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Investigating the Determinants of Big Data Analytics Adoption in Decision Making: An Empirical Study in New Zealand, China, and Vietnam

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Abstract

Background: *As a breakthrough technology, big data provides an opportunity for organizations to acquire business value and enhance competitiveness. Many companies have listed big data analytics (BDA) as one of their top priorities. However, research shows that managers are still reluctant to change their work patterns to utilize this new technology. In addition, the empirical evidence on what determines their adoption of BDA in management decision making is still rare.*

Method: *To more broadly understand the determinants affecting managers' actual use of BDA in decision making, a survey was conducted on a sample of 363 respondents from New Zealand, China, and Vietnam who work in different managerial roles. The dual process theory, the technology–organization–environment framework, and the key associated demographic characteristics are integrated to form the theoretical foundation to study the internal and external factors influencing the adoption.*

Results: *The findings illustrate that the common essential factors across countries linking BDA in decision making are technology readiness, data quality, managers' and organizational knowledge related to BDA, and organizational expectations. The factors that are more situation-dependent and evident in one or two countries' results are managers' predilection toward valuing intuition and experience over analytics and organizational size.*

Conclusion: *The findings enrich the current literature and provide implications for practitioners on how they can improve the adoption process of this new technology.*

Keywords: Big Data Analytics, Managerial Decision Making, the Technology–Organization–Environment Framework, Dual Process Theory, Demographic Characteristics.

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Introduction

Data can facilitate decision making to support the development of organizations (Sun et al., 2018). With new technologies, such as Web 3.0, mobile devices, and the Internet of Things, a huge amount of data is produced daily (Abdel-Basset et al., 2018; Shorfuzzaman et al., 2019). Every digital action, such as online transactions and a company's social media-based communications with customers, generates data (Baig et al., 2019). Given this tremendous growth in data, the word 'big' is now associated with 'data' (Tyagi et al., 2015).

Big data, commonly defined by the "5Vs" of volume, variety, value, velocity, and veracity, has become increasingly important for organizations (Gahi et al., 2016). It provides a unique opportunity to innovate and enhance competitiveness (Bärenfänger et al., 2014). Along with big data, the demand for data analytics has also increased. Big data analytics (BDA) refers to the "application of multiple analytic methods that address the diversity of big data to provide actionable descriptive, predictive and prescriptive results" (Lamba & Dubey, 2015, p.5). Because of its potential strategic and operational advantages, BDA can help organizations to optimize their effectiveness and efficiency, and make better decisions in the constantly changing business environment (Jiang et al., 2019; Maroufkhani et al., 2020a; Ren et al., 2017). For example, a study conducted in North America demonstrates that BDA use is instrumental in enhancing organizational decision-making ability (Chen et al., 2021). In the Asia Pacific area, organizations are increasingly using BDA to achieve their goals (Perdana et al., 2019). Recent research in this region reveals that 82% of the data-driven organizations that responded have obtained critical business benefits, such as making strategic decisions faster and communicating with their stakeholders more effectively, during the Covid-19 pandemic (Pook, 2020). Compared to non-data-driven ones, data-driven organizations demonstrate a higher level of business resilience and confidence (Pook, 2020).

Despite successful testimonies from the big data first movers, many companies are still seeking to understand the functionality and potential of big data (Chen et al., 2015). A Gartner survey shows that while many respondents are willing to invest in BDA, only 15% of companies reported that they have successfully deployed their analytics projects (Gartner, 2016). Often, the failure can be attributed to the big data capability issues, such as insufficient management support, inadequate IT infrastructure and technological resources (Maroufkhani et al., 2020b). More importantly, the success of organizational adoption of an innovation depends on how their employees actually implement the innovation (Talukder, 2011). However, researchers report that managers are often reluctant to change their work patterns (Mikalef et al., 2017). Even though they may be optimistic about BDA adoption, when it comes to decision making, they still value their own intuition and experience (Mikalef et al., 2018a). They also worry that decision making may come to rely on analytics, thereby replacing them (Mikalef et al., 2018b). Hence, it is vital to examine the critical factors that impact individual managers' BDA adoption, and investigate ways to enhance their use of BDA, which, to date, has been a relatively less studied area (Müller et al., 2018).

This article asks, what are the internal and external determinants affecting individual managers' use of big data analytics in different countries (i.e., New Zealand, China, and Vietnam)?

To answer this question, a survey was conducted in three countries of the Asia Pacific region: New Zealand, China, and Vietnam. According to Baig (2019), in most BDA studies, researchers have collected data from one country, so the outcomes cannot be generalized to other countries having different social, technological, and economic circumstances. To reduce the effect of single-country bias and expand our view of BDA adoption factors (Schmidt et al., 2001), we included three countries that are different in terms of their economies (i.e., developed and developing, large and small, and socialist-oriented and free market), but are similar in their intention and support of BDA adoption (Auckland Unlimited, n.d.; Gorman, 2021; Sharwood, 2021). They provide interesting contexts to investigate the commonalities and

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differences in BDA adoption in managerial decision making, and the results may be more generalizable to countries in similar situations.

To study the internal and external factors impacting managers' BDA adoption, we employed the dual process theory, the technology–organization–environment (TOE) framework, and key associated demographic characteristics as the theoretical underpinnings for the proposed research model (Awa et al., 2017; Mishra et al., 2007). For internal factors, individuals' characteristics and attitudes significantly affect their adoption of an innovation (Mwambia, 2015), so we used the dual process theory to investigate how managers make decisions and how BDA can be incorporated into their decision-making process. Related demographic factors were also examined. For external factors (e.g., technology readiness and organizational support) that influence individuals' awareness of the features and application of an innovation and its fit with their job (Ajzen & Fishbein, 1980; Frambach & Schillewaert, 2002; Mir & Padma, 2020; Talukder, 2011), we utilized the TOE framework (Tornatzky & Fleischer, 1990) to examine them.

The rest of the article is structured as follows. The next section provides the theoretical background of this study. This is followed by the research model and hypotheses. Then, the research method, results and discussion are presented. The article closes with the study's contributions, implications, and limitations.

Theoretical Background

In this section we introduce big data analytics and adoption literature, the theories – the dual process theory and the TOE framework – and key demographic characteristics that form the basis of the conceptual research model developed in this article.

Big Data Analytics and Adoption

The definition of big data keeps changing to include new and important details (Gahi et al., 2016). Currently, it is commonly measured by 5 Vs: 1) Volume is the amount of data. Big data is much larger than normal datasets (Mneney & Van Belle, 2016); 2) Variety refers to the dataset's heterogeneity, i.e., structured, semi-structured, and unstructured datasets derived from text, photos, audio, and video (Mneney & Van Belle, 2016); 3) Velocity is about the data generation speed, including the availability of real-time data (Gahi et al., 2016); 4) Veracity refers to the accuracy of the data, whether the data can be verified to ensure its integrity (Gahi et al., 2016); and 5) Value is the degree to which the data is useful in decision making (Gahi et al., 2016).

Because of these distinct characteristics, organizations cannot use their existing systems, such as traditional relational databases, to store and process big data, and they are encountering challenges in using new approaches to manage and capitalize on big data (Ahmed et al., 2019). These challenges include the technical issues of storing, verifying, and analyzing large volumes of fast moving and diverse data, as well as the human capability to gain insights from data and analysis for decision making (Gandomi & Haider, 2015). Hence, it is vital for organizations to adopt technologies that can help them address these challenges, and big data analytics has emerged as such a technology (Ahmed et al., 2019; Gandomi & Haider, 2015).

Big data analytics (BDA) is defined as the "application of multiple analytic methods that address the diversity of big data to provide actionable descriptive, predictive and prescriptive results" (Lamba & Dubey, 2015, p.5). BDA can play a crucial role in supporting companies to succeed in market competition. For example, through analyzing a large amount of related data, companies can reduce their costs, improve the quality and functions of their products and services, and increase sales. Wal-Mart's semantic analysis search engine has improved the likelihood of completing an online order for its shoppers by 10% to 15% (Raguseo, 2018). Researchers have also identified a positive correlation between BDA adoption and organizational performance or agility (Hyun, 2020; Mikalef et al., 2019b; Raguseo & Vitari, 2018). The literature demonstrates that in general, by adopting BDA, companies can obtain an advantage over competitors of 5% in productivity and 6% in profitability (Côrte-Real et al., 2017). These potential benefits have encouraged companies to invest heavily in the adoption of BDA.

The adoption can be improved if the factors affecting adoption and its use are appropriately analyzed and addressed (Weerasinghe et al., 2018), and the potential value of BDA can only be realized through processing huge amounts of heterogeneous and quickly changing data into meaningful insights to be utilized by managers in their decision making (Verma & Bhattacharyya, 2017). Lewis et al. (2003) found that individual-level implementation of an innovation is one of the major determinants of the adoption.

