Examining the Behavioral Intention of Philippine MSMEs Toward Business Intelligence Adoption

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Abstract

Purpose – *This work focuses on understanding the factors affecting the behavioral intention of micro, small, and medium enterprises (MSMEs) in the Philippines towards business intelligence and analytics (BI&A) systems adoption.*

Method – *The study applied Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the data collected from 202 MSMEs in the manufacturing, wholesale and retail, and services sectors.*

Findings – *The research findings revealed that perceived relative advantage, complexity, top management support, competitive pressure, and innovativeness are determinants of behavioral intention to adopt business intelligence. Of these factors, personal innovativeness and relative advantages were identified as the strongest determinants of MSMEs' adoption intention.*

Limitations – *The study has limited generalizability considering that the data used are only from the three largest MSME industry sectors.*

Implications – *The study contributes to research and practice and enables the adoption of BI&A in small businesses. The findings also provide valuable insights into developing government strategies and policies to build technological capabilities and understanding the importance of innovation advancement among MSMEs.*

Originality – *This empirical study is based on the combined concepts of the Technology-Environment-Organization framework and Personal Innovativeness in the Domain of Information Technology to understand the underlying factors affecting the behavioral intention to adopt advanced technology in the context of small businesses and non-adopters.*

Keywords: SMEs, PLS-SEM, business intelligence, Technology-Organization-Environment framework, Personal Innovativeness in the Domain of IT

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Introduction

The emergence of the digital revolution is fundamentally changing organizations' value chains that lead to the increasing strategic significance of information technology (IT) in businesses. In the new data-driven environment, firms recognized the importance of transforming data into valuable information resources for decision making. These changes led to the emergence of decision support technologies commonly known today as business intelligence and analytics (BI&A) (Cristescu, 2016). The onset of the knowledge economy and rapid development in IT resulted in further advancement of BI&A technology that significantly lowered its implementation costs (McLuhan, 2020; Tutunea & Rus, 2012). Establishing BI&A capability provides potential benefits even for small business organizations to enable data-driven processes and decision-making. Previous empirical evidence maintains that BI&A helps organizations gain competitive advantage (Wang, Yeoh, Richards, Fan, & Chang, 2019) and enhance firm performance (Popovic, Puklavec, & Oliveira, 2018). For instance, small retail businesses can use basic descriptive analytics to identify their fast-moving and most profitable products for store layout strategies, managing stocks, and marketing promotions (McLuhan, 2020). In addition, the combined use of social media and BI&A can also provide a strategic advantage for small and medium enterprises (SMEs) to monitor consumer behavior during the spread of COVID-19 as most buyers shifted to online shopping and collaborative commerce.

In the Philippines, a micro, small, and medium enterprise (MSME) refers to any form of business with a maximum asset size of Php100,000,000 and an employment size of fewer than 200 employees (MSMED Council, 2017). Around 99.5% of the total business population in the Philippines are MSMEs, and their utilization of IT is still limited to simple applications (DICT, 2017). This business sector plays an essential role in the country's economy, and their IT knowledge and skills are crucial to this modern business landscape. However, extant literature in technology adoption emphasized that, unlike large enterprises, most small businesses are hesitant to adopt new technologies despite the benefits and availability of relevant information systems (IS) (Boonsiritomachai, McGrath, & Burgess, 2016; Ramayah, Ling, Taghizadeh, & Rahman, 2016). The Lack of resources and internal IS experts is the main barrier to their inclination to adopt innovations (Ghobakhloo *et al.*, 2011).

Prior studies have produced valuable contributions toward understanding the different aspects related to BI&A, including adoption (Popovic *et al.*, 2018), value creation (Bozic & Dimovski, 2019), maturity (Tan, Sim, & Yeoh, 2011), and capability (Kulkarni, Robles-Flores, & Popovic, 2017). However, previous studies have focused on large enterprises, current adopters, implementation processes, and critical success factors, while understanding non-adopters, especially those from developing countries, has received less attention. This particular area in the IS adoption literature also needs critical examination as previous empirical findings revealed significant differences between existing adopters and non-adopters of innovation (Ghobakhloo *et al.*, 2011; Thong, 1999). Furthermore, frameworks and empirical findings from the context of large enterprises cannot be generalized to MSMEs because of their differences in terms of resources and IS capabilities (Ramayah *et al.*, 2016).

This work aims to address this gap by investigating the factors affecting the intention of MSMEs in the Philippines towards the adoption of BI&A from the lens of the Technology-organization-environment (TOE) framework (DePietro, Wiarda, & Fleischer, 1990), Diffusion of innovations (Rogers, 1962), and Personal innovativeness in the domain of IT (PIIT) (Agarwal & Prasa, 1998). The study contributes to business and IS literature by providing a basic framework for future researchers focusing on emergent technologies for small businesses. The test of the research framework also contributes to empirical findings from the perspective of non-adopters by explaining their difference with current adopters of BI&A. Furthermore, the results of this work also provide strategic insights for the development of IT capability programs for MSMEs in the country. Accordingly, this study seeks to address the following research question: "What factors significantly influence Philippine MSMEs' intention of adopting business intelligence and analytics?".

The remainder of this paper covers the following: Section 2 presents a literature review of BI&A, Philippine MSMEs, and technology adoption of small and medium enterprises (SMEs). Section 3 discusses the conceptual model and hypothesized relationship of latent variables. The methodology applied in the study is outlined in Section 4, and the results of quantitative data analysis are presented in Section 5. Section 6 covers a discussion and interpretation of the findings, while Section 7 and 8 discuss the limitation, recommendations for future research, and conclusion.

Literature Review

Business intelligence

Negash (2004) defines business intelligence as a method that involves "data gathering, data storage, and knowledge management using relevant tools for analysis to present complex and competitive information to decision-makers". The earlier version of BI&A platforms evolved from decision support systems and is commonly known today as traditional enterprise BI&A. Williams & Williams (2007) emphasized that the technology has provided opportunities for firms to enhance management, revenue generation, and operating processes. Similarly, the recent emergence of the digital economy brought relevant enterprise technologies, including BI&A, at significantly lower costs (McLuhan, 2020). Modern BI&A systems are now available as Software-as-a-Service (SaaS) or On-Demand BI&A, Mobile BI&A, self-service BI&A, and desktop and browser-based BI authoring tools (Cristescu, 2016). The modular software design of BI&A also enables small organizations to choose software packages suitable for their current needs. These changes created opportunities for organizations with limited resources to equip themselves with the same technologies as large enterprises do (Boonsiritomachai *et al.*, 2016).

The utilization of the technology encompasses three main phases based on different levels of complexity (Lepenioti, Bousdekis, Apostolou, & Mentzas, 2020): descriptive, predictive, and prescriptive analytics. BI&A is commonly perceived as too complex for SMEs because it is associated with data science, big data, and machine learning. In contrast, SMEs can start with a set of transactional data using basic descriptive methods as a starting point for examining the changes that have occurred to their businesses. The approach is also called the reporting layer of analytics that focuses on "What happened?" (McLuhan, 2020). Adoption and organizational learning is a continuous process that could eventually move them to the next level of BI&A applications, such as analysis and monitoring layers that focus on questions "Why did it happen?" and "What is happening now?", respectively (Lepenioti *et al.*, 2020). Thus, the utilization of BI&A in smaller businesses does not necessarily mean they need to be at the same level as large organizations. They can start with any basic methods to develop internal knowledge and skills. Table 1 shows examples of the applications of BI&A in SMEs.

