	0.242	0.021	0.056	0.102	<b>0.775</b>	0.201
<b>BU1</b>	3.949	0.067	0.086	0.177	0.051	0.102	0.104	0.355	<b>0.724</b>
<b>BU2</b>	3.301	0.085	0.060	0.017	0.030	0.019	0.018	0.275	<b>0.730</b>

※DC = Data Connectivity, DI = Data Integrity, DT = Data Timeliness, OR = Organizational Readiness, RK = Relational Knowledge, SAT = Satisfaction BU = BDA Usage



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