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Determinants of Big Data Analytics System Use: The Roles of Data Quality, Organizational Support, and User Satisfaction

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Abstract

This research examines the key determinants influencing the utilization of Big Data Analytics (BDA) systems, focusing on data quality, organizational support, and user satisfaction. A total of 236 BDA system users from various industries participated in the survey, and the collected data were analyzed using the PLS-SEM technique. The results reveal that data integrity and timeliness play a critical role in shaping data connectivity within BDA systems, which in turn influences user satisfaction alongside the relational expertise of IT staff. Moreover, the analysis demonstrates that while user satisfaction positively impacts BDA system use, data connectivity does not exhibit a significant effect. These findings suggest that users' experiences substantially affect business professionals' intentions to utilize BDA systems, whereas data connectivity alone does not. Drawing on these empirical insights, the study contributes theoretical and practical perspectives for enhancing the effective implementation and success of BDA systems.

Keywords: User satisfaction, Big data analytics, Data connectivity

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Introduction

In today's highly competitive global marketplace, businesses are under increasing pressure to meet rising customer expectations. To gain innovative and competitive advantages that sustain profitability, many companies are turning to big data technologies [1, 2]. Research has demonstrated that the use of BDA systems enhances business performance, competitiveness, and overall value creation [3]. For instance, a large-scale study involving top executives from 330 North American firms revealed that data-driven companies outperform their peers, achieving 5% higher productivity and 6% greater profitability, while over 30% of executives expressed concern about relying too heavily on intuition rather than data [4].

The adoption of BDA has been steadily increasing—from 17% in 2015 to 59% in 2018—and continues to grow [5]. Nonetheless, numerous organizations still face significant difficulties in successfully implementing and integrating these systems. Reports suggest that nearly 77% of leading firms, including Ford and American Express, identify BDA integration as a persistent challenge [6].

Existing studies confirm that many firms struggle with the successful use of BDA systems [7]. Among the primary barriers are poor data quality and insufficient organizational support. The vast volume of distributed data, combined with issues of security and platform incompatibility, creates serious data quality concerns that discourage the adoption of BDA [8]. Furthermore, a lack of adequate organizational support makes many employees hesitant to use these systems even after implementation [9]. To encourage active BDA use, companies must address challenges related to data quality and organizational readiness, ensuring users have access to reliable data that supports effective decision-making.

Although prior research has examined topics such as practitioners' perceptions of BDA [10], cultural differences in perceptions [11], and adoption factors [12-15], little attention has been paid to the underlying factors influencing *actual* BDA use. This study aims to fill that gap by examining how data quality and organizational support impact satisfaction and continued usage of BDA systems. Specifically, it investigates how data integrity and timeliness enhance IT data connectivity and how organizational preparedness and the relational expertise of data analytics staff promote user satisfaction and system usage. The next section reviews relevant literature, followed by the development of the research model and hypotheses, the research methodology, results and implications, and finally, the study's limitations and suggestions for future research.

Literature Review

Recent years have seen a surge in academic interest in big data analytics due to technological advancements that enable the processing and analysis of massive and complex datasets for diverse applications. Big data has become vital not only to businesses but also to academia, government, and policymakers [16]. As data analytics provides avenues for discovering new business opportunities and reinforcing market competitiveness—particularly among large corporations—it has become a priority for organizations aiming to enhance performance [3, 17]. Given the diversity of motivations behind adopting BDA systems, it is important to identify the specific factors influencing firms' adoption and usage decisions.

Empirical research has demonstrated that data quality is a major determinant of BDA utilization. Data quality encompasses multiple dimensions. The International Data Management Association identifies six key dimensions: completeness, uniqueness, timeliness, validity, accuracy, and consistency [18]. *Completeness* refers to the extent to which data entries are non-missing. *Timeliness* represents the lag between an event's occurrence and its recording; more timely data better reflect reality. *Uniqueness* ensures that data are not duplicated, while *validity* measures conformance to syntax, format, and documentation standards. *Accuracy* assesses how precisely data represent real-world phenomena, and *consistency* indicates uniformity across datasets. Data *integrity*, encompassing accuracy and consistency, is a core component of data quality and has been shown to be essential for deriving business value and supporting sound decision-making [19]. Similarly, *data timeliness* plays a crucial role in determining the usefulness of data for business purposes [20]. Together, these attributes contribute significantly to the value generated from big data initiatives [21].