Table 1: Application of BI&A in small businesses

Major types of BI opportunity	Analysis	Application
BI for management process	Merchandise planning and allocation	Retailers can examine the patterns in stores or regions with similar demographic characteristics for merchandise planning and allocation for market expansion.
	Sales forecasting	Examining time-based and location-based sales patterns help retailers to understand buying seasonality for supply optimization and stocking decisions.
BI revenue-generating process	Market basket analysis	Understanding customers' buying behaviors and the products they purchase to improve stocking, store layout strategies, and marketing promotions.
	Predictive life-cycle value	Data mining can help operators predict each customer's lifetime value and behavior patterns to service segments and individuals (e.g., time-based offers of special deals and discounts).
BI for operating process	Distribution logistics	Distribution companies can apply visualization of routes based on GPS data to enhance the delivery of services to customers and route optimization to save fuel costs.
	Credit decision analysis	Micro-finance operators can optimize and reduce the transaction costs from previous credit decisions by examining transactions that were known to be fraudulent or to default.

Source: (McLuhan, 2020; Williams & Williams, 2007)

Philippine MSMEs and IT capabilities

Each country has different criteria for classifying small business organizations. The IS literature presented in Table 2 reveals that SMEs or MSMEs are classified based on the size of employment, capital assets, and turnover levels (Maduku, Mpinganjira, & Duh, 2016). For example, Alshamaila, Papagiannidis, & Li (2013) define SMEs as those businesses in northeast England with less than 250 employees. The study of Kumar *et al.* (2017) describes MSMEs in India based on their investment in plants and machinery. Also, the definition of South African SMEs presented in the study of Maduku *et al.* (2016) is based on employment size and annual turnover.

Hence, it is evident from the literature that there is no universal definition or method in defining small businesses. For this reason, MSMEs in this study are defined based on Philippine Republic Act No. 6977 (Magna Carta for Micro, Small, and Medium Enterprises (MSMEs). An MSME in the Philippines is defined as any business involved in the industry, agri-business, or services and is classified based on its asset and employment size, regardless of whether they are single proprietorship, cooperative, partnership, or corporation (Gov Ph, 2008). Micro enterprises are businesses with an investment size of up to Php3 million and an employment size of fewer than 10 employees. Small enterprises are categorized as businesses with an investment size of up to Php15 million and an employment size of fewer than 100 employees. Medium enterprises are firms with an investment size of up to Php100 million and an employment size of fewer than 200 employees (MSMED Council, 2017).

Philippine MSMEs play an essential role in the economic development of the country. The current statistics show that 99.52% of the businesses in the country are classified as MSMEs. The MSME sector contributes around 62.4% to the total employment (DTI, 2018) and 35.7% share to GPD (MSMED Council, 2017). The Survey on Information and Communications Technology (SICT) in 2017 reported that an average of 98.9% of business enterprises (core and non-core ICT industries) own computers and communication equipment, and 98.6 have access to the internet used for business transactions. However, their use of these technologies is limited to simple activities, such as obtaining information or forms from government organizations and using spreadsheet and document processing applications (DICT, 2017).

Previous literature (see Table 2) also suggests that limited financial and human resources are some of the prevailing problems of SMEs that compel them to be cautious in investing in innovations (Thong, 1999) and slow in adopting technologies (Alshamaila *et al.*, 2013; Ramdani, Chevers, & Williams, 2013). Moreover, despite that technologies are becoming inexpensive and more relevant for SMEs nowadays, they still have limited capability in management techniques such as financial analysis and forecasting (Ghobakhloo *et al.*, 2011; Ramdani *et al.*, 2013). One of the reasons is that chief executive officers (CEO) make most of the decisions related to IS adoption as SMEs tend to have a highly centralized organizational structure (Thong, 1999). Another difficulty is recruiting and retaining IS staff because of limited career opportunities in SMEs (Ghobakhloo *et al.*, 2011; Thong, 1999). It is, therefore, reasonable to consider that lacking internal IS knowledge in SMEs causes a lack of understanding of the benefits and low adoption rate of technological innovations.

Theoretical background

The literature in technological innovation adoption currently has two separate areas: the technology adoption of individuals and the technology adoption of organizations. The studies focusing on technology adoption of individuals apply intention-based models, such as the Theory of Reasoned Action (Fishbein & Ajzen, 1975), Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003), Technology Acceptance Model (TAM) (Davis, 1986), Theory of Planned Behavior (Ajzen, 1991), and Task-Technology Fit (Goodhue, 1995). On the other hand, organizational technology adoption studies are based on multi-perspective theories, such as the Diffusion of innovations (DOI) (Rogers, 1962) and the Technology-Organization-Environment framework (DePietro *et al.*, 1990).

The adoption of different types of technologies in SMEs has been part of these streams of literature. Previous studies have successfully examined this area of research using TOE, DOI, or a combination of both theories (Alshamaila *et al.*, 2013; Ghobakhloo *et al.*, 2011; Puklavec, Oliveira, & Popovic, 2017). The advantage of the TOE is that it considers an environmental context that is not included in DOI, whereas DOI's innovation attributes are commonly integrated as constructs to broaden the technological context of the TOE (Alshamaila *et al.*, 2013; Ramdani *et al.*, 2013). Theoretical and empirical evidence suggests that the TOE has substantial support and is a well-grounded theoretical foundation suitable for examining intra-firm adoption of innovations (Alshamaila *et al.*, 2013; Maduku *et al.*, 2016). Previous literature in technology adoption shows that the TOE framework is a dominant theory used in examining the technology adoption of SMEs, including e-commerce (Ghobakhloo *et al.*, 2011), mobile marketing (Maduku *et al.*, 2016), website (Ramayah *et al.*, 2016), enterprise resource planning (Ramdani *et al.*, 2013), cloud computing (Alshamaila *et al.*, 2013; Kumar *et al.*, 2017), and general information systems (Thong, 1999).

The IS literature also reveals that innovativeness is also associated with technology adoption in small businesses (Boonsiritomachai *et al.*, 2016; Ghobakhloo *et al.*, 2011; Ramayah *et al.*, 2016; Thong, 1999). Rogers's (1962) prominent work in innovation diffusion suggests that individuals with a high level of innovativeness tend to seek information from new ideas and can cope with a high degree of uncertainty about adoption. In the same view, Agarwal & Prasa (1998) describe innovativeness as the willingness of an individual to test any emergent IT. Innovativeness is a personality trait independent from the subjective evaluation of other system members. Advanced technologies, like BI&A, often involve a stringent evaluation process in determining their significance to an organization. Thus, only innovative individuals are more likely to spend their time examining the potential benefits of technological innovations for their organization. For this reason, the study will also test the relationship between PIIT and adoption intention based on the previous work of Agarwal & Prasa (1998).

Table 2 summarizes some of the previous technology adoption studies in SMEs. The discussion of selected variables and proposed research hypotheses are presented in the following sections.

Table 2: Summary of prior technology adoption studies in SMEs using TOE framework