However, people will often refuse change if they do not feel direct advantages from the change (Ajzen, 1991). Mikalef et al. (2017) demonstrate that despite organizational strategies to implement BDA, employees are reluctant to change their work patterns. Some employees fear that BDA and related tools will make their knowledge and decision-making skills redundant, and that they may lose their jobs (Mikalef et al., 2018b). Hagen (2021) found that the longer the employee's tenure, the less trust they have in new technology and the greater the concern of being replaced. In their study about BDA use in the hotel industry, Egan and Haynes (2018) report that managers seem to consider revenue management as an art, which cannot be replaced by BDA. They believe that big data can only detect broad trends and is not sensitive to the characteristics of the local market, knowledge of which is crucial for managers to make reliable decisions (Egan & Haynes, 2018).

In spite of the research on the broad adoption issues exemplified above, less research has focused on individuals' use of this new technology in organizations (Demoulin & Coussement, 2018; Verma et al., 2018). Hence, this study intends to examine managers' actual in situ use of BDA to better understand and improve the situation.

We investigate internal and external factors impacting managers' BDA adoption. For internal factors, individuals' characteristics and attitudes significantly affect their adoption of an innovation, so understanding these factors is important (Mwambia, 2015). In the current study, we use dual process theory to investigate how managers make decisions and how BDA can be incorporated into their decision-making process. Related demographic factors are also examined. Researchers (e.g., Ajzen & Fishbein, 1980; Frambach & Schillewaert, 2002) illustrate that factors external to the individual can influence individuals' awareness of the features and application of an innovation and its fit with their job. Studies (e.g., Mir & Padma, 2020; Talukder, 2011) show that these factors mainly include the facilitating conditions, such as the technology readiness of an organization, organizational support, and incentives. In this study, we use the TOE framework (Tornatzky & Fleischer, 1990) to examine them. The synthesis of these theories serves as the basis of the research model developed in this article through which the survey data is analyzed. The two theories and associated demographic characteristics are discussed in the following sections.

Dual Process Theory in Managerial Decision Making

The art and science of management revolves around good decision making (Gressel et al., 2020; Intezari & Pauleen, 2018). According to dual process theory, decision making occurs within and between two cognitive systems (Turel & Qahri-Saremi, 2018). System 1 is a fast, automatic and intuitive system (Bazerman & Moore, 2012). It operates first through instinctive behavior when making a decision (Arnott et al., 2017). System 1 presents the oldest mode of

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decision making, and it requires minimal cognitive effort (Hodgkinson et al., 2009). System 2 is a slow and deliberate system. It is not innate and requires considerable cognitive endeavor (Arnott et al., 2017). People have to improve their capabilities in System 2 by learning (Bazerman & Moore, 2012). The core of System 2 is to utilize some form of logic and/or systematic approaches for decision making (Turel & Bechara, 2016).

System 1 and System 2 can operate and interact at the same time. “System 1 quickly proposes intuitive answers to judgment problems as they arise, and System 2 monitors the quality of these proposals, which it may endorse, correct, or override.” (Kahneman & Frederick, 2002, p. 51) System 1 is related to people’s expertise, whereas System 2 reflects their rational thinking and reasoning (Evans, 2003). The tasks of System 2 can be converted into System 1 when such tasks and judgments become habituated over time (Arnott et al., 2017).

Understanding when to switch from System 1 to System 2 is difficult (Wray, 2017). It depends on the knowledge and experience of managers and the context of the decision (Arnott et al., 2017). A complete System 2 process may not always be necessary. Essentially, managers should be able to figure out when they should move from the intuitive System 1 to leverage the deliberation inherent in System 2 (Wray, 2017).

As a rational process, data analytics fits with System 2. In data-driven decision making (DDDM), data analytics (i.e., System 2) is leveraged to make decisions, rather than relying purely on experience and intuition (i.e., System 1) (Lu et al., 2021). DDDM is a process where Systems 1 and 2 interact, complement, and strengthen each other to achieve optimal decisions (Gressel et al., 2020). For example, when selecting advertisements, marketing managers can make decisions based on data-based analysis of customer reactions to ads as well as their experience (Provost & Fawcett, 2013). The advantages of DDDM have been demonstrated conclusively by researchers (e.g., Akhtar et al., 2019; Brynjolfsson et al., 2011). For instance, in a study conducted on an Australian organization, the authors claim that mobile business intelligence can provide fact-based information to help managers mitigate their cognitive biases derived from System 1 and achieve System 2 thinking (Hou & Gao, 2018).

The dual process theory acknowledges and emphasizes the value and collaboration of both Systems 1 and 2 working together (Gressel et al., 2020). It explains how managers make decisions in a data-driven manner, integrating BDA with their intuition and experience when dealing with a variety of factors (Gressel et al., 2020). Hence, dual process theory is employed in this study to explain how managers utilize BDA in their decision making.

Demographic Characteristics

Managers determine organizational strategic thrusts (Awa et al., 2011). They are the major drivers and practitioners of new technology adoption (Awa et al., 2015). In their study, Caldeira and Ward (2002) found that the inclination and attitudes of the top management team towards the adoption of information and communications technology explain success and failure stories in organizations. According to Ajzen and Fishbein (1980) demographic characteristics play an important role in affecting people’s attitudes toward new technology adoption. Information Systems scholars have utilized these characteristics to study managers’ attitudes and actual use of various new technologies (e.g., Chuang et al., 2009; Matikiti et al., 2018). They illustrate that the demographic factors, e.g., age, gender, experience, and education level, have significant correlations with new technology adoption (Awa et al., 2015; Dwivedi & Lal, 2007).

The Technology–Organization–Environment Framework

As mentioned above, individuals' awareness and attitudes toward innovation are also affected by external influences. In this study we use the technology–organization–environment (TOE) framework (Tornatzky & Fleischer, 1990) to examine these influences. According to the TOE framework, there are three contexts – technological, organizational, and environmental – affecting the technology innovation adoption process of a company. This framework is used as one of the theoretical foundations of this study for the following reasons.

First, a considerable number of studies have illustrated the wide application of this framework in new technology adoption across different technological, industrial, and cultural contexts (e.g., Lee & Lee, 2011). For example, based on the TOE framework, Yoon and George developed a model to investigate the factors affecting organizational adoption of virtual worlds, and found that emulative and normative pressures are the most significant determinants of organizations' intentions to adopt them (Yoon & George, 2013). The TOE framework has also been used to examine organizational BDA adoption (Baig et al., 2019). A variety of factors have been identified. The key technological factors include perceived benefit, perceived complexity, and technology readiness. The important organizational factors are perceived financial readiness, IT structure, organizational support, and data environment. Environmental determinants are competitive pressure, government support, and security (Baig et al., 2019; Sun et al., 2018). In this study, we focus on the factors that seem to have direct impacts on individuals' adoption intention, such as technology readiness and organizational encouragement (Mir & Padma, 2020; Talukder, 2011).

Second, compared to other widely used theories in innovation adoption, such as Diffusion of Innovation (Rogers, 2010), the TOE framework extends the domination of the technical perspective (Rui, 2007). The TOE framework provides a useful landscape to examine and differentiate between the essential nature of the new technology, the adopting organization's motivations and abilities, and the broader external environment (Rui, 2007).

While the TOE framework presents an elegant classification for investigating technology adoption (Mishra et al., 2007), it does not constitute a fixed model with assigned factors in each category, and it does not provide justifications for the causal relationships between the factors and the adoption (Awa et al., 2017; Mishra et al., 2007). The specific factors identified within the three categories may vary in different situations. Hence, researchers have attempted to combine the TOE framework with other theories to identify determinants and establish causal relationships in various innovation adoption cases (Alatawi et al., 2012; Zhu & Kraemer, 2005). For example, Awa et al. (2017) proposed a model by integrating the TOE framework, the task technology fit, and the Unified Theory of Acceptance and Use of Technology to examine new technology adoption factors. The results demonstrated that the technological, organizational, environmental, and task-related factors such as perceived value, top management support, and the complexity of tasks, and social factors such as social influence have statistically positive effects on the adoption (Awa et al., 2017).

Accordingly, in this research the TOE framework, dual process theory, and the related demographic characteristics are combined to classify the factor groups and specify the individual determinants affecting BDA adoption. Table 1 summarizes the internal and external factors impacting managers' use of BDA, which have been discussed in this section.