Beyond the technical aspects of data quality, organizational and environmental factors are also crucial to the effective use of BDA. Prior studies have emphasized that organizational readiness, culture, and managerial commitment are key enablers of successful BDA adoption and continued usage [19, 22]. Developing a data-driven culture that prioritizes analytics-based decision-making can greatly enhance an organization's capacity to leverage BDA for competitive advantage [23]. Furthermore, internal organizational relationships and knowledge-sharing practices—highlighted by Brock and Khan [12] and Ravichandran *et al.* [24]—promote collaboration and knowledge exchange, both of which facilitate more effective data analytics processes.

Research on big data adoption encompasses a wide range of literature examining the determinants that influence the use and implementation of BDA systems. These studies often propose research models that identify factors such as perceived ease of use, managerial and organizational support, system and information quality, user satisfaction, and organizational impact as predictors of successful adoption [25]. Brock and Khan [12] highlighted how the Technology Acceptance Model (TAM) has been applied to empirically explore the relationships among perceived usefulness, ease of use, and other variables such as effectiveness, intrinsic motivation, and organizational beliefs. However, there remains a need for more empirical research investigating the interrelationships among these theoretical constructs to better understand their influence on BDA usage and adoption. Building on prior theoretical and empirical frameworks, the present study utilizes these established characteristics to examine whether its empirical findings can contribute new evidence to this growing field.

Hypothesis Development

The effect of data integrity on data connectivity

Among the key dimensions of data quality, data integrity and data timeliness play crucial roles [26]. Users tend to be more inclined to adopt and rely on BDA systems when they are confident that the data they work with is accurate, complete, and up-to-date. High-quality data facilitates smoother integration and analysis processes [19], providing users with broader perspectives and deeper insights, which ultimately enhance user satisfaction and continued system usage.

As the volume, velocity, and variety of data continue to expand, integrating data from multiple and diverse sources while ensuring its quality has become increasingly difficult. Many firms are responding to this challenge by fostering an analytics-driven culture and establishing robust data management procedures to uphold data quality [20]. Because data quality directly influences the information used for decision-making, some researchers advocate applying the Deming quality improvement cycle—defining, measuring, analyzing, and improving—to the Total Data Quality Management (TDQM) framework [27].

Enhancing data quality is therefore a continuous and multifaceted process. Improvements in any of its dimensions—accuracy, integrity, timeliness, or readability—can enhance the benefits derived from BDA systems and motivate broader adoption [19]. Data integrity, specifically, represents the overall completeness, consistency, and accuracy of data. Unlike traditional data management, maintaining integrity in big data environments is complex because data sources are highly dynamic, volatile, and heterogeneous [28]. Poor data integrity undermines the reliability and accuracy of analytics outcomes, regardless of the dataset's size. Given the distributed and unstructured nature of big data, preserving integrity across multiple sources and formats poses a significant challenge.

Information technology (IT) connectivity refers to an organization's technical ability to link its internal and external IT components effectively [29]. In the context of big data, data connectivity describes the capacity to integrate and synchronize data from multiple internal and external sources. As BDA systems often replicate data across several data centers, maintaining the integrity of these distributed datasets can enhance overall connectivity, supporting more accurate analytics and predictive modeling [30]. When users perceive that their organization's data is reliable and consistent, they are more likely to believe that their firm possesses strong IT connectivity, thereby improving analytical capabilities [31]. Based on this reasoning, the study proposes:

H1: Higher data integrity positively influences data connectivity.

The Effect of data timeliness on data connectivity

Achieving a first-mover advantage is often critical for organizations seeking to respond rapidly to market changes, counter competitive threats, or reshape industry dynamics [32]. Firms pursuing such strategies rely heavily on timely data to make prompt, informed decisions that can yield sustainable competitive advantages [33].