Author and Technology	Theory and Dependent Variable	Technological context	Organizational and Individual contexts	Environmental context	Sample and method
Ghobakhloo *et al.* (2011) E-Commerce	TOE framework Initial^{1} and Post^{2} adoption	Relative advantage$^{1*\ 2*}$, Compatibility$^{1*\ 2*}$, Cost	Information intensity^{2*}, CEO's IS knowledge, CEO's innovativeness^{1*}, Business Size	Competition, Buyer/supplier pressure$^{1*\ 2*}$, Support from technology vendors$^{1*\ 2*}$	235 SME CEO Adopters and non-adopters *(Multiple Regression)*
Maduku *et al.* (2016) Mobile marketing	TOE framework Intention to adopt^{1}	Relative advantage^{1*}, Perceived complexity, Cost^{1*}	Top management support^{1*}, Availability of financial resource, Employee IT capability^{1*}	Vendor support, Competitive pressure, Customer pressure^{1*}	511 SME Owners/decision-makers Non-adopters only *(CB-SEM)*
Puklavec *et al.*, (2017) Business intelligence	TOE Framework Evaluation^{1}, Adoption^{2}, Use^{3}	Relative advantage Cost$^{2*\ 3*}$ BIS as part of ERP$^{1*\ 2*\ 3*}$	Management support$^{1*\ 3*}$, Rational decision-making culture^{1*}, Project champion$^{1*\ 2*\ 3*}$, Organizational data environment^{3*}, Organizational readiness$^{1*\ 2*}$	External support	181 SMEs CIOs, management, senior IS personnel Adopter and non-adopters *(PLS-SEM)*
Ramayah *et al.*, (2015) Website	TOE Framework Continuance intention^{1}	Relative advantage^{1*}, Compatibility, Cost^{1*}, Security	Size Employee IS knowledge Innovativeness^{1*}, IT knowledge, IT adoption attitude^{1*}	External pressure, External support	108 SMEs Owners or key executives ICT, manufacturing Adopters only *(PLS-SEM)*
Boonsiritomachai *et al.* (2016) Business intelligence	TOE framework Maturity level^{1}	Relative advantage^{1*}, Complexity^{1*}, Compatibility^{1*}	Absorptive capacity, Organizational resource availability^{1*}, Owner-managers' innovativeness^{1*}, Owner-managers' IT knowledge	Competitive pressure^{1*} Vendor selection^{1*}	427 SMEs Adopters only *MN logistic regression*
Kumar *et al.* (2017) Cloud computing	TEO and DOI Intention to adopt^{1}	Cost benefit^{1*}, *Relative advantage, reliability*	Top management support^{1*}, Security and privacy	Competitive pressure^{1*}, Perceived concerns^{1*}	121 SMEs Owners, director, manager Adopter and non-adopters *(Multiple Regression)*
Awa (2016) Enterprise Resource Planning	TOE framework Adoption decision^{1}	ICT infrastructure^{1*}, Technical know-how^{1*}, Compatibility^{1*}, Values^{1*}, Security^{1*}	Subjective norms^{1*}, Size^{1*}, Demographic composition^{1*}, Scope of business operations^{1*}	External support^{1*}, Competitive pressure^{1*}, Trading partners' readiness^{1*}	373 SMEs Owners and executives Adopter and non-adopters *(Logistic regression)*
Yoon (2020) Smart farm	TEO framework Adoption decision^{1}	Relative advantage Compatibility^{1*}, Complexity,	Financial cost^{1*}, Lack of skills, Human resource vulnerability, CEO innovativeness, CEO IT knowledge	Government support, Digital environment change^{1*}	232 SMEs Farmers *(PLS-SEM)*
Ramdani *et al.* (2013) Enterprise systems	TOE framework Adoption decision^{1}	Relative advantage^{1*} Compatibility^{1*}, Complexity^{1*}, Trailability^{1*}, Observability^{1*}	Top management support^{1*}, Organizational readiness, ICT experience, Size^{1*}	Industry^{1*}, Market scope^{1*}, Competitive pressure^{1*}, External ICT support	300 SMEs Owners *(PLS-SEM)*

*Note Numbers 1, 2, and 3 represent the dependent variable/s (DV); * indicates a significant independent variable (IV); (ex. IV^{2*} implies that the IV is a significant predictor of DV^{2})*

Theoretical framework and hypotheses

Built on the seminal work of DePietro *et al.* (1990), the TOE framework is an organizational-level theory that explains the three contexts that drive organizations' adoption decisions. The theory posits that technological, organizational, and environmental conditions influence the innovation adoption of an organization. The research framework in this study also incorporates the concept of innovativeness in an individual context based on the empirical findings indicating that the construct is associated with SMEs at the pre-adoption (Ghobakhloo *et al.*, 2011; Thong, 1999) and adoption (Alshamaila *et al.*, 2013; Boonsiritomachai *et al.*, 2016; Ramayah *et al.*, 2016) innovation stages. Figure 1 shows the proposed research framework of this study.

The technological condition represents the essential technologies for an organization. These include internal technologies currently utilized in the organization and available external technologies available but not currently in use (DePietro *et al.*, 1990). The organizational condition denotes the characteristics and resources of the organization, including the link between its members, the methods of communication, their size, and slack resource (DePietro *et al.*, 1990). The environmental condition refers to the arena in which the organization conducts its business, which involves industry structure, competition, technology providers, and regulatory setting (DePietro *et al.*, 1990).

Technological context

Relative advantages are defined in this study as the expected benefits of MSMEs from BI&A. Rogers (1962), from his seminal work in innovation diffusion theory, emphasized that an individual's understanding of the relative advantages of innovation is a factor for his/her decision of adoption. In the same way, the construct corresponds to perceived usefulness in TAM (Davis, 1989) as one of the antecedents of the adoption and usage of new technologies. Previous studies suggest that the relative advantage is a significant and positive determinant of SMEs' adoption of IS (Ghobakhloo *et al.*, 2011; Maduku *et al.*, 2016; Ramayah *et al.*, 2016; Ramdani *et al.*, 2013). BI&A systems offer various potential benefits for MSMEs to enhance existing processes at the different organizational levels (Boonsiritomachai *et al.*, 2016; McLuhan, 2020). However, technology adoption is also a trade-off between the overall benefits and the factors they need to sacrifice. It also implies that small firms are more likely to invest in BI&A if they have an assurance that these potential benefits are viable and relevant for business growth (Ramayah *et al.*, 2016; Ramdani *et al.*, 2013). Hence, the relative advantage of BI&A is much crucial for small businesses, because unlike other technologies such as e-commerce or online marketing, BI&A is composed of broad functionalities, methodologies, and processes that need careful evaluation to determine the appropriateness of its use (Llave, 2017). For example, using BI&A for sales forecasting is relevant in wholesale and retail businesses but not in the financial service industry. Based on these perspectives, the relative advantage of BI&A is applied as one of the determinants of Philippine MSMEs' intention to adopt. Thus, the study hypothesizes that:

H1: Perceived relative advantage is positively associated with the intention of MSMEs in the Philippines to adopt BI&A applications.

Complexity in this study refers to the degree of MSME's perception of how difficult it is to understand and use BI&A. The DOI of Rogers (1962) emphasized that the complexity of new technology is a barrier to adoption. This construct is the opposite view of perceived ease of use from the concepts of TAM of Davis (1989). While these views are defined differently, both suggest that technology is more likely to be adopted if it is easy to learn and understand. This view has support from prior studies suggesting that technologies involving a steep learning curve negatively affect the adoption decisions of SMEs as it raises uncertainty and risk (Alshamaila *et al.*, 2013; Boonsiritomachai *et al.*, 2016; Ramdani *et al.*, 2013). Although the user interface of BI&A applications is much easier to use nowadays, potential adopters still need to have knowledge and skills in other areas to generate reliable results (Olszak & Ziemba, 2012). For example, BI&A requires expertise in data preparation and basic statistics. Such requirement is a problem for small firms because they lack internal knowledge and in-house IS experts (Ghobakhloo *et al.*, 2011; Thong, 1999). Thus, the complexity of BI&A is a concern for small businesses because of their limited technological capability. For these reasons, complexity is applied in this study as a factor affecting the intention of Philippine MSMEs to adopt BI&A. Accordingly, the study proposes the following hypothesis:

H2: Perceived complexity is negatively associated with the intention of MSMEs in the Philippines to adopt BI&A applications.

Perceived cost in this study refers to the financial resources involved in the adoption and implementation of BI&A. The lack of resources and technical capability are some of the prevailing problems of most SMEs worldwide that compel them to be cautious in investing in technological innovation (Maduku *et al.*, 2016; Thong, 1999). IS literature in technology adoption of SMEs (Kumar *et al.*, 2017; Maduku *et al.*, 2016; Puklavec *et al.*, 2017; Ramayah *et al.*, 2016) has identified this construct as negatively associated with adoption intention. In their study, Maduku *et al.* (2016) and (Ramayah *et al.*, 2016) identified cost as one of the main factors affecting mobile marketing adoption and website continuance of SMEs. Considering that BI&A involves a much complex implementation process, therefore, it is practical to expect that cost is a factor that affects MSMEs' decision to adopt the technology as they need to invest in upgrades of computer hardware, software, employee training, and IS consulting services (Cristescu, 2016). Consequently, the overall implementation cost needed for BI&A adoption will also depend on the current technological capabilities of MSMEs instead of mainly on the cost of software alone. Thus, the perceived cost of BI&A implementation was applied in this study as it is a potential determinant of MSMEs' intention to adopt due to their limited financial resources for innovations. Similarly, the study hypothesizes that:

H3: Perceived cost is negatively associated with the intention of MSMEs in the Philippines to adopt BI&A applications.