https://aisel.aisnet.org/pajais/vol14/iss4/3
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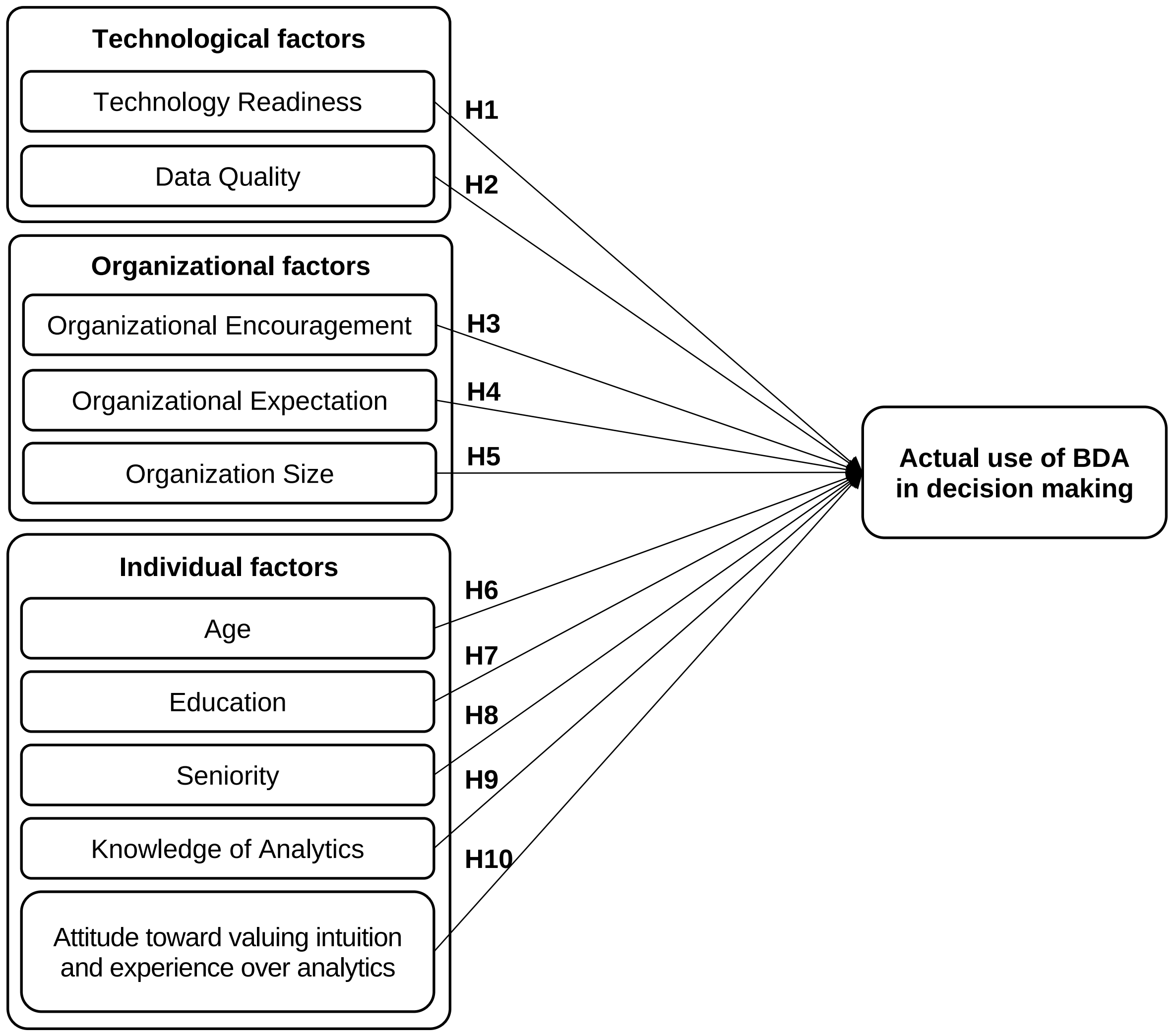
Table 1 - Internal and External Factors Impacting Managers' Use of BDA

<table>
<tr><th></th><th>Theoretical base</th><th colspan="2">Factors</th></tr>
<tr><td rowspan="2">Internal (individual) factors</td><td>Individuals' characteristics</td><td colspan="2">Demographic factors, such as age, gender, experience, and education level, have demonstrated significant correlations with new technology adoption in previous research (Awa et al., 2015; Dwivedi & Lal, 2007).</td></tr>
<tr><td>Individuals' attitudes, which are examined using the dual process theory</td><td colspan="2">Individual managers' attitudes towards valuing intuition and experience over analytics</td></tr>
<tr><td rowspan="3">External factors</td><td rowspan="3">Factors affecting individuals' awareness of the features and application of BDA and its fit with their job (Frambach & Schillewaert, 2002; Mir & Padma, 2020), which are examined using the TOE framework</td><td>Technological factors</td><td>The key technological factors include perceived benefit, perceived complexity, technology readiness, etc. (Baig et al., 2019; Sun et al., 2018)</td></tr>
<tr><td>Organizational factors</td><td>The important organizational factors are perceived financial readiness, IT structure, organizational support, data environment, etc. (Baig et al., 2019; Sun et al., 2018)</td></tr>
<tr><td>Environmental factors</td><td>Environmental determinants are competitive pressure, government support, security, etc. (Baig et al., 2019; Sun et al., 2018)</td></tr>
</table>

Research Model and Hypotheses

This study integrates dual process theory, the TOE framework, and the associated demographic characteristics as its theoretical foundation to examine the determinants of managers' actual use of BDA within an organizational environment. It does not include external environmental factors such as competition and government regulations, as it investigates and compares BDA adoption status across three countries (i.e., New Zealand, China, and Vietnam) which have very different social, economic, and governmental circumstances, which may not be comparable.

Based on a wide-ranging literature review, the factors affecting managers' adoption of BDA in decision making are identified and categorized into three contexts: technological, organizational, and individual (Baig et al., 2019; Lai et al., 2018; Park et al., 2015; Sun et al., 2018). Technological and organizational contexts reflect the external factors impacting the adoption, and individual context represents the internal factors. Ten hypotheses are generated in these three categories. Figure 1 depicts the conceptual model constructed for this study.



Note: Factors from the TOE framework: Technology Readiness, Data Quality, Organizational Encouragement, Organizational Expectation, Organization Size; Factors from dual process theory: Attitude toward valuing intuition and experience over analytics; Demographic factors: Age, Education, Seniority, Knowledge of Analytics.

Figure 1 - Factors Affecting Managers' Use of BDA

Technological Context

Based on the TOE framework, the technological context is the organization's internal technological capability and the available external technology, such as the necessary equipment, processes, and software (Sun et al., 2020). In this context, the model factors are technology readiness and data quality as they are two of the most important technological determinants impacting managers' adoption according to previous studies (e.g., Baig et al., 2019).

Technology readiness is sometimes referred to as technology competence (Sun et al., 2018). It emphasizes that companies should have the appropriate technology resources, e.g., finance, talent, and IT infrastructure, to support the adoption (Ahmad Sallehet al., 2015). These resources affect adoption because of costs and issues associated with bringing new systems and software into existing IT systems in the organization. Studies (e.g., Matsebula & Mnkandla, 2016; Ahmad Salleh et al., 2015) demonstrate that technology resources are crucial for successful adoption of big data. They also significantly affect an individual's intention and actual use of new technology (Mir & Padma, 2020).

Data quality. Data is the foundation of BDA. Data quality can be viewed from accessibility, consistency, and completeness perspectives (Lai et al., 2018; Rai et al., 2006). The timely availability of a variety of high quality data is essential for successful big data adoption and use; data consistency ensures that the same data is transferred across the organization; data completeness is the degree to which data is available in the organizational repository (Kwon et al., 2014). Data quality is crucial for data analysis used in decision making; low data quality can be a major obstacle of big data adoption (Lai et al., 2018).

Hypothesis One (H1): Technology readiness has a positive influence on managers' use of BDA in decision making.

Hypothesis Two (H2): Higher levels of data quality have a positive influence on managers' use of BDA in decision making.

Organizational Context

According to the TOE framework, the organizational context involves the resources, structure and other characteristics of a company (Sun et al., 2020). Previous studies (e.g., Lai et al., 2018; LaValle et al., 2011; Mneney & Van Belle, 2016; Yin & Kaynak, 2015) demonstrate that a data-driven culture and perceived financial readiness are the most important organizational determinants affecting the adoption process. While many organizations use big data in their decision making, the majority of their managers may still rely on their experience and intuition rather than on BDA (Mikalef et al., 2018a). The major reasons include their cognitive inertia of staying in their old work patterns that have already demonstrated positive outcomes, the negative perceptions of analytics, the lack of knowledge of and trust in BDA and data, and the fear of losing their power in decision making and being replaced by the technology (Conboy et al., 2020; Mikalef et al., 2021; Mikalef et al., 2017; Mikalef et al., 2018b). To change this situation, establishing a data-driven culture (e.g., top management's encouragement and expectation toward fact-based decision making) is crucial (Gressel et al., 2020; Lamba & Dubey, 2015). Hence, this study investigates the related factors: organizational encouragement, expectation, and size, which is directly related to the amount of available organizational resources (Baig et al., 2019).

Organizational encouragement represents management's willingness to take risks and support the use of new technology (ElMelegy et al., 2016). A supportive environment can be an effective way to promote the adoption of new technology in an organization (Al-Shohaib et al., 2010). Studies (e.g., Al-Shohaib et al., 2010; Al-Yaqoub et al., 2019; Ebrahimi & Mirbargkar, 2017; Lee et al., 2005) illustrate that organizational encouragement critically and positively influences new technology adoption, and a lack of organizational support is a critical obstacle to the adoption and effective use of such technology.

Organizational expectation refers to the internal pressure in organizations to make individuals comply with rules or directions (Jamali et al., 2015). Organizations pursuing innovation goals strongly demand alignment between their members' perceived organizational expectations and the actual actions needed to accomplish the goals (Tung et al., 2014). Members who adapt appropriately to these expectations are more likely to achieve defined objectives (Townsend et al., 2010). Previous research suggests that clear and emphasized organizational expectations play a critical role in enhancing the intrinsic motivation and beliefs of individuals in terms of behaving as expected (Cialdini, 2005; Liou et al., 2019).