Effective BDA systems utilize a value chain approach to transform raw data into actionable information [34]. Data from diverse sources must first be cleaned and standardized before being merged for analysis. Once prepared, business analysts select appropriate datasets and apply analytical models—descriptive, predictive, or prescriptive—to address specific business needs. This iterative process involves multiple stages, including data ownership and privacy considerations, ensuring accuracy, managing data volume, and resolving inconsistencies or gaps [35]. Because each stage requires time and human collaboration, maintaining data timeliness—defined as the extent to which data reflect the current state of reality—remains a considerable challenge [20].

As data volume grows exponentially, the lag between data collection and its availability for analysis tends to increase, reducing its immediacy and usefulness [36]. Moreover, these time delays can differ across stakeholders depending on their technical capacity to process information efficiently. When users perceive that the data produced by a BDA system accurately represents the organization's current situation—that is, when they experience high data timeliness—they are more likely to infer that the system effectively connects and integrates multiple data sources, reflecting strong data connectivity. Therefore, this study proposes:

H2: Improved data timeliness has a positive effect on data connectivity.

The effect of organizational readiness on user satisfaction

Organizational readiness encompasses the alignment of people, processes, technologies, culture, and performance measurement systems within a company to facilitate organization-wide utilization of BDA systems [37]. Firms demonstrating higher levels of readiness typically achieve stronger returns on their investments in BDA-related infrastructure—such as data warehouses and virtualization technologies—by recruiting employees equipped with analytical expertise and nurturing a data-driven culture [17]. Employees in such environments tend to report higher satisfaction levels when using BDA systems, as they recognize their roles in driving data-enabled competitiveness.

While data quality is fundamental, it alone does not guarantee the success of BDA initiatives, which also depend heavily on human, procedural, and technological components. Organizational readiness serves as a key indicator of whether a company is prepared to embrace BDA-driven transformation. It is a multidimensional construct reflecting the collective belief and shared commitment among members that the organization possesses the necessary capabilities to implement change effectively [38]. The people component may include motivation and leadership, while process elements involve institutional resources, climate, and communication structures. Prior research highlights that organizational readiness is critical to the successful implementation of new technologies [39].

In organizations with strong readiness, employees tend to accept innovations more readily, display persistence in overcoming challenges, and engage cooperatively in implementing new systems [40]. Because the BDA process often uncovers unforeseen data management or organizational challenges, flexibility and quick responsiveness become vital. Organizations with high readiness can more effectively identify and resolve such issues, increasing both project success rates and user satisfaction.

H3: Higher organizational readiness positively influences user satisfaction.

The effect of relational knowledge on user satisfaction

Relational knowledge refers to the interpersonal and collaborative skills of IT personnel that enable effective communication and coordination with business users [29]. This capability is crucial for designing effective IT solutions and fostering user engagement with technological systems [41].
In the context of BDA, relational knowledge plays a pivotal role in ensuring that users can interact productively with IT teams to address technical challenges. Data in many organizations often reside in isolated silos, limiting the discovery of new insights. The support of IT personnel is therefore indispensable for integrating these data sources. However, when IT staff lack sufficient communication or collaboration skills, issues such as workflow delays or inaccurate data handling can emerge—ultimately reducing user satisfaction with BDA systems. Thus, strong relational knowledge fosters smoother problem resolution and increases user confidence and satisfaction with the system.
H4: Higher relational knowledge positively influences user satisfaction.

The effect of data connectivity on user satisfaction

The ability of a BDA system to connect to multiple data sources and execute ad hoc queries directly impacts applications, business processes, and user experiences [42]. The success of BDA systems relies on effective integration across data, application, process, and user dimensions. Ensuring strong data connectivity enhances data preparation and analysis processes [43], enabling business analysts to derive more accurate insights and actionable results. When users perceive that the system efficiently connects various data sources, they experience greater trust and satisfaction with its analytical performance [44].
H5: Higher data connectivity positively influences user satisfaction.