Organizational context

Resource-based view theory (Barney, 1991) defines top management support as an essential relationship resource of an organization. Thong (1999) stressed that a supportive environment is necessary to maintain organizational climate and boost employee motivation towards successful innovation adoption. Prior studies have identified top management as a positive driver of technology adoption in SMEs (Kumar *et al.*, 2017; Maduku *et al.*, 2016; Puklavec *et al.*, 2017; Ramdani *et al.*, 2013). One of the reasons is that the adoption of enterprise technology heavily relies on the commitment of top management to provide sufficient resources throughout its implementation (Alshamaila *et al.*, 2013). Organizations are commonly confronted with difficulties when adopting technological innovations as it impacts organizational processes and their ways of doing business. Kulkarni *et al.* (2017) emphasized that maintaining top management commitment is an enabling factor in innovation adoption of organizations as it helps facilitate changes and reduce user resistance. This factor is more crucial for small firms because of their highly centralized structure wherein the owner makes most decisions to align IT utilization to organizational objectives and strategies (Thong, Yap, & Raman, 1996). Based on these perspectives, top management commitment is applied in this study as a determinant of MSMEs' adoption intention towards BI&A. Accordingly, the study proposes the following hypothesis:

H4: Top management support is positively associated with the intention of MSMEs in the Philippines to adopt BI&A applications.

Cohen & Levinthal (1990) define absorptive capacity as *"the ability of an organization to recognize the value of new, external information, assimilate it, and apply it to commercial ends."* This capability develops based on the previous involvement of an organization in activities that will enhance the individual absorptive capacity of its members (Bozic & Dimovski, 2019). Organizations with a high absorptive capacity tend to recognize innovations and opportunities more than those with a moderate absorptive capacity (W. Cohen & Levinthal, 1990). However, most MSMEs have limited resources that impede them from adopting advanced technological innovations. Unlike large enterprises, small firms have low internal IS knowledge because of their inability to hire IT staff, which causes a lower level of awareness of the benefits of technological innovations. Moreover, small firms can only provide a limited career path that constrains them from retaining IS professionals (Thong, 1999). Following this viewpoint, this study includes the level of absorptive capacity as a positive driver of MSMEs' intention to adopt BI&A (Boonsiritomachai *et al.*, 2016; Maduku *et al.*, 2016; Ramayah *et al.*, 2016). Therefore, MSMEs are more likely to adopt the technology if they have sufficient organizational absorptive capacity. In the same way, this study hypothesized that:

H5: Absorptive capacity is positively associated with the intention of MSMEs in the Philippines to adopt BI&A applications.

The availability of organizational resources is defined in this study as the level of technological and financial readiness of MSMEs to adopt BI&A. Technological capability refers to the current IT usage and level of sophistication of an organization. On the other hand, financial capacity denotes the availability of resources for acquiring computer hardware, software, and other relevant IT consulting services (Iacovou, Benbasat, & Dexter, 2013). Both are considered necessary resources for an organization to adopt and implement technological innovations. In addition, Boonsiritomachai *et al.* (2016) suggest that time is also an essential organizational resource needed for technology adoption. However, small firms have very limited technological, financial, and human resources compared to large enterprises. In his study, Thong (1999) refers to this condition as resource poverty caused by severe constraints on financial resources and internal IS expertise (Ghobakhloo *et al.*, 2011; Maduku *et al.*, 2016). For these reasons, small firms face significant challenges and barriers to innovation, which compels them to be cautious in investing in modern IS. In a previous study by Maduku *et al.* (2016), the availability of financial resources was identified as a non-significant factor in the adoption of mobile marketing of SMEs in South Africa. In contrast, this study involves a much more complex enterprise technology compared to mobile marketing. Hence, previous findings may not be applicable in the context of BI&A in MSMEs. This study addresses this gap by examining the availability of organizational resources in the context of BI&A and MSMEs' adoption intention. Thus, this study proposes the following hypothesis:

H6: Organizational resource availability is positively associated with the intention of MSMEs in the Philippines to adopt BI&A applications.

The concept of information intensity denotes the volume of information present in an organization's commodity, services, and value chain (Ghobakhloo *et al.*, 2011). Businesses have different needs for information processing depending on the industry sector. For example, SMEs in the retail industry are information-intensive because of the volume of information in every product they sell. Also, the manufacturing value chain is information-intensive due to the interdependent activities involved in their production process. The intensity of information in an organization's products or services was identified in previous literature as a positive determinant of SMEs' decision to use IS (Ghobakhloo *et al.*, 2011; Thong, 1999). BI&A is a form of technology designed for transforming data into critical information for decision making and is, therefore, a competitive tool for information-intensive business organizations. On the other hand, firms from less information-intensive industries may find the technology unsuitable for their current needs. Thus, MSMEs are more likely to adopt BI&A if they are part of an information-intensive industry and are familiar with the uses of information for developing strategic and competitive advantages. Thus, information intensity was applied in this study as a decision factor for MSMEs to adopt BI&A. In the same way, the study hypothesized that:

H7: Information intensity is positively associated with the intention of MSMEs in the Philippines to adopt BI&A applications.

Environmental context

Business organizations adopt technological innovation to enhance existing processes and maintain a competitive position within their external environment (Ramdani *et al.*, 2013). In this study, competitive pressure refers to the degree of competition from the external environment experienced by business organizations. Competitive pressure was found as a positive determinant of technology adoption in SMEs (Boonsiritomachai *et al.*, 2016; Ghobakhloo *et al.*, 2011; Iacovou *et al.*, 2013). This internal pressure forms in an organization when the technology used by the industry, trading partners, and competitors is more advanced than what they are currently using. It causes firms to seek strategic advantage through technology upgrades and innovations (Paydar, Endut, Yahya, & Rahman, 2014). Competitive pressure can also emerge from the spread of technology adoption in other industries that are not considered competitors or trading partners (Alshamaila *et al.*, 2013). For example, as the number of BI users in a specific industry increases, non-adopters will start to appreciate the benefits of the technology. This condition also causes internal pressure and a tendency to adopt the same technology into their existing system to achieve the same level of capability. Thus, firms are more likely to adopt technology if they are operating in a highly competitive business environment. For these reasons, competitive pressure is included as an essential factor for MSMEs' intention towards BI&A adoption. Similarly, the study proposes that:

H8: Competitive pressure is positively associated with the intention of MSMEs in the Philippines to adopt BI&A applications.

This study defines vendor support as the external IS expertise and assistance from software companies to their respective customers (Ifinedo, 2011). This aids firms, irrespective of their size, during IS implementation process as software vendors generally provide computer hardware, software, maintenance, user training, and other technical support (Ramayah *et al.*, 2016; Thong, 1999). Previous empirical evidence shows that support from software vendors positively affects SMEs' decision towards innovation adoption as they are restrained by their limited IS expertise (Awa, 2016; Kumar *et al.*, 2017; Ramdani *et al.*, 2013). Thus, SMEs would greatly rely on external support as it helps reduce risk and uncertainty to ensure successful implementation, particularly on complex forms of IS. Furthermore, according to Ifinedo (2011), technology vendors serve as change agents in the planning and implementation stage, especially for organizations with insufficient internal IS capability, to bridge knowledge gaps and reduce user resistance (Alshamaila *et al.*, 2013). Based on these concepts, vendor support was applied in this study as a driver of MSMEs' intention to adopt BI&A. Accordingly, the following hypothesis is proposed:

H9: Vendor support is positively associated with the intention of MSMEs in the Philippines to adopt BI&A applications.