Organization size is directly associated with the amount of available organizational resources, e.g., IT tools and technical experts (Baig et al., 2019). Research shows that among the organizational factors, organization size is one of the most frequently found determinants, and it is also likely to directly impact managers' use of BDA (Yoon & George, 2013). With an increase in organizational size, the complexity of tasks and the coordination efforts among different teams or members tend to grow, so more advanced technologies may be required to facilitate the operations (Stair & Reynolds, 1997). Larger organizations also have a greater economy of scale, greater strength, and more resilience in managing the risks related to adoption (Zhu & Kraemer, 2005). Conversely, it is difficult for small organizations to invest sufficiently in the time and resources for new technology adoption (Sun et al., 2018). Studies (e.g., Awa et al., 2017; Balaid et al., 2014) illustrate the significant positive effect of organization size on new technology adoptions.

Hypothesis Three (H3): Organizational encouragement has a positive influence on managers' use of BDA in decision making.

Hypothesis Four (H4): Organizational expectation has a positive influence on managers' use of BDA in decision making.

Hypothesis Five (H5): Larger organizational size leads to a higher degree of managers' use of BDA in decision making.

Individual Context

An individual's characteristics and attitudes significantly affect his or her adoption of an innovation, so understanding these factors is vital (Mwambia, 2015). In this study the individual context of BDA adoption is measured by the demographic factors – age, education level, seniority, and managers' knowledge of BDA – and the key factor derived from dual process theory: the attitude of valuing intuition and experience over analytics.

Age. Previous studies suggest that age is negatively related to an individual's decision to adopt new technology (Morris & Venkatesh, 2000; Ruggeri et al., 2018). This effect is also shown in studies of senior executives (Awa et al., 2015; Pijpers et al., 2001). The younger the executives in an organization, the more likely that the organization successfully adopts new technology (Awa et al., 2015; Chuang et al., 2009).

Researchers suggest that younger managers may be more interested in innovative ideas, and more likely to take risks than older managers (Chuang et al., 2009; Hambrick & Mason, 1984). One explanation is that younger managers may have higher levels of the physical or mental strength needed to grasp and adopt new ideas than older managers (Child, 1974). The second possible reason is that research has shown that older managers may eschew analytics in decision making as they have proven themselves to be successful over their careers by relying on their judgment and intuition (Gressel et al., 2020). The third possible explanation may be that older managers tend to be more risk averse due to their established social connections, career prospects, and lifestyles (Hambrick & Mason, 1984). New technology adoption may be risky to organizations and thereby may cause negative consequences to managers' careers. Hence, older managers may be less likely to embrace adoption (Chuang et al., 2009).

Education. Formal education is commonly considered to be one of the most important aspects of human capital (Becker, 2009) in dynamic political and economic circumstances in which new information and technology are emerging (Gardner et al., 2001). Education levels are associated with an individual's knowledge and skills that may have an impact on their behavioral intention towards the adoption and use of new technology (Rogers, 2010; Tarhini et al., 2016).

Researchers (e.g., Becker, 1970; Hambrick & Mason, 1984) suggest that education affects people's innovativeness, value systems, risk-taking and predilection for accepting new ideas. Well-educated managers are more likely to acquire information from scientific sources and experts. They tend to be more innovative and are more likely to search for, learn, and diffuse new ideas; they are more able to leverage their advanced knowledge and skills to manage uncertainties introduced by the changes in organizations (Rogers, 2010). In contrast, managers with lower levels of education may be more risk averse as they worry about the downsides of change and hence may only invest when the advantages of first movers have already been realized (Awa et al., 2015). A number of studies (e.g., Chuang et al., 2009; Federici, 2009) have demonstrated the positive impacts of education on new technology adoption. For example, education positively influences the adoption of computer technology (Putler & Zilberman, 1988) and the use of the Internet (Mishra et al., 2009; Uematsu & Mishra, 2010).

Seniority. Researchers (e.g., Calabretta et al., 2017; Constantiou et al., 2019) have investigated how senior managers incorporate their intuition into decision making. This especially happens when the decision situation is complex and some information is missing (Orlandi & Pierce, 2020). However, due to technological advances and the increasing use of BDA, previous scenarios characterized by a lack of data and effective analytics tools have changed significantly (George et al., 2014; Orlandi & Pierce, 2020; Van Knippenberg et al., 2015). This study explores the impact of BDA and whether senior managers have started to increase the use and importance of analytics in their decision making, and the relationship between seniority and managers' actual use of analytics.

Knowledge of analytics. In order to effectively leverage BDA in decision making, managers should have sufficient related knowledge. If managers have a higher level of IT knowledge and competence, they can play a more influential role in the adoption (Sun et al., 2018). Studies (e.g., Awa et al., 2015; Yoon & George, 2013) have found that top executives' knowledge of the benefits of new technology significantly affects technology adoption. On the other hand, researchers report that the lack of knowledge about analytics and related tools is a major barrier for managers to use BDA in their decision making, and this may also trigger other people-related barriers such as distrust of the data and BDA results (Côrte-Real et al., 2020; Li et al., 2019).

Attitude toward valuing intuition and experience over analytics. According to dual process theory, decision making occurs between cognitive Systems 1 and 2 (Turel & Qahri-Saremi, 2018). System 1 is an intuitive system, and it operates quickly and automatically (Arnott et al., 2017). The core of System 2 is to use some form of systematic approach for decision making (Turel & Bechara, 2016). Managers who mainly rely on System 1 in their decision making will likely use analytics less than those who mainly use System 2 in their decision making.

Although Systems 1 and 2 are different, they usually complement each other in decision making. As mentioned in the dual process theory section, data analytics is a rational process and fits with System 2. In DDDM, Systems 1 (i.e., experience and intuition) and 2 (i.e., data analytics) interact, complement, and strengthen each other to achieve optimal decisions (Gressel et al., 2020). Managers usually have the cognitive inertia of staying in their old work patterns (Mikalef et al., 2021; Mikalef et al., 2017). To value and leverage data analytics in decision making, they should have appropriate knowledge and skills with such technology, and confidence in the data. Their lack of knowledge about analytics may cause managers' doubts about the data and outcomes generated through BDA (Li et al., 2019). Consequently, they may prefer to value their own intuition and experience over analytics and rely on System 1 in decision making.

In addition, the type of decisions may have an impact on their intention towards valuing intuition and experience over analytics. According to Ackoff (1990), organizational decisions can be categorized into operational, tactical, and strategic ones. Operational decisions are primarily routine and well-defined, and most often apply to current issues (Ackoff, 1990); they often heavily rely on data or information (Gressel et al., 2020). Tactical decisions are mid-term decisions often related to organizational efficiency and effectiveness (Ackoff, 1990); they often involve an interplay between Systems 1 and 2 decision-making processes. However, tactical decisions can be complicated so it may not be worth spending much time and cost to collect data that may assist in addressing them (Gressel et al., 2020). Although some relevant data may be gathered, tactical decisions tend to rely on managers' judgment (Gressel et al., 2020). Strategic decisions are long-term decisions, and they have profound influences on organizational goals (Ackoff, 1990); they often require prolonged interaction between Systems 1 and 2. They tend to involve a large amount of data and information, and ultimately, these may be balanced with the experience and judgment of senior managers (Gressel et al., 2020).

Hypothesis Six (H6): Age is negatively related to managers' use of BDA in decision making.

Hypothesis Seven (H7): Education level is positively related to managers' use of BDA in decision making.

Hypothesis Eight (H8): Seniority is negatively related to managers' use of BDA in decision making.

Hypothesis Nine (H9): Knowledge of analytics has positive effects on managers' use of BDA in decision making.

Hypothesis Ten (H10): Attitudes toward valuing intuition and experience over analytics have negative effects on managers' use of BDA in decision making

Methods

Investigation across Three Countries

According to Baig (2019), in most BDA studies, researchers collected data from one country, so the outcomes cannot be generalized to other countries that have different social, technological, and economic environments, highlighting the need to study BDA adoption across countries. In this study, three countries in the Asia Pacific area – New Zealand (NZ), China (CN), and Vietnam (VN) – were surveyed to investigate the determinants of managers' use of BDA. Differences between these countries include economies that are developed and developing, large and small, and socialist-oriented and free market. This approach can reduce the effect of a single-country bias and expand our view of BDA adoption factors (Schmidt et al., 2001). In spite of the differences, the three countries are similar in terms of their intention and support of BDA adoption. In addition, the three countries are in the same area (i.e., Asia Pacific), which is characterized by high economic openness and activity. Therefore, they provide interesting contexts to investigate the commonalities and differences in BDA adoption in managerial decision making, and the results can be more generalizable to countries in similar situations. The characteristics of these countries associated with BDA adoption are compared in Table 2 and discussed below.

In recent years, VN's economy has improved significantly (Lazarus, 2020). In 2021, it ranked 44th in the Global Innovation Index (GII), jumping 27 places since 2014 (WIPO, 2021). Its technology sector is targeted for development. The country has established a ten-year plan to become a middle power in the field of artificial intelligence, and big data is part of this plan (Sharwood, 2021). Although VN is still characterized as having low technological readiness and low data quality, significant promise is shown for the growth of BDA in the coming years (Bui et al., 2021).