The effect of data connectivity on BDA system usage

The integration of BDA capabilities as a driver of competitive advantage typically unfolds through three stages: acceptance, routinization, and assimilation [45]. Throughout this progression, IT connectivity and information sharing serve as critical success factors that enhance user acceptance of BDA technologies [3]. Because data connectivity represents an organization's ability to link multiple business units and deliver timely, unified information, it becomes a decisive factor influencing users' willingness to utilize BDA systems.
When users perceive that the system provides seamless data access across functions, they are more likely to engage with it frequently to improve efficiency and performance. Hence, improved data connectivity not only enhances analytical outcomes but also increases users' intention to adopt and use BDA systems consistently.
H6: Higher data connectivity positively influences BDA system usage.

The effect of user satisfaction on BDA system usage

User satisfaction and system usage are widely recognized as fundamental indicators of information system success [26]. When users are satisfied with their experience using BDA systems, they are more likely to continue engaging with them. Given that BDA systems require specialized skills and involve multiple technological components, maintaining high levels of satisfaction is essential for ensuring sustained use [46].
User satisfaction acts as a strong predictor of continued intention to use an information system. Therefore, enhancing satisfaction among BDA users can significantly improve adoption rates, integration depth, and overall system utilization across the organization.
H7: Higher user satisfaction positively influences BDA system usage.
Figure 1 presents the conceptual research model summarizing the hypothesized relationships among the seven constructs influencing the use of Big Data Analytics systems.

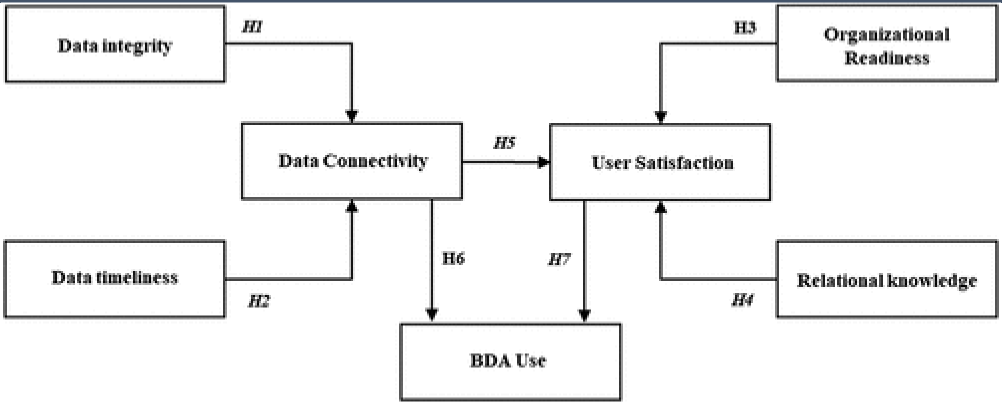

Figure 1. Research model

Research Methodology

We employed a survey-based research design to empirically test the proposed hypotheses. The survey method was deemed appropriate for this study as it enables the collection of data from a broad range of respondents, thereby enhancing the generalizability of the findings to other BDA users who have already implemented analytics applications. Additionally, this approach offered a cost-effective and dependable means of data collection, which was particularly advantageous given the limited research budget available for the project.

To mitigate common limitations associated with survey methods—such as inflexibility and concerns over validity—we carefully selected participants to ensure they were knowledgeable and experienced users of BDA systems. Furthermore, we strengthened the content and construct validity of the questionnaire by adapting measurement items from previously validated studies and incorporating expert feedback from professionals and scholars specializing in Big Data Analytics. Details of the measurement items and their sources are provided in **Table 1**.