Individual context

The marketing and consumer behavior literature describes innovativeness as *"the degree to which an individual makes decisions independent from the communicated experience of others"* (Flynn & Goldsmith, 1993). The study of Agarwal & Prasa (1998) introduced the concept of PIIT as a personality trait associated with a person's willingness to test emerging computer-based technologies. According to Rogers's (1962) work in innovation diffusion theory, innovative individuals are novelty-seekers and can handle high levels of risk and uncertainty. Furthermore, it has been identified in the previous study by Thong (1999) that CEOs' innovativeness influences organizational change because of their willingness to evaluate the potential advantages of IS. Empirical evidence also shows that the level of innovativeness positively affects the decision of SMEs to adopt technologies that involve relatively simple implementation such as websites (Ramayah *et al.*, 2016) and e-commerce (Ghobakhloo *et al.*, 2011). Hence, innovativeness is a critical factor for MSMEs' decision to adopt because BI&A is an intricate technology that requires cautious assessment to determine its potential value to their organization. For instance, using BI&A for market-basket analysis is appropriate for the retail sector but may not be perfectly suitable for the accommodation and food services industry. For these reasons, personal innovativeness was applied in this study as a determinant of MSMEs' intention to adopt BI&A. In turn, the study proposes the following hypothesis:

H10: Innovativeness is positively associated with the intention of MSMEs in the Philippines to adopt BI&A applications.

The proposed research framework and the hypothesized relationships are illustrated in Figure 1.

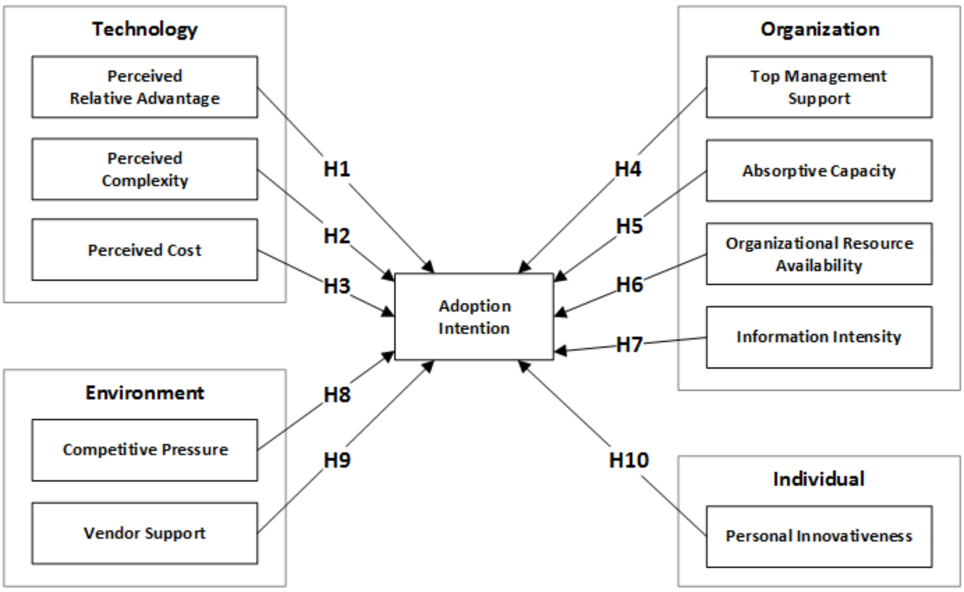

Figure 1: The research model

Methodology

The following section outlines the research methodology applied in this study to test the hypotheses, including measurement, sampling, data collection, and the examination of data for non-response bias and common method bias.

Measures

Ten independent variables were hypothesized as determinants of intention to adopt BI&A. All constructs have a minimum of three items to ensure that the results will yield adequate reliability. All constructs were measured using a 5-point Likert-type scale with values ranging from 1 (strongly disagree) to 5 (strongly agree). The measurement items were adopted from previously validated scales and aligned to the context of this study. The preliminary version of the survey instrument was administered to ten participants from the target population to gather some suggestions regarding the clarity of the instructions and questions. Enhancement of the questionnaire was applied based on the recommendations of the respondents. Before data collection, a pilot test with 40 MSMEs was conducted for preliminary examination of the measures. All measurement items of the questionnaire were above the recommended threshold of 0.70, indicating an adequate level of internal consistency and reliability based on Cronbach's Alpha coefficient.

Sampling and data collection

The study gathered the data from the National Capital Region (NCR) and Region 4A because the regions are two of the main contributors to the country's economy and the home of more than 35% of the total MSME population in the Philippines. NCR is the major contributor to the Philippine economy, concentrating on the production of industry-related goods and services with 36% GDP (DTI, 2018). Similarly, Region 4A is the second-largest contributing region hosting the highest concentration in the manufacturing of semi-processed industrial raw materials and components with around 17% GDP (DTI, 2018). Lists of registered MSMEs were requested from the Department of Trade and Industry (DTI) provincial office and were used to gather initial details. Four hundred MSMEs were randomly selected from the three largest industries, including manufacturing, wholesale and retail, and accommodation and food services sectors. Selected respondents are owner-managers or managers who are responsible for or have significant involvement in IT adoption decisions.

The survey was administered in government-sponsored training and seminars for MSMEs within the regions through collaboration with Negosyo Centers and SME-Roving Academy program coordinators. These are programs spearheaded by the DTI to facilitate access to services, training, and development programs for MSMEs. The data gathering processes collected a total of 244 survey responses, and all of them indicated that they are not currently using BI&A. Survey questionnaires from unqualified respondents based on the stated criteria or with more than 15% incomplete answers were, therefore, dropped for further analysis (Hair, Hult, Ringle, & Sarstedt, 2017). This data filtering process yields 202 valid responses, indicating a 51% response rate.

Non-Response Bias & Common method bias

A test for potential non-response bias was conducted by comparing the distribution of early and late respondents using the Kolmogorov-Smirnov test. The results indicate a significant dissimilarity among early and late respondents (p-value > .10 for all variables), indicating that potential non-response bias is not present in the model (Ryans, 1974). Considering that the data in the study were from self-contained questionnaires, a test for possible common method bias was also performed using Herman's single factor test method (Podsakoff, Mackenzie, Lee, & Podsakoff, 2003). The result shows that the first factor accounted for approximately 14% of the variation present in the model, indicating the absence of common method bias (Harman, 1976). A further test was conducted using the full collinearity assessment approach (Kock & Lynn, 2010). The findings show that the variance inflation factors (VIFs) of all latent variables are below the recommended threshold (3.3), which further indicates that the model is free from common method bias.

Results

The descriptive analysis was performed using SPSS v.22 to examine the profile of the respondents. The dataset for the research framework was examined using partial least squares structural equation modeling (PLS-SEM) with SmartPLS v.3 to test the hypothesized causal relationship between latent variables. PLS-SEM is the most suitable method for this research because it works efficiently for relatively sample size and non-normal data distribution (Hair *et al.*, 2017). The subsequent sections present the data analysis, including descriptive statistics, the assessment of measurement, and structural models to test the proposed hypotheses.

Descriptive Statistics

The profile of research participants is composed of owners and managers with 70.3% and 29.7%, respectively. The majority of the respondent are between 31 to 50 years old and are mostly are females (72.3%). Their highest level of education shows that 75.2% of them are college graduates, 14.9% have completed a vocational or diploma course, and the rest have master's and doctoral degrees. The results also show that most of the respondents are from the manufacturing (43.6%), wholesale and retail industries (33.2%), and accommodation and food services (23.3%).