Since its reform and opening in 1978, CN's gross domestic product (GDP) has increased about 10% on average per year (World Bank, 2022). It is now an upper-middle-income country, and ranked 12th in the GII 2021 (WIPO, 2021). CN's technology sector has grown remarkably in the past years, and its digital economy, which refers to the integration of Internet-based

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technologies with the entire economy, accounted for about 30% of its GDP in 2020 (Dace, 2020). CN's big data strategy was established in 2014. Financial services, healthcare, and government affairs are the three largest sectors using big data, and others, such as education, transportation, and manufacturing, have also emerged (Gorman, 2021).

NZ is ranked 26 in GII 2021(WIPO, 2021). It is an established test market for new technology and has been recognized as an early adopter of such technology (Auckland Unlimited, n.d.). Its technology sector is diversified and highly developed; it is a source of innovation and competes successfully in the world; this industry is a primary growth area of the NZ economy, which represents 8% of NZ GDP (INZ, 2021)

Table 2 - Comparison among Countries

Country	Population	GDP (USD billions) 2020	Type of economy	GII ranking 2021	BDA related policies
Vietnam	98.90 million (Worldometers, 2022)	343.114(IMF, 2021)	Socialist-oriented market economy	44, ranked #1 in lower middle-income group	Big data is one of the key areas being promoted by the government.
China	1.45 billion (Worldometers, 2022)	14,866.74(IMF, 2021)	Socialist market economy	12, ranked #1 in upper middle-income group	Its big data strategy was officially established in 2014. Financial services, healthcare, and government affairs are the three largest sectors using big data.
New Zealand	4.89 million (Worldometers, 2022)	209.384(IMF, 2021)	Free market	26, ranked #25 in high-income group	It is a test market of new technology and has been recognized as an early adopter of new technology.

Research Method

The survey questions were developed from questions used in a study by Gressel (2020). A pilot survey was first conducted with a small academic group, and questions were revised according to the feedback. The final questionnaire contained 43 questions, including 9 open-ended questions and 34 multiple-choice questions. The original English version was translated into Chinese and Vietnamese by two academics and verified by another academic (Harkness et al., 2004). Using convenience sampling, the questionnaire was first sent to NZ managers in 2018, and then by using snowball sampling, we asked the managers to pass the recruitment information to potential participants they knew through social media channels such as LinkedIn (Leighton et al., 2021). After analyzing the NZ data, the second round of data collection was conducted by sending the translated questionnaire to CN and VN participants in 2019. We used the same convenience and snowball sampling methods in CN and VN to recruit participants.

In total, 363 valid responses – 116 from NZ, 140 from CN, and 107 from VN – were received. The respondents are mainly from large or medium sized companies across a wide range of industries (see Table 3), including finance, insurance, manufacturing, and retail trade. There is less variation in the age groups amongst CN respondents, compared to the age distribution of NZ and VN respondents. The average age of VN participants is lower than those of NZ and

CN participants. Most participants hold at least a bachelor's degree. In the three countries, NZ respondents have the highest seniority levels, whereas VN managers have the lowest.

Table 3 - Demographic Details of Survey Respondents

		NZ	CN	VN
Company size in employee numbers	0-20	3.50%	33.60%	15.10%
	21-100	27.70%	21.40%	16%
	>100	68.80%	45%	68.90%
Top five sectors	Manufacturing	11.21%	48.20%	15.09%
	Retail trade	6.03%	5.04%	8.49%
	Finance and insurance	0.86%	7.19%	32.08%
	Professional, scientific, and technical services	7.76%	3.60%	3.77%
	Education and training	9.48%	7.19%	4.72%
Distribution of age	<= 24 years	0%	0%	8.40%
	25-34 years	2.60%	10.10%	62.60%
	35-44 years	19%	51.80%	17.80%
	45-54 years	40.50%	32.40%	7.50%
	55-64 years	31.90%	5.70%	3.70%
	>65 years	6%	0%	0%
Education level	PhD	3.48%	8.03%	3.74%
	Master's degree	26.09%	34.31%	42.06%
	Postgraduate diploma/certificate	17.39%	16.06%	0%
	Bachelor's degree	25.22%	29.20%	52.34%
	Diploma/certification	13.04%	10.95%	0%
	High school qualification	6.96%	0.73%	0.93%
	Other	7.82%	0.72%	0.93%
Distribution of senior levels	Directorship/board member	12.10%	13.60%	12.30%
	Executive management	50.90%	7.10%	5.70%
	Senior management	21.60%	24.30%	12.30%
	Middle management	6%	37.10%	20.80%
	First-level management	2.60%	10%	8.50%
	Supervisory level	0.90%	0.70%	14.20%
	Others	2.60%	2.20%	6.60%
	No management/supervision responsibility	3.30%	5%	19.60%
Frequency of using analytics	Every day	20.40%	6.40%	21.60%
	2-3 times a week	15.00%	4.80%	11.40%
	Once a week	15.90%	4.80%	9.10%
	1-2 times per month	12.40%	24.00%	20.50%
	1-2 times per quarter	15.90%	32.00%	20.50%
	1-2 times per 6 months	16.80%	17.60%	14.80%
	Never	3.60%	10.40%	2.10%

The main types of quantitative data gathered by the survey were Likert scale and Likert items. After checking its assumptions (i.e., the variables are measured at the ordinal; they represent paired observations; and there is a monotonic relationship between two variables), Spearman rank correlation was run to test the hypotheses. It was used because the data in this study is not normally distributed. It refers to a measure of linear correlation (i.e., Pearson correlation coefficient) applied to the two ranked random variables (Denault et al., 2009). Its formula is shown below. The value of r_s is from +1 to −1, representing a perfect positive correlation to a perfect negative one (Kumar & Abirami, 2018).

$$r_s = 1 - \frac{6\sum d_i^2}{\mathrm{n}(n^2-1)}$$

where d_i is the difference between the two ranked variables, and n is the number of observations.

To investigate the similarities and differences among the three countries, the Kruskal–Wallis H test was employed, and all its assumptions were checked (i.e., the variables are ordinal data; the independent variables consist of two or more categorical and independent groups; and there is independence of observations). It is a rank-based test that can be used to determine whether there are statistically significant differences between two or more groups of an independent variable (Liu & Weistroffer, 2020). It is the non-parametric analog of a one-way ANOVA, and it does not make assumptions about normality and homogeneity of variance, which are the assumptions of ANOVA but not satisfied in this study (Lix et al., 1996). To calculate the effect size, which quantifies the magnitude of a treatment effect in a way that allows comparison across studies or in the same study, the Epsilon-squared method was used (Tomczak & Tomczak, 2014). It indicates that the percentage of the weighting can be explained by the independent variable (Kirby & Sonderegger, 2018). Compared to the other most popular effect size measures in this area such as Eta-squared, Partial Eta-squared, and Omega-squared, the Epsilon- and Omega-squared estimates are relatively unbiased (Yigit & Mendes, 2018), which means reporting Epsilon- or Omega-squared estimates is more appropriate in assessing the practical significance of the observed differences (Yigit & Mendes, 2018). Finally, a post hoc test was performed to reveal statistically significant differences between the groups. All the analyses were conducted in SPSS v.26.

Results

Table 4 demonstrates the results from the Spearman rank correlation in the three countries. In general, technology readiness, data quality, organizational expectations, and knowledge of analytics (e.g., familiarity with the analytics tools), are the statistically significant factors in each country. Thus, H1, H2, H4, and H9 are supported in this study. Compared to NZ, CN and VN managers' use of analytics is significantly affected by their attitude valuing intuition and experience over analytics. Hence, H10 is supported by CN and VN's data, but is not supported by NZ data. Beside these factors, CN managers' use of analytics is also related to the organizational size. Thus, H5 is supported by CN data. Organizational encouragement, and managers' age, education level, and seniority do not appear to be significant factors in any of the three countries. Therefore, H3, H6, H7, and H8 are not supported. Table 5 summarizes the status of the hypotheses.

Table 4 - Factors Affecting Managers' Use of BDA

		NZ		CN		VN	
Categories	**Factors**	Correlation coefficient	Sig. (2-tailed)	Correlation coefficient	Sig. (2-tailed)	Correlation coefficient	Sig. (2-tailed)
Technological	Technology readiness	.387**	.000	.185*	.043	.331**	.002
	Data quality	.297**	.001	.239**	.009	.262*	.014
Organizational	Organizational encouragement	-.083	.384	-.005	.955	-.150	.174
	Organizational expectation	.509**	.000	.447**	.000	.333**	.002
	Organization size	.163	.085	.195*	.030	.119	.271
Individual	Age	.027	.778	.004	.962	-.045	.675
	Education	-.047	.624	-.046	.616	.167	.119
	Seniority	-.023	.805	.016	.861	-.036	.738
	Knowledge of analytics	.547**	.000	.474**	.000	.541**	.000
	Value intuition and experience over analytics	.105	.266	.220*	.014	.376**	.000

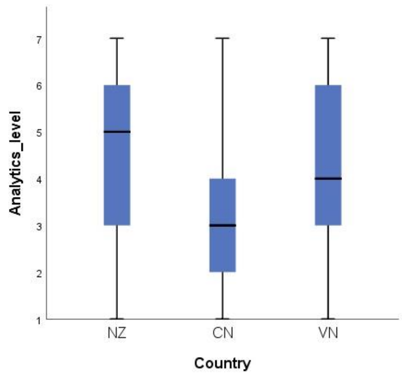
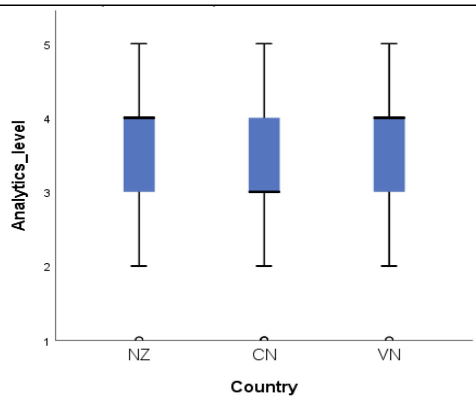
* Correlation is significant at the 0.05 level (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed).