Table 1. Survey items

Construct	Item	Reference
Data Connectivity (DC)	• Relative to competitors within the same industry, the organization's information technology (IT) and big data analytics (BDA) systems exhibit superior interconnectivity (DC1). • The organization employs a centralized control system that integrates all functional units, equipment, and the BDA infrastructure (DC2). • The organization implements open systems network protocols to enhance interconnectivity (DC3).	Kim *et al.* [29]
Data Integrity (DI)	• Data utilized by the BDA system adhere to a standardized, unambiguous format consistent with established library conventions (DI1). • Information processed by the BDA system maintains structural consistency (DI2). • Data employed by the BDA system demonstrate content-level congruence (DI3).	Cai and Zhu [20]
Data Timeliness (DT)	• Information processed by the BDA system can be transmitted within predefined temporal constraints (DT1). • The BDA system performs periodic database updates (DT2). • Data utilized by the BDA system remain temporally aligned with antecedent systems across collection, processing, and dissemination stages (DT3).	Cai and Zhu [20]
Organizational Readiness (OR)	• Insufficient financial resources impede organizational adoption of BDA (OR1). • Inadequate IT infrastructure constrains organizational implementation of BDA systems (OR2). • Deficient analytical competencies hinder organizational utilization of BDA systems (OR3).	Chen *et al.* [47]
Relational Knowledge (RK)	• BDA personnel within the organization possess competencies in project planning, coordination, and leadership (RK1). • BDA personnel demonstrate proficiency in collaborative planning and execution within team settings (RK2). • BDA personnel exhibit instructional capabilities toward colleagues (RK3). • BDA personnel foster close collaboration with clients and sustain positive interpersonal relationships (RK4).	Kim *et al.* [29]
Satisfaction (SAT)	• The BDA system substantially facilitates fulfillment of professional duties and obligations (SAT1). • The BDA system significantly enhances operational efficiency (SAT2). • The BDA system proves efficacious in supporting work-related tasks (SAT3).	Urbach *et al.* [25]
BDA Usage (BU)	• Frequency of BDA system utilization (BU1). • Weekly duration of BDA system engagement (BU2).	Urbach *et al.* [25]

After designing the initial version of the survey instrument, we conducted a pilot study to refine its clarity, validity, and reliability. The preliminary pilot involved Information Systems (IS) faculty members, graduate students, and five actual BDA users, whose feedback was instrumental in improving the questionnaire’s quality. They pointed out several issues, such as an excessive number of items within certain constructs that could discourage participation, ambiguous wording in some questions, and a few items that did not fully align with the specific context of the study.

Following these revisions, a second pilot test was conducted with 21 executive MBA students who represented the intended population of BDA users for the main survey. Their feedback further enhanced the survey's realism and ensured that each question accurately captured practical, real-world experiences with BDA systems. After incorporating their suggestions, the online questionnaire was finalized and distributed to actual users of BDA systems. All constructs were measured using a five-point Likert scale ranging from 1 = "strongly disagree" to 5 = "strongly agree."
To identify suitable participants for the survey, we adopted a two-step sampling strategy. In the first step, we selected the top 1,000 companies in Taiwan based on the rankings published by two leading recruitment platforms, 104 and 1111. In the second step, employees from these companies were contacted and asked to distribute between five and ten surveys among their colleagues or counterparts working in other companies within the same list of top organizations. To ensure data quality, each respondent was first asked whether their company had already adopted, or was in the process of testing or evaluating, a Big Data Analytics (BDA) application. Those who answered "NO" were automatically directed to the end of the survey to prevent unqualified responses and ensure the validity of the data collected.
A total of 236 valid responses were obtained and used for hypothesis testing. Among these respondents, 71 percent reported that their companies had already implemented BDA applications, while 29 percent were in the adoption phase, indicating that all participants had practical exposure to BDA systems. The majority of respondents were between 20 and 29 years old (47.5 percent), followed by those between 30 and 39 years old (35.6 percent). Regarding gender, 72 percent of the respondents were male and 28 percent female, showing that most participants were male. In terms of education level, 97 percent of the participants held at least a bachelor's degree, with many having pursued postgraduate studies. Most respondents worked in large organizations with more than 500 employees (64.8 percent). The primary professional fields of the participants were IT, R&D, and sales, which together accounted for 74.15 percent of the total respondents. These demographics indicate that the participants were well-educated professionals with relevant experience, ensuring that the findings reflect knowledgeable and informed perspectives on BDA system use and user satisfaction.