The descriptive statistics of measurement items have a mean above the midpoint with standard deviations between 0.792 to 1.268. Data distribution was also assessed based on the values of skewness and kurtosis. The recommended threshold for examining normality is that indices should be within +1 and -1 (Hair *et al.*, 2017). The skewness values are between -1.400 and 0.501, and kurtosis values are between -0.770 and 1.460. The skewness and kurtosis values of ACAP4, PRAV1 PRAV2, and PRAV3 are higher than the recommended threshold, indicating a slight non-normality. Thus, the result of the normality test further suggests the appropriateness of a non-parametric method for analysis.

Measurement Model Evaluation

The measurement model was assessed for internal consistency reliability, indicator reliability, convergent validity, and discriminant validity (Hair *et al.*, 2017). Internal consistency reliability was evaluated using Cronbach's alpha (CA) and composite reliability (CR) values of all dependent and independent variables (Benitez, Henseler, Castillo, & Schuberth, 2020). The values presented in Table 3 indicate that the CA and CR coefficients of constructs are above the 0.70 threshold (Chin, 2010), which implies that all measurement items have a substantial level of internal consistency.

In Table 3, indicator loadings of measures are mostly higher than the threshold value of 0.70 and significance levels less than 0.001. The outer loadings of IINT4 (0.6965) and INNO2 (0.6708), which were slightly below the critical value and items, should be dropped from the model to increase composite reliability (CR) or average variance extracted (AVE) values. The CR of IINT4 and INNO2 are 0.8585 and 0.8427 and are above the critical value of 0.70. Furthermore, the average variance extracted (AVE) values of IINT4 (0.5491) and INNO2 (0.5736) are also higher than the recommended threshold of 0.50, which therefore suggests that there is no need to drop the measures from the model.

Table 3: Results of measurement validity

Construct	Item	Factor loading	CA	CR	AVE	VIF
Perceived relative advantage	PRAV1	0.8635	0.9042	0.9329	0.7766	1.1642
	PRAV2	0.8878				
	PRAV3	0.8862				
	PRAV4	0.8874				
Perceived complexity	PCMP1	0.7155	0.8222	0.8809	0.6503	1.1443
	PCMP2	0.7781				
	PCMP3	0.8677				
	PCMP4	0.8550				
Perceived cost	PCST1	0.8560	0.8868	0.9209	0.7443	1.1252
	PCST2	0.8622				
	PCST3	0.8824				
	PCST4	0.8501				
Top management support	TMSP1	0.7914	0.8138	0.8750	0.6370	1.0984
	TMSP2	0.8278				
	TMSP3	0.8378				

	TMSP4	0.7312				
Absorptive capacity	ACAP1	0.8473	0.8832	0.9142	0.7273	1.0829
	ACAP2	0.8806				
	ACAP3	0.8680				
	ACAP4	0.8138				
Organizational resource availability	ORAV1	0.9144	0.8953	0.9233	0.7507	1.1241
	ORAV2	0.8484				
	ORAV3	0.8392				
	ORAV4	0.8617				
Information intensity	IINT1	0.7105	0.8096	0.8585	0.5491	1.0833
	IINT2	0.7933				
	IINT3	0.7108				
	IINT4	*0.6965*				
	IINT5	0.7880				
Competitive pressure	CPRE1	0.7641	0.7862	0.8610	0.6079	1.1686
	CPRE2	0.7828				
	CPRE3	0.8141				
	CPRE4	0.7564				
Vendor support	VNSP1	0.8507	0.8792	0.9146	0.7284	1.1266
	VNSP2	0.9022				
	VNSP3	0.8468				
	VNSP4	0.8116				
Innovativeness	INNO1	0.7995	0.7523	0.8427	0.5736	1.2002
	INNO2	*0.6708*				
	INNO3	0.7520				
	INNO4	0.7999				
Intention to adopt	IADP1	0.9019	0.8606	0.9150	0.7820	
	IADP2	0.8711				
	IADP3	0.8798				

The convergent validity of variables was examined based on the AVE coefficients. The AVE values of latent variables should be higher than the recommended threshold of 0.50 (Chin, 2010; Hair *et al.*, 2017). As presented in Table 3, the results indicate that all constructs explain more than half of the variance of its indicators, which also implies that convergent validity of the measurement model was achieved (Hair *et al.*, 2017; Sarstedt, Ringle, Smith, Reams, & Hair, 2014).

The discriminant validity was examined based on the cross-loadings, Fornell-Larcker criterion, and the heterotrait-monotrait ratio of correlation (HTMT). All indicator loadings of constructs are greater than the loadings on other constructs. Furthermore, factor loadings of primary constructs are 0.2 higher than the loadings with other constructs, indicating the absence of major cross-loadings between latent variables. Fornell-Larcker's criterion requires that the square root of AVE of a construct should be greater than its correlation with other constructs (Fornell &

Larcker, 1981). Table 4 shows that each construct's square root of AVE (on-diagonal) is greater than its correlation with any other latent variable (off-diagonal), thus providing additional support for the model's discriminant validity.

HTMT is also a recommended measure of discriminant validity in PLS-SEM (Henseler, Ringle, & Sarstedt, 2015). Examining a model using this criterion requires values to be lower than the threshold of 0.90 ($HTMT_{.90}$) or a more conservative threshold of 0.85 ($HTMT_{.85}$) to be considered acceptable (Henseler *et al.*, 2015). As shown in Table 5, HTMT values of all constructs are less than 0.85, indicating that the measurement model has substantial support for discriminant validity.

Table 4
Square root of AVE and correlation of constructs

	ACAP	CPRE	IINT	INNO	IADP	ORAV	PCMP	PCST	PRAV	TMSP	VNSP
ACAP	**0.8528**										
CPRE	0.1392	**0.7797**									
IINT	0.0153	0.0039	**0.7410**								
INNO	0.1159	0.2391	0.0506	**0.7574**							
IADP	0.2036	0.4339	0.1078	0.5344	**0.8843**						
ORAV	0.1364	0.0445	0.1570	0.2086	0.1853	**0.8664**					
PCMP	-0.1251	-0.2526	-0.0035	-0.2277	-0.3979	-0.1300	**0.8064**				
PCST	-0.1011	-0.1898	-0.0795	-0.2042	-0.2957	-0.1163	0.1758	**0.8628**			
PRAV	0.1693	0.2008	0.1076	0.2440	0.5136	0.1328	-0.1749	-0.1971	**0.8813**		
TMSP	0.0838	0.1409	0.1537	0.1182	0.3392	0.0214	-0.0043	-0.1803	0.1828	**0.7981**	
VNSP	0.1829	0.1555	-0.1111	0.1877	0.1170	0.1779	-0.1302	-0.0558	0.1271	0.0561	**0.8534**

Note: on-diagonal values are the square root of AVE; off-diagonal values are inter-construct correlations

Table 5
Heterotrait-monotrait ratio of correlation

	ACAP	CPRE	IINT	INNO	IADP	ORAV	PCMP	PCST	PRAV	TMSP	VNSP
ACAP											
CPRE	0.1441										
IINT	0.0665	0.0994									
INNO	0.1478	0.2985	0.1148								
IADP	0.2072	0.5200	0.1146	0.6565							
ORAV	0.1411	0.0832	0.2037	0.2249	0.1835						
PCMP	0.1453	0.3043	0.1231	0.2725	0.4587	0.1405					
PCST	0.1069	0.2364	0.1151	0.2542	0.3299	0.1215	0.2060				
PRAV	0.1858	0.2400	0.1501	0.2830	0.5797	0.1345	0.1942	0.2190			
TMSP	0.0997	0.1811	0.2322	0.1545	0.3900	0.0703	0.0745	0.2015	0.2114		
VNSP	0.2086	0.1738	0.1245	0.2265	0.1267	0.2092	0.1570	0.0730	0.1361	0.0935	

Structural Model Evaluation

The structural model was examined for potential collinearity, path coefficient and significance, predictive accuracy, effect size, and predictive relevance (Chin, 2010; Hair *et al.*, 2017). The collinearity between latent variables was examined based on each construct's variance inflation factors (VIF). High levels of collinearity (or multi-collinearity) can lead to insignificant estimates that can also change the signs of weaker constructs (Benitez *et al.*, 2020; Hair *et al.*, 2017; Kock & Lynn, 2010). A construct VIF value greater than the threshold of 5.0 (Hair *et al.*, 2017) or 3.3 (Kock & Lynn, 2010) indicates a presence of collinearity. As presented in Table 3, VIF values of constructs are all below the recommended 3.3 threshold value, indicating support for the absence of collinearity between latent variables (Hair *et al.*, 2017; Kock & Lynn, 2010).