Table 5 - Hypotheses Results

Hypotheses	Status	Comments
H1: Technology readiness has a positive influence on managers' use of BDA in decision making.	Supported	
H2: Higher levels of data quality have a positive influence on managers' use of BDA in decision making.	Supported	
H3: Organizational encouragement has a positive influence on managers' use of BDA in decision making.	Not supported	
H4: Organizational expectation has a positive influence on managers' use of BDA in decision making.	Supported	
H5: Larger organizational size leads to a higher degree of managers' use of BDA in decision making.	Partially supported	Supported by CN data
H6: Age is negatively related to managers' use of BDA in decision making.	Not supported	
H7: Education level is positively related to managers' use of BDA in decision making.	Not supported	
H8: Seniority is negatively related to managers' use of BDA in decision making.	Not supported	
H9: Knowledge of analytics has positive effects on managers' use of BDA in decision making.	Supported	
H10: Attitudes toward valuing intuition and experience over analytics have negative effects on managers' use of BDA in decision making.	Partially supported	Supported by CN and VN data

In addition, to further understand the actual use of BDA in participants' decision making, and the factors impacting them in valuing intuition and experience over analytics, additional questions and analysis were conducted. Table 6 compares the actual use of BDA among three countries based on the Kruskal–Wallis H test. Table 7 summarizes the key determinants generated from the open question about what factors impact managers valuing their own intuition and experience over analytics in their decision making. Most participants across three countries mentioned data source, familiarity of BDA, and decision type. Few people talked about other factors such as political implications and competition.

Table 6 - Actual Use of BDA in Decision Making

Questions	Post hoc	Effect size	Group comparison
Frequency of relying on analytics for decision making	CN-NZ: p<.001 CN-VN: p<.001 NZ-VN: p=.828	0.077	
Use outputs from data analytics for decision making	CN-NZ: p=.005 CN-VN: p<.001 NZ-VN: p=.281	0.047	

The significance level is 0.05.

Table 7 - The Top Three Factors Affecting Valuing Intuition and Experience over Analytics

Country	The top three factors affecting valuing intuition and experience over analytics	%*
NZ	Data source	38%
	Decision type	17%
	Familiarity with BDA	18%
CN	Data source	38%
	Familiarity with BDA	29%
	Decision type	17%
VN	Data source	42%
	Decision type	16%
	Familiarity with BDA	34%

* % is the percentage of the times that participants mentioned a factor. The top three factors in terms of the percentage are listed here for each country.

Discussion

This research investigated the determinants of managers' actual use of BDA. The TOE framework, dual process theory, and the key demographic characteristics were integrated to form the research model to examine the external (i.e., technological and organizational contexts) and internal (i.e., individual context) factors. Table 8 summarizes the findings.

Table 8 - The Research Findings

Categories	Factors	Significant factors across NZ, CN, and VN	Significant factors shown in CN and VN	Significant factors shown in CN only
Technological factors	Technology readiness	X		
	Data quality	X		
Organizational factors	Organizational encouragement			
	Organizational expectation	X		
	Organization size			X
Individual factors	Age			
	Education			
	Seniority			
	Knowledge of analytics	X		
	Attitude toward valuing intuition and experience over analytics		X	

Common Determinants across Three Countries

Technology readiness. The study shows that managers' use of analytics positively depends on the technology readiness of an organization. They care about having well-developed infrastructure before the adoption. This finding supports previous research that technology readiness is crucial in the organizational adoption of new technology (Matsebula & Mnkandla, 2016; Park & Kim, 2021; Ahmad Salleh et al., 2015).

Data quality. Managers are also significantly concerned with data quality, which is essential to generate high-quality decisions through analytics (Lai et al., 2018). This is consistent with previous studies (e.g., Park et al., 2015; Park & Kim, 2021; Verma et al., 2018).

Knowledge of analytics. Managers with higher levels of analytical knowledge and skills use analytics more in their decision making. This supports the findings of previous studies that higher levels of technical skills lead to a higher level of intention and actual use of information and communications technology to achieve organizational goals (Liu et al., 2018; Mikalef & Krogstie, 2020).

Organizational expectation and encouragement. Somewhat surprisingly, organizational encouragement does not demonstrate a significant impact on individual level of adoption. Encouragement represents an organization's willingness to take risks and support using new technology, but it may not be closely related to an individual manager's performance (ElMelegy et al., 2016). On the other hand, organizational expectation can be more goal oriented to drive managers' actions toward desired outcomes and performance (Reynolds & Curtin, 2009). One study indicates that managers' perceived organizational expectation is

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crucial to increase the effects on their adoption behaviors (Liou et al., 2019). Another possible explanation of the finding may be derived from organizational culture which includes organizational expectations regarding using judgment and data analytics in decision making (Gressel et al., 2020). Organizational culture plays a key role in achieving BDA adoption at an individual level. It may be more important to managers than overcoming technical challenges to become proficient in data analytics. This is because in a data-driven culture, organizations largely value and often require analytics as an objective validation to support decision making (Mikalef et al., 2019a). Therefore, in such organizations, managers are more likely to conform to expectations and utilize data analytics in their decision making. This finding is consistent with previous research that a clearly emphasized organizational expectation can lead to better alignment of employee actions (Cialdini, 2005). This is especially important for organizations that are implementing innovation and changes such as BDA adoption (Liou et al., 2019).

Key Factors Supported by Part of the Research Results

Beside the above factors supported by the data across the three countries, the following factors demonstrate statistically significant effects in one or two countries.

Attitude towards valuing intuition and experience over analytics. Compared to NZ managers, CN and VN managers' use of analytics are significantly related to their attitude towards valuing intuition and experience over analytics. The more they value analytics, the more they use it. The relationship between valuing intuition and experience over analytics and the adoption level can be explained by dual process theory. Managers who mainly rely on System 1, intuition, in decision making, may not actively leverage analytics that requires System 2 effort. Managers who usually employ System 2 in decision making are more likely to use analytics outputs to endorse, correct, or override the decisions made by System 1. In this study, the top three determinants affecting valuing intuition and experience over analytics across the three countries are data source, decision type, and familiarity with BDA (see Table 7). The importance of data quality and familiarity with BDA have been discussed above. Regarding decision type, as mentioned in the research model and hypotheses section, there are three types of decisions commonly made in organizations: operational, tactical, and strategic (Ackoff, 1990). In general, the results of this study are consistent with researchers' suggestions on how different types of decisions can be made in DDDM (Gressel et al., 2020).

Tables 3 and 6 demonstrate that the extent of BDA use in decision making is higher in the VN and NZ business environments, compared to CN. Consistent with the use frequency, there are also significant differences in leveraging outputs from data analytics for decision making between CN, and VN and NZ. In VN and NZ, more than 60% of managers often use the outputs in their decision making, while in CN this number is about 45% and nearly 20% of CN managers rarely or never use analytics outputs (see Appendix). In VN, participants are mainly in lower management positions (see Table 3), so they are more likely to make routine decisions in their daily work. Their decisions may rely more on data and analytics, and the results reveal that VN managers use analytics more frequently compared to CN managers (see Table 3). In addition, it is worth noticing that since VN managers leverage data and analytics to make routine decisions, their use may be simpler than those of CN and NZ managers who tend to utilize the outputs for tactical and strategic decisions. In NZ, participants are mostly at senior management level or above. These managers usually focus on corporate strategy-related decisions, which require the outputs of data analytics. In this study, it seems that while NZ senior managers may value their own intuition, they still use analytics more than CN managers do. This can also explain why there is no significant relationship between valuing intuition and experience over analytics and the use of analytics in NZ. When making judgments for important strategic decisions, while NZ managers may prefer to leverage their own experience, they still utilize analytics based on the necessity. Conversely, in CN, a majority of participants are in middle-level management, so they may be more likely to make tactical decisions, which are considered to rely more on managers' judgments. The results show that most CN managers do not often rely on data analytics in decision making, but this may also be attributed to the lower level of familiarity with data analytics.