Table 2. Demographical analysis

Categories	Variables	Frequency (%)
Age	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)
Gender	Female	67 (28.3)
	Male	169 (71.7)
Education	High school	4 (1.7)
	Vocational school	3 (1.3)
	Bachelor	66(28.0)
	Graduate degree	153(64.8)
	Doctorate	10(4.2)
Business Domain	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)
Company Size	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)
BDA Stage in Company	Adopted	168 (71.1)
	In the adoption process	68 (18.9)

Validity and Reliability

We conducted a series of analyses to confirm that the constructs used in this study were both valid and reliable. Internal consistency was assessed using Cronbach's α, and all constructs exceeded the recommended minimum of 0.7 [48, 49], indicating reliable measurements. Convergent validity was evaluated through composite reliability and average variance extracted (AVE). All constructs had composite reliability values above 0.7, while the lowest AVE observed was 0.64, surpassing the 0.5 threshold typically considered acceptable [50, 51].

Discriminant validity was confirmed by comparing the square root of each construct's AVE with the correlations among constructs. In all cases, the square root of AVE was higher than the inter-construct correlations, demonstrating that each construct was distinct from the others [48]. Multicollinearity was not detected, indicating that the constructs were statistically independent.

The quality indicators for the model are summarized in **Table 3**. In addition, a Partial Least Squares (PLS) confirmatory analysis was conducted to further verify convergent and discriminant validity. The results showed that items loaded more strongly on their intended constructs than on other constructs, providing additional evidence that the measurement model was both valid and reliable [52].

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 α, **CR**: Composite Reliability, **AVE**: Average Variance Extracted, Square of AVE on the diagonal, ** $p < 0.01$, *$p < 0.05$

To test the proposed hypotheses, we applied Structural Equation Modeling (SEM) using the Partial Least Squares (PLS) approach. SEM is a widely recognized method for examining complex causal relationships among multiple variables [53] and has the advantage of being less affected by sample size, measurement scale type, or deviations from normality [54, 55].

We selected PLS regression as the primary analysis technique because it is particularly suitable for datasets that do not meet normality assumptions and can be effectively applied even with relatively small sample sizes [52]. Before conducting the analysis, the Jarque-Bera test was performed, confirming that the key variables were not normally distributed. This made PLS an appropriate choice over traditional covariance-based SEM techniques, as it provides more robust results under such conditions. The findings from the hypothesis testing are presented in **Table 4** and illustrated in **Figure 2**.

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**

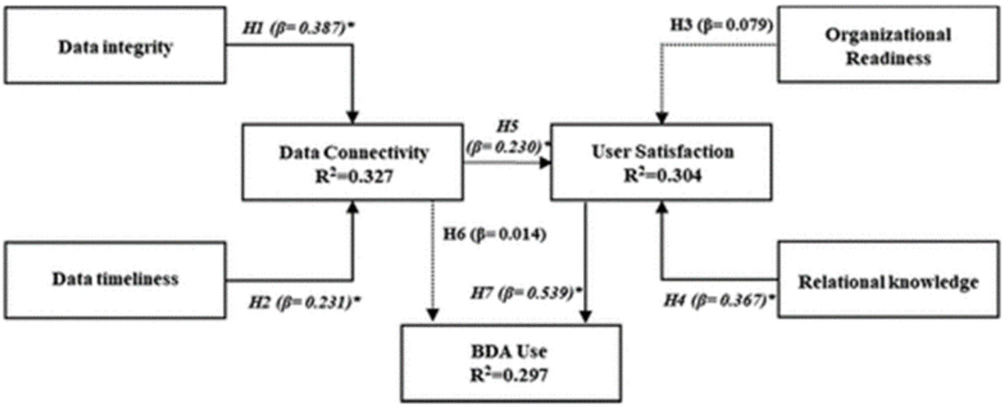

Figure 2. Theoretical model with results of hypothesis testing.※ Significance: *$p < 0.01$