The path coefficients of each hypothesized causal relationship and their corresponding *p*-values are presented in Table 6. The results of hypothesis test and path coefficients show significant positive relationships of PRAV (H1) (*ß* = 0.3042, *p*-value<0.001), TMSP (H4) (*ß*=0.2038, *p*-value<0.001), CPRE (H8) (*ß*=0.2065, *p*-value<0.001), and INNO (H10) (*ß*=0.3296, *p*-value<0.001) on IADP. Moreover, the test also indicates a significant negative relationship between PCMP and IADP (H2) (*ß*=-0.2066, *p*-value<0.001). The *p*-values of path relationships from PRAV, TMSP, CPRE, INNO, and PCMP to IADP are significant at a 0.1% error probability (Hair *et al.*, 2017). Therefore, the structural model evaluation supports H1, H2, H4, H8, and H10.

In contrast, the findings also reveal that the path relationships from PCST (H3), ACAP (H5), ORAV (H6), IINT (H7), and VNSP (H9) to IADP are non-significant. The associated *p*-values of these path relationships are higher than the significance level of 0.05; therefore, these relationships are insignificant and are not supported. Furthermore, the H9 was hypothesized to have a positive relationship, but the results reveal it was negative. Thus, H9 is still unsupported even if the path relationship is significant.

Table 6
Results of hypothesis testing

Path coefficient and significance						Effect size	
Hypothesis	Hypothesis path	Path coefficient	T-value	*p*-value	Decision	f^2	Interpretation
H1	PRAV->IADP	0.3042***	5.5178	<0.001	**Supported**	0.1971	**Medium**
H2	PCMP->IADP	-0.2066***	3.5827	<0.001	**Supported**	0.0925	**Small**
H3	PCST->IADP	-0.0509	1.0705	0.2845	Not Supported	0.0057	No Effect
H4	TMSP->IADP	0.2038***	4.3362	<0.001	**Supported**	0.0937	**Small**
H5	ACAP->IADP	0.0451	0.8844	0.3765	Not Supported	0.0047	No Effect
H6	ORAV->IADP	0.0350	0.6166	0.5375	Not Supported	0.0027	No Effect
H7	IINT->IADP	0.0075	0.1204	0.9041	Not Supported	0.0001	No Effect
H8	CPRE->IADP	0.2065***	3.7375	<0.001	**Supported**	0.0905	**Small**
H9	VNSP->IADP	-0.0704	1.2520	0.2106	Not Supported	0.0109	No Effect
H10	INNO->IADP	0.3296***	6.4075	<0.001	**Supported**	0.2243	**Medium**

*Note: f^2 0.02=small effect; 0.15=medium effect; 0.35=large effect; *** $p < 0.001$*

Aside from the values of path coefficients and significance level, R^2 was also examined using a bootstrap process with 5000 iterations to test the model's level of predictive accuracy. Hair *et al.* (2017) suggested that values of 0.25, 0.50, and 0.75 of an endogenous variable can be interpreted respectively as weak, moderate, and substantial moderate. Based on the result, the IADP R^2 value of 0.5966 suggests that the model had gained a moderate level of predictive accuracy.

Effect size (f^2) is another path coefficient measure that indicates the impact of a specific independent construct when omitted from the model. Chin (2010) suggests that $f2$ values of 0.02, 0.15, 0.35 are equivalent to small, medium, and large effect sizes, respectively (J. Cohen, 1988). Based on this criteria, the effect sizes of PRAV (f^2 = 0.1971) and INNO (f^2= 0.2243) indicates a medium effect, while PCMP (f^2 = 0.0925), TMSP (f^2 = 0.0937), and CPRE (f^2 = 0.0905) represents small effect (J. Cohen, 1988).

The predictive relevance of the model was examined based on Stone-Geisser's Q^2 and blindfolding procedure. Q^2 values of 0.02, 0.15, and 0.35, represent small, medium, and large predictive relevance. The result shows that the IADP Q^2 value of 0.4417 is substantially large, indicating strong support for the predictive relevance of the model (Hair *et al.*, 2017).

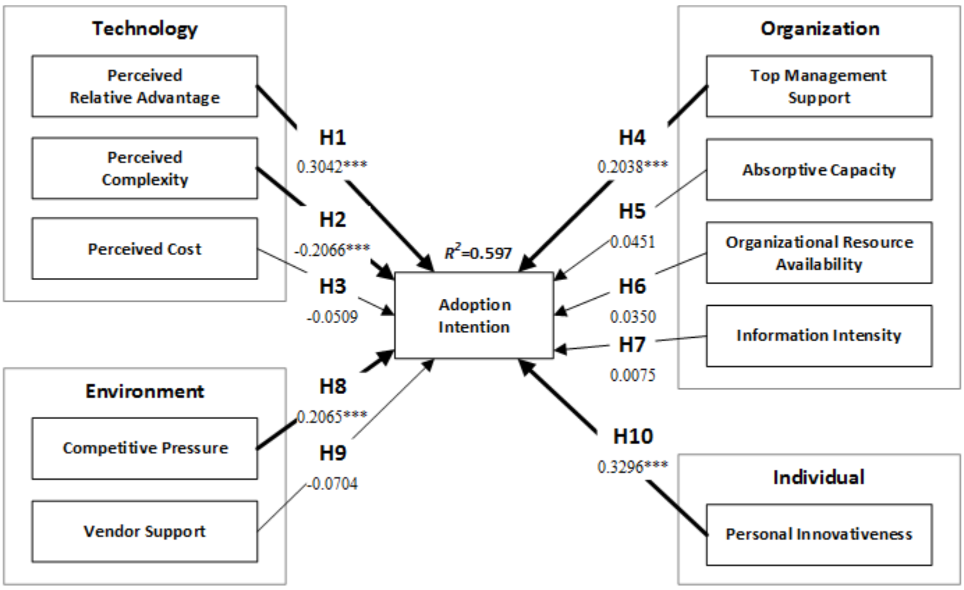

Figure 2: Results of the research model

Additionally, model fit was also evaluated to determine the model's exploratory power based on standardized root mean square residuals (SRMR), RMStheta, and exact model fit measure (Hair *et al.*, 2017). The results indicate that the model has a good fit with an SRMR value of 0.0591 below the cut-off value of 0.08. Moreover, the model's RMStheta value of 0.1197 is also lower than the recommended threshold of 0.12. (Benitez *et al.*, 2020). Lastly, the exact model fit criterion test reveals that the model's SRMR (0.0591) is lower than the HI95 of SRMR (0.0753), d_ULS (3.4586) is lower than the HI95 of d_ULS (5.6280), and d_G (1.2595) is lower than the HI95 of d_G (.17378), which also indicates that the model has an acceptable overall fit.