Organization size. Many studies (e.g., Awa et al., 2017; Sun et al., 2018) have found that organization size is an important factor affecting new technology adoption. The correlation is only shown in CN's data in this study. This may be because: 1) in NZ, respondents are mainly from large or medium sized companies (see Table 3). Around 41% of respondents in NZ report that the adoption of analytics has surged in their organizations in the past three years, so whatever the size, their adoption stages may be similar; 2) in VN, the respondents are also primarily from large or medium sized companies. About 42% of respondents state that the adoption of analytics has increased greatly in their organizations in the past three years. However, the companies that have already adopted BDA mainly involve Foreign Direct Investment, while others are still trying to understand the benefits of such technology and catch up with this trend. There is not much difference between large and small companies in terms of BDA adoption; 3) in CN, the distribution of the organizational size is relatively average, and the number of participants mentioning the moderate or significant increase of analytics in their organizations is about 27%. Hence, it seems that CN's data reflects the correlation between organizational size and managers' use of analytics more.

Insignificant Factors

There are four factors – organizational encouragement, managers' age, education level, and seniority – that do not demonstrate significant influences on managers' actual use of BDA in decision making. Organizational encouragement has been discussed above. The other three factors are discussed below.

Age. Managers' age is not shown to be a significant factor in any of the three countries. Previous studies demonstrate that (higher) age is negatively related to an individual's decision on new technology adoption and use (Morris & Venkatesh, 2000; Ruggeri et al., 2018). However, in this study, this effect does not seem to be significant. This may be because in each country the participants mainly come from a relatively narrow age group, and the group members seem to possess similar characteristics.

In NZ, most participants are in the 45-64 age group. As a developed country, information technology has been commonly used in NZ for at least two generations. Even for older managers, they are likely to have been exposed to such technology (e.g., personal computers) from an early age, probably from their secondary or tertiary studies. Hence, they have already experienced significant changes in utilizing new information technologies in businesses. It is also likely that they have accumulated experience in how to adopt new technology in their daily work, and how new technology can bring advantages to organizations, such as improving productivity and performance. Thus, they may be willing to adopt BDA.

In CN and VN, participants are primarily from the 35-54 (for CN) or 25-44 (for VN) age groups. These younger managers may have started to interact with information technology as early as their childhood. Having grown up in the information technology era, younger managers may have more experience and confidence in making independent judgments about technology (Morris & Venkatesh, 2000). They tend to rely on using new technology to complete work. Studies show that younger executives often introduce innovations related to enhancing organizational performance (Child, 1974; Chuang et al., 2009; Morris & Venkatesh, 2000).

As a result, although participants across the three countries come from different age groups, they do not demonstrate significant differences in terms of BDA adoption.

Education. Previous research shows that education levels significantly influence people's intention to adopt IT technology (e.g., Abu-Shanab, 2011; Choden et al., 2019). This study does not support previous findings, but it resembles the study by Awa et al. (2011) which found the education level of the top management team does not significantly affect IT adoption in small and medium-sized enterprises. This is probably because in previous studies the adopters usually hold a tertiary degree (e.g., diploma or above), whereas the non-adopters mainly hold a secondary degree or below (Anderson et al., 2002; Chuang et al., 2009). In this study, a majority of participants hold a bachelor's degree or above (see Table 3). It seems that education level becomes insignificant when participants hold a higher level of degree, i.e., bachelor's or postgraduate degrees.

Seniority. The study does not demonstrate a significant relationship between seniority and managers' use of analytics in the three countries. In NZ, more than 80% of participants are in senior management or higher positions, whereas in CN and VN over 50% of participants are from middle management or lower levels (see Table 3). Considering their age groups, it seems that their seniority is consistent with their age groups (i.e., in NZ senior managers are likely to be from senior age groups, whereas in CN and VN, the lower-level managers may be primarily from lower age groups). Therefore, the explanation of the insignificant correlation between age and the use of analytics can be applied to seniority as well.

General Discussion

In general, this research demonstrates some common factors affecting managers' actual use of BDA in decision making across three countries. There are also several factors showing significance in one or two countries, but not in others. For example, organizational size is found in CN's data, but not NZ and VN's. This supports our contention that single-country sampling may not be able to identify important factors, which are situation-dependent, and that cross-country studies can provide a broader view (Schmidt et al., 2001).

Overall, whatever the country and the adoption stage of an organization, the study highlights the importance of improving technology readiness and cultivating a data-driven culture, including clearly emphasized organizational expectations and the development of sufficient knowledge about and skills in BDA among managers. Enhancing data quality is also essential in terms of changing managers' attitude of valuing analytics over intuition and experience in their decision making. These findings are consistent with previous studies in that top management support, having a culture of evidence-based decision making, providing employee training for learning new technologies, and higher levels of technology readiness and data quality are the main drivers of big data adoption (Almoqren & Altayar, 2016; Lai et al., 2018; Sun et al., 2018; Verma & Bhattacharyya, 2017).

The variances among the three countries illustrate the different focal points for organizations in different adoption and use stages of BDA. For organizations that are in the early stages of adoption, similar to CN, their size may be an important factor for the use of analytics. Depending on decision-making types, the BDA adoption may be different. While operational and strategic decisions may rely more on BDA, tactical decisions may still rely more on managers' judgments although some relevant data can be collected and analyzed (Gressel et al., 2020). In addition, managers' use of analytics may be not only attributed to their inclination of valuing their own intuition and experience over analytics but also to the necessity. For example, when making strategic decisions, they may use analytics even if they value their own intuition more

Conclusion

With the advent of new technologies, a huge amount of data is produced on a daily basis. BDA provides tremendous opportunities for organizations to acquire business value and enhance competence. In this research, the determinants of managers' actual use of BDA were examined. The TOE framework, dual process theory, and the related key demographic characteristics were integrated to compose the research model to study the internal and external factors influencing the adoption.

The findings demonstrate that the common essential factors across three countries affecting managers' use of BDA are technology readiness, data quality, managers' knowledge of analytics, and organizational expectations. The factors that are more situation-dependent and evident in one or two countries' results are managers' inclination towards valuing intuition and experience over analytics and organizational size. The adoption of BDA is also related to the decision-making type. Operational and strategic decisions may depend more on BDA, whereas tactical decisions can still be made mainly by using managers' judgments. When making important strategic decisions, while managers prefer to leverage their own experience, they may still use analytics based on the necessity.

The major contributions of this study include: 1) extending the BDA literature by analyzing and comparing the determinants of the adoption among three countries, including developed and developing ones, large and small economies, and socialist-oriented and free markets, 2) leveraging the TOE framework to examine the external factors in the individual context, which is an under-utilized approach, 3) using the dual process theory to study managers' attitudes towards valuing their own intuition and experience over analytics, 4) adding the organizational expectation factor into the research model and illustrating its impacts on individual managers' BDA adoption, and 5) including demographic characteristics, which are usually treated as control variables (e.g., Gupta et al., 2016; Hoffmann et al., 2022; Melitski et al., 2010), in the research model and examining their roles in influencing managers' use of BDA. The following sections illustrate the theoretical contributions, practical implications, and limitations of this study in detail.

Theoretical Contributions

The findings of this study extend various theoretical perspectives. First, the recent BDA literature has highlighted the need for expanding empirical studies to more than one country (Verma & Bhattacharyya, 2017; Verma et al., 2018). This study extends the literature by analyzing and comparing the determinants of the adoption among three countries, including developed and developing ones, large and small economies, and socialist-oriented and free markets. Despite the differences, they are similar in their intention toward and support of BDA adoption (Auckland Unlimited, n.d.; Gorman, 2021; Sharwood, 2021). In addition, they are all in the Asia Pacific area, which is characterized by high economic openness and activity. Hence, they provide interesting contexts to investigate the commonalities and differences in BDA adoption in managerial decision making. Overall, this research reveals some common factors affecting managers' use of BDA in decision making across three countries. There are also factors demonstrating significance in one or two countries, but not in others. This supports our argument that single-country sampling may not be able to identify important situation-dependent factors, and cross-country studies can provide a broader view (Schmidt et al., 2001), so the results can be more generalizable to countries with similar environments. In addition, to the best of our knowledge, while researchers have conducted BDA studies in the NZ and CN contexts (e.g., Salleh & Janczewski, 2016; Sun et al., 2020), no current studies have been found on the adoption of BDA in managerial decision making in VN companies. Hence, this research is one of the earliest studies talking about BDA in decision making in VN.

Second, although research shows that there are serious issues in the individual-level adoption of BDA, previous studies mainly explored the factors affecting an organization's BDA adoption and did not investigate how managers actually use this technology in their decision making. By integrating the TOE framework, dual process theory, and the associated demographic characteristics, this study examined the internal and external factors affecting managers' actual use from technological, organizational, and individual perspectives. Leveraging the TOE framework to examine the external factors in the individual context is unique, as in previous research (e.g., Salleh & Janczewski, 2016; Yoon & George, 2013), this framework was mostly used to study the determinants impacting organizational adoption.