Data integrity (DI) was found to account for 38.7% of the variation in data connectivity (DC), demonstrating a significant positive effect ($\beta = 0.387$; $t = 3.646$), which supports Hypothesis 1. Data timeliness (DT) also showed a positive influence on DC ($\beta = 0.231$; $t = 2.388$), confirming Hypothesis 2 at a 99% confidence level. Together, DI and DT explained 32.7% of the variance in DC ($R^2 = 0.327$).
The hypothesized effect of organizational readiness (OR) on user satisfaction (SAT) was not significant ($\beta = 0.079$; $t = 0.967$), indicating that Hypothesis 3 was not supported. In contrast, relational knowledge (RK) exerted a significant positive impact on SAT ($\beta = 0.367$; $t = 4.306$), supporting Hypothesis 4. Similarly, DC had a positive effect on SAT ($\beta = 0.230$; $t = 2.609$), confirming Hypothesis 5. Collectively, OR, RK, and DC accounted for 30.4% of the variance in SAT ($R^2 = 0.304$).
When examining BDA system usage (USE), DC did not significantly affect actual usage ($\beta = 0.01$; $t = 0.233$), meaning Hypothesis 6 was not supported. However, user satisfaction strongly influenced system use ($\beta = 0.539$; $t = 10.261$), supporting Hypothesis 7. Together, DC and SAT explained 29.7% of the variance in USE ($R^2 = 0.297$).

Discussion

This study aimed to understand how aspects of data quality and user satisfaction drive continued use of BDA systems. The results indicate that data integrity and timeliness are important precursors to data connectivity, confirming Hypotheses 1 and 2. These findings align with prior research emphasizing that high-quality data is fundamental for effective big data analytics [19, 21].
Regarding organizational support, relational knowledge among BDA personnel had a significant positive impact on user satisfaction, confirming Hypothesis 4. This supports the idea that collaborative and communicative IT staff can enhance users' experiences and engagement with BDA systems [29]. By contrast, organizational readiness did not show a meaningful effect on satisfaction, suggesting that mere preparedness at the organizational level may not directly influence users' perception of BDA systems—a result that differs from some previous studies that reported a positive relationship [47].
Data connectivity also contributed to improving user satisfaction, consistent with prior research showing that connectivity facilitates better use of BDA systems [3]. Nevertheless, while both relational knowledge and connectivity help shape a positive user experience, only user satisfaction significantly influenced actual system usage. This suggests that technical infrastructure and connectivity alone are insufficient to drive adoption; instead, the quality of users' experiences, fostered through supportive interactions with skilled BDA personnel, is crucial. These findings reaffirm the importance of user satisfaction as a key predictor of IT system success, consistent with the models proposed by Delone and McLean [26] and Urbach *et al.* [25] and supported here by the strong relationship observed in Hypothesis 7.

Theoretical Implications

The results of this study offer several contributions to theory. First, they provide a structured framework for understanding the use of BDA systems. Unlike earlier studies that mainly examined BDA adoption from an organizational perspective [56], this research takes a broader view by considering multiple dimensions of BDA use. Adoption of BDA systems often faces high failure risks due to the complex and multidisciplinary challenges encountered by users [57]. Our study highlights three essential dimensions influencing BDA use: data quality, organizational support, and user satisfaction. The data dimension encompasses data integrity, data timeliness, and data connectivity, while organizational support includes organizational readiness and relational knowledge. User satisfaction represents the user dimension, reflecting the perceived value of BDA systems.
Notably, user satisfaction emerged as the most influential factor affecting business analysts' decisions to engage with BDA systems. Relational knowledge and the quality of data—including integrity, timeliness, and connectivity—also significantly affect user satisfaction. However, data connectivity alone does not directly drive active system usage; it primarily motivates use when it contributes to a satisfactory user experience.
Another theoretical insight is that organizational readiness may not play a critical role in determining user satisfaction post-adoption, which contrasts with some earlier research [39]. This finding can be explained by the already high level of organizational support observed in our sample. Respondents rated organizational readiness items around 4.2 out of 5, suggesting that sufficient infrastructure and resources were already in place, limiting its additional influence on satisfaction. Instead, relational knowledge—the ability of IT personnel to collaborate effectively with users—appears to be more important in enhancing satisfaction. This underscores the significance of interpersonal relationships between users and IT staff as a critical factor in understanding user engagement.
Finally, the study confirms that data integrity and timeliness shape perceived data connectivity, which reflects an organization's ability to link multiple data sources effectively. In turn, this highlights that perceived IT system quality is determined not only by the availability of data but also by how well data outputs are integrated across business functions and delivered in a timely manner.