Discussion and implications

Technological Context

The hypothesis test shows a positive relationship between the relative advantage of BI&A and behavioral intention. This relationship implies that MSMEs which are knowledgeable about the advantages and benefits of BI&A are more likely to have a higher propensity towards adoption. This result supports previous findings on the influence of relative advantage on the level of BI&A adoption (Boonsiritomachai *et al.*, 2016). Thus, the assessment of the construct further confirms this relationship in the context of MSMEs in the Philippines. A negative influence of perceived complexity on intention towards BI&A adoption also emerged from the findings. This relationship implies that MSMEs which believe that the technology is hard to incorporate into their existing tasks because their limited IS knowledge are less likely to have the propensity towards its adoption (Maduku *et al.*, 2016). In contrast with previous findings, the results also reveal that perceived cost is not associated with the adoption intention of MSMEs (Kumar *et al.*, 2017; Ramayah *et al.*, 2016). A plausible explanation for this is the availability of free and trial versions of basic BI&A software packages for learning its fundamental applications.

Organizational Context

Among the factors of organizational context, the support of top management exhibits a positive impact on the intention of MSMEs to adopt BI&A. This result implies that critical decisions related to management and investment are all part of the responsibilities of top managers (Puklavec *et al.*, 2017; Ramdani *et al.*, 2013). Thus, this finding further revalidates this relationship in the context of non-adopters of BI&A. On the other hand, the test of hypotheses indicates no significant link between absorptive capacity and intention to adopt BI&A, which means that organizational absorptive capacity does not influence the adoption intention of MSMEs toward BI&A. A possible explanation for this is that Philippine MSMEs tend to be reactive and develop internal capacity only when needed because of their limited resources. (W. Cohen & Levinthal, 1990).

Similarly, this study found that organizational resource availability has no significant relationship with adoption intention. The result is potentially affected by the availability of relevant BI&A desktop applications that Philippine MSMEs can use for initial learning and testing. These software products provide basic functionalities sufficient for planning and technology evaluation. Hence, the availability of their resources for adoption is initially less significant during the technology evaluation stage. This result also indicates that their need for more advanced capabilities in the future would lead organizations to consider the availability of their resources.

Information intensity also reveals no relationship with intention to adopt BI&A. This result implies that MSMEs' decision to adopt BI&A is not affected by the volume of information from their goods, services, or processes. While this result contradicts Ghobakhloo *et al.* (2011) and Paydar *et al.* (2014), it reveals the difference between potential and existing adopters of technology. A plausible explanation for this result is that potential adopters of BI&A are still in the early stages of the innovation-decision process (Rogers, 1962). Potential adopters are currently more concerned about the functionalities, relevance, and benefits of the technology to their business. Thus, MSMEs would consider the intensity of their information resources if they already understand the usefulness of BI&A to improve their existing processes.

Environmental Context

Competitive pressure shows a positive relationship with adoption intention in the environmental context. This finding suggests that MSMEs' intention of adopting BI&A is affected by the level of competitiveness from their external business environment. Consistent with previous findings, this study further revalidates that competitive pressure is an enabling factor for Philippine MSMEs to adopt BI&A (Ghobakhloo *et al.*, 2011; Kumar *et al.*, 2017). In contrast, vendor support is not associated with the intention of MSMEs to adopt BI&A. This finding suggests that the availability of support from vendors is not a factor for MSMEs to adopt BI&A. A possible reason for this finding is that potential adopters are still examining the capabilities of the technology and its appropriateness to their existing practices. Hence, MSMEs may rely on vendor support as they progress to a more complex implementation of BI&A, for example, integration to their database system to develop a real-time analytics dashboard.

Individual Context

Personal innovativeness shows a positive influence on MSMEs’ adoption intention. This finding suggests that their willingness to evaluate new technologies significantly affects their decision to adopt BI&A. This result is consistent with Puklavec *et al.* (2017), who identified rational decision-making culture as a driver of the early stage of BI&A adoption. Thus, the study further confirms that personal innovativeness determines the propensity to adopt advanced technology in Philippine MSMEs.

Practical Implications

This study has several implications for organizational decision-makers, technology vendors, and government agencies regarding the growth of MSMEs. BI&A vendors should offer their products to innovative business owners for testing and evaluation to help increase awareness of the potential benefits and relevance of the technology to their business operations. Technology vendors and online learning websites for analytics could provide specifically designed courses in basic analytics for small businesses. Government agencies and BI&A consultants may also promote and regard attitude and innovativeness as crucial psychological components of technology decisions that drive innovation adoption aside from technical knowledge and skills. Furthermore, it is also necessary to enlighten small business owners and managers on the importance of top management involvement in innovation adoption. Capability-building programs of the government should be in line with the advantages and perspectives of using the technology as it aids in developing a positive behavioral attitude of top management towards adoption. The knowledge of top management is essential in adopting advanced technologies, particularly when the benefits of an innovation outweigh its costs. For example, the utilization of BI&A for predicting and monitoring the spread of a global pandemic could greatly help different MSME sectors to devise appropriate business strategies that will help increase their capability to survive an economic downturn.

Research contribution

The study contributes to both business and IS literature as it supports the TOE framework and PIIT in the context of BI&A. Previous studies have focused on existing adopters, whereas non-adopters have received less attention. The findings of this study reveal that PIIT plays a very significant role in the innovation adoption decision of non-adopters. Moreover, the study underscores the unique characteristic of non-adopters of technology, which implies that strategies and support for existing adopters are not entirely suitable for non-adopters. Finally, the work also contributes to the extensive literature on technology adoption in SMEs and information system models. It verifies the uniqueness of factors affecting non-adopters in the context of advanced IS and MSMEs in the Philippines. Thus, the results presented in the study would serve as a basis in developing models for future research on the adoption of innovations in small businesses.

Limitation and future research

This work also has several limitations to be considered for future investigations. First of all, this research covered modern business intelligence that refers to desktop and cloud-based BI&A applications. Therefore, it is recommended for future studies to assess the adoption of traditional BI&A in MSMEs. Further, the unit of analysis of this study only includes MSMEs from the three largest industry sectors. A study focusing on technology adoption of a specific business industry sector could yield different findings. Comparing the BI&A adoption of MSMEs from urban and rural areas is also a relevant research subject for future studies. It is also recommended for future studies to examine other related constructs. For example, government support and perceived risk are also potential variables associated with MSMEs' adoption intention. Future research may also consider examining the mediating role of perceived risk. Previous literature in business shows that the relationship of personal innovativeness on individuals' adoption intention is associated with risk and uncertainty. Lastly, the moderating effect of perceived risk on the relationship between top management support and adoption intention is also a factor to be considered in future studies.

Conclusion

The study examined the factors affecting the intention of Philippines MSMEs to adopt BI&A systems through the development and examination of the conceptual framework. The overall findings revealed that the determinants of Philippine MSMEs' intention to adopt BI&A are the advantages and complexity of the technology, support from top management, intensity of competition, and level of innovativeness of the members of an organization.

Among these five significant factors, personal innovativeness and relative advantage of technology are the most influential drivers of behavioral intention. In contrast, the remaining constructs (perceived cost, absorptive capacity, organizational resources availability, information intensity, and vendor support) indicate no direct impact on the intention of MSMEs. Thus, the study suggests that the adoption of advanced technology in Philippine MSMEs is highly associated with technology and individual factors than internal organizational knowledge and capability, which further confirms the significant difference between adopters and non-adopters of innovations. The study contributes to the literature on technology adoption by centering on understanding the differences among potential users of innovations. These findings also contribute valuable insights for government agencies in charge of developing strategies and programs for the MSMEs in the country.

References

Agarwal, R., & Prasa, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, *9*(June), 204–215. https://doi.org/10.1287/isre.9.2.204

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*, 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Al-Qirim, N. (2005). An empirical investigation of an e-commerce adoption-capability model in small businesses in New Zealand. *Electronic Markets*, *15*(4), 418–437. https://doi.org/10.1080/10196780500303136

Alshamaila, Y., Papagiannidis, S., & Li, F. (2013). Cloud computing adoption by SMEs in the northeast of England: A multi-perspective framework. *Journal of Enterprise