Third, this study contributes to the BDA literature by using the dual process theory to examine managers' attitudes towards valuing their own intuition and experience over analytics. Originally stemming largely from work in the cognitive psychology field (e.g., Epstein, 1994; Hammond, 1996), the dual process theory has been widely used in the field of information systems to understand various phenomena such as technology adoption (Watts, 2015). However, few studies have employed it in the BDA adoption context. Further, in this study, we asked participants to list the determinants affecting them in valuing intuition and experience over analytics, and the top three ones they mentioned are data source, decision type, and familiarity with BDA. While high-quality data and familiarity with BDA show the positive effects on managers' attitudes towards valuing analytics and the actual use of BDA, the study illustrates that managers may adjust their behavior according to the decision type. In particular, in NZ, although senior managers value their own intuition over analytics, they may still use analytics when making important strategic decisions, demonstrating that the decision making is an interactive process between Systems 1 and 2, and depending on the context of the decision (Arnott et al., 2017), managers may switch from the intuitive System 1 to the rational and BDA-employed System 2 to achieve optimal decisions.

Fourth, previous research reveals that managers are reluctant to use BDA in their decision making due to reasons such as cognitive inertia in maintaining their old work patterns, and the fear of losing their power in decision making and being replaced by the technology (Mikalef et al., 2021; Mikalef et al., 2017; Mikalef et al., 2018b). To change this situation, top management's support and cultivating a data-driven culture may be necessary (Gressel et al., 2020; Lamba & Dubey, 2015). In this study, we examined two related factors: organizational encouragement and expectation (Al-Shohaib et al., 2010; Liou et al., 2019). The former has been studied by many researchers (e.g., Al-Yaqoub et al., 2019; Ebrahimi & Mirbargkar, 2017) in the new technology adoption context and has demonstrated positive influences. On the other hand, the latter is rarely studied in this context. Our results are somewhat surprising. Compared to organizational encouragement, organizational expectation seems to be more crucial in terms of affecting managers' BDA adoption, as the expectation can be more goal oriented to drive managers' actions toward desired outcomes and performance (Reynolds & Curtin, 2009). Hence, this study enriches the BDA literature by adding the organizational expectation factor into the research model and illustrating its impacts on individual managers' BDA adoption.

Finally, in many new technology adoption studies (e.g., Gupta et al., 2016; Hoffmann et al., 2022; Melitski et al., 2010), demographic characteristics, such as age and education level, are usually treated as control variables, whereas in this study we included them in the research model and examined them as independent variables because previous research shows that they can have direct effects on individuals' behavioral intention and actual use of new technology (e.g., Ruggeri et al., 2018; Tarhini et al., 2016).

Practical Implications

In addition to its theoretical contributions, this article provides valuable practical implications for organizations looking to adopt BDA in their decision-making process. First, although organizations may expect significant benefits from the BDA adoption, and invest heavily in its implementation projects, they should be aware that such projects may encounter resistance from their employees due to the potential changes in their work patterns. In particular, when it comes to decision making, managers may still prefer to leverage their intuition and experience rather than analytics because of cognitive inertia, and the fear of losing control and being replaced, etc. (Mikalef et al., 2021, Mikalef et al., 2018a; Mikalef et al., 2018b; Mikalef et al., 2017). To solve these issues, cultivating a data-driven culture is essential. The top management team should serve as a role model in using BDA in their decision making. Then, their employees may be motivated to adopt BDA in their daily work. Clearly emphasized organizational expectations are also crucial to enhance employee motivation to use BDA.

Second, from a technological perspective, improving technology readiness and data quality is vital. Having the appropriate BDA infrastructure and tools, and reliable data can enhance managers and employees' confidence in and intention to use BDA. Organizations should investigate manager and employee requirements to understand in what situations BDA can be used and how it can be helpful and then deploy the technologies accordingly. To produce high-quality BDA outcomes, they should establish rules in data management to ensure that data is collected from reliable sources, and it is properly stored, transferred, analyzed, and applied within the organization.

Third, offering sufficient learning opportunities to managers and employees to help them build up adequate knowledge and skills in BDA is crucial. Organizations may also provide a BDA help desk and various online resources, so managers and employees can locate and receive timely support.

Fourth, BDA should be integrated into organizational processes, such as managers' decision-making process, so that it can be used in organizational daily business. For instance, organizations can demand analytics as an objective validation to support decision making. In addition, depending on different situations, organizations may encourage and expect different levels of adoption. For example, in decision making, operational and strategic decisions may rely more on BDA, while tactical decisions may still depend on managers' judgments.

Finally, having successful use cases to demonstrate tangible advantages of BDA to support organizational objectives and priorities can enhance managers' and employees' motivation for using BDA in their daily work.

Limitations and Future Studies

This study mainly focused on the factors that have an impact on managers' BDA adoption and use within an organization and did not examine the effects of the external environment, such as competition and government regulations. Future studies may include more countries with diverse environments in the investigation, and these countries can be divided into different groups. Hence, the differences and similarities of the internal and external factors within and across the groups can be examined, and more generalizable results can emerge.

In addition, this study only used a survey as the research approach, which may have limitations such as the lack of detailed explanations of participants' choices. In future research, a mixed method approach with two stages may be employed. In the first stage, quantitative survey data can be collected and analyzed, and in the second stage the qualitative data can be gathered to help explain confusing, contradictory, or unusual survey responses in the initial quantitative results (Creswell & Creswell, 2018).

Finally, this research employed convenience sampling and snowball sampling methods to recruit participants. Although we collected data from diverse sources (e.g., countries, sectors, company size, age, education level, and seniority of participants), these methods may have limitations. For example, the participants in each country are not equally distributed among groups. In future research, researchers may use proportional stratified sampling to create a stratified sampling frame and determine the proportion and size of each sample group, and then employ simple random sampling techniques to select the cases within each group (Gideon, 2012). By using this method, the research results can be more generalizable.

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Appendix.

Table 9 - Key Survey Results among Three Countries

Questions	Answers	NZ	CN	VN
The change in use of analytics in the past 3 years	Significantly increased	28.00%	6.00%	17.90%
	Moderately increased	13.00%	20.70%	25.50%
	Somewhat increased	23.00%	16.30%	21.70%
	Slightly increased	22.00%	34.10%	19.80%
	No change	10.00%	16.30%	4.70%
	Decreased	1.00%	3.00%	2.80%
	N/A	3.00%	3.60%	7.60%
Existing analytics tools meet the needs	Strongly disagree	0.80%	2.30%	3.00%
	Disagree	2.70%	3.00%	1.90%
	Somewhat disagree	16.10%	12.10%	12.50%
	Neither agree nor disagree	13.40%	35.60%	11.50%
	Somewhat agree	37.50%	24.20%	27.90%
	Agree	26.80%	20.50%	36.50%
	Strongly agree	2.70%	2.30%	6.70%
Frequency of using analytics	Every day	20.40%	6.40%	21.60%
	2-3 times a week	15.00%	4.80%	11.40%
	Once a week	15.90%	4.80%	9.10%
	1-2 times per month	12.40%	24.00%	20.50%
	1-2 times per quarter	15.90%	32.00%	20.50%
	1-2 times per 6 months	16.80%	17.60%	14.80%
	Never	3.60%	10.40%	2.10%
Use outputs from data analytics for decision making	Never	1.74%	2.90%	1.90%
	Rarely	6.96%	17.39%	0.95%
	Sometimes	32.17%	32.61%	29.52%
	Often	48.70%	44.20%	60.00%
	Always	10.43%	2.90%	7.63%
Organization expects you to incorporate analytics into decision making	Never	0.00%	2.90%	1.96%
	Rarely	8.70%	18.12%	2.94%
	Sometimes	33.04%	30.43%	21.57%
	Often	40.00%	40.58%	52.94%
	Always	18.26%	7.97%	20.59%
Encouragement level of the use of analytics	Far too much	0.00%	11.90%	0.90%
	Moderately too much	0.00%	32.60%	5.60%
	Slightly too much	4.40%	25.90%	3.70%
	Neither too much nor too little	38.90%	18.50%	54.20%
	Slightly too little	31.00%	8.10%	18.70%
	Moderately too little	18.60%	0.70%	7.50%
	Far too little	7.10%	2.30%	5.60%
	N/A	0.00%	0.00%	3.80%
Familiarity with analytics tools	Not at all familiar	3.50%	7.90%	1.90%
	Slightly familiar	16.40%	26.40%	9.40%
	Somewhat familiar	26.70%	40.70%	31.10%
	Moderately familiar	47.40%	24.30%	48.10%
	Extremely familiar	6.00%	0.70%	9.50%
Reliability of data sources	Absolutely unreliable	2.60%	6.80%	4.80%
	Slightly unreliable	4.30%	4.50%	2.90%
	Neutral	9.50%	25.00%	21.20%
	Slightly reliable	18.10%	22.70%	29.80%
	Reliable	58.60%	38.60%	39.40%
	Absolutely reliable	6.90%	2.40%	1.90%

Table 9 - Key Survey Results among Three Countries				
Questions	**Answers**	**NZ**	**CN**	**VN**
Value intuition and experience over analytics	Tend to greatly value analytics over intuition and experience	1.70%	9.40%	9.60%
	Tend to somewhat value analytics over intuition and experience	26.70%	15.80%	27.90%
	Tend to value them equally	46.60%	48.20%	43.30%
	Tend to somewhat value intuition and experience over analytics	19.80%	16.50%	13.50%
	Tend to greatly value intuition and experience over analytics	5.20%	10.10%	5.70%

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