Practical Implications

This study also provides practical guidance for cultivating a business analytics culture and promoting active use of BDA systems within organizations. The recommendations focus on three areas: data, organizational factors, and user experience.

First, user satisfaction is closely tied to robust data connectivity, which depends on both data integrity and timeliness. Maintaining data integrity across the analytics lifecycle is challenging because stakeholders may interact with datasets differently, modifying data models, updating records, or aggregating results independently. These uncoordinated actions can unintentionally compromise integrity, eroding users' trust and their ability to interpret data accurately [58]. For organizations leveraging IoT and cloud computing, ensuring data integrity is essential to support reliable, data-driven decision-making processes [59]. High-quality data also contributes to competitive advantage, emphasizing its importance for business analysts actively using BDA systems [60].

Second, the timeliness of data is crucial for effective BDA use. An efficient BDA system processes large volumes of data quickly, allowing stakeholders to make timely decisions [61]. In fast-moving industries, recent data is often considered valuable while older data may be less useful [62]. Timely data is particularly critical for predictive analytics, where recent inputs enhance model accuracy [63]. Our findings reinforce that timely data is indispensable for users to derive meaningful insights from BDA systems.

Finally, while organizational readiness encompasses financial resources, IT infrastructure, analytics capabilities, skilled personnel, and agile management practices, it did not significantly influence user satisfaction in our study. Instead, relational knowledge—the collaborative and communicative abilities of IT personnel—was strongly associated with user satisfaction. This suggests that organizations should prioritize building strong relationships between IT staff and BDA system users, particularly after adoption, to encourage actual system usage and maximize the benefits of BDA investments.

Limitations and Future Research

While this study represents an early effort to examine the use of BDA systems, several limitations should be noted. First, the survey data were collected from BDA users within the top 1,000 companies in Taiwan, aiming to capture a representative sample of the BDA user population. To improve response rates, executive MBA students assisted in distributing the survey to contacts holding BDA-related positions. However, this prescreening and convenience-based distribution may have biased the sample toward more accessible respondents. Therefore, the findings should be interpreted with caution and are most applicable to users within large Taiwanese companies. Future studies could expand the scope by collecting data from different geographic regions and diverse industry sectors to enhance generalizability.

Second, although the research model incorporates data, organizational, and user-related factors, it explained only 29.7% of the variance in BDA system usage. This indicates that additional factors could influence the adoption and active use of BDA systems. Future research could extend the model to include other aspects of data quality, such as accuracy, completeness, readability, or contextual relevance, to assess whether these directly affect system usage. Furthermore, scholars could explore additional organizational, managerial, technical, process, or user-related variables that might promote active engagement with BDA systems [37]. As BDA technologies evolve, a dynamic research approach may be warranted to examine organization-wide capabilities, contributions to performance, and the role of organizational policies in shaping system use [46]. For instance, whether BDA system usage is mandatory or voluntary in different business units could affect user engagement and compliance, as suggested by dissonance theory in early-stage IS adoption [24].

Finally, although organizational readiness was not found to significantly influence user satisfaction in this study, future research could examine this relationship using more granular measures. Readiness could be broken down into technical versus non-technical support, infrastructure adequacy, or training effectiveness to determine which aspects, if any, impact user satisfaction with BDA systems. Exploring these finer dimensions may provide additional insights into how organizational readiness interacts with user experiences and contributes to the active use of BDA systems.

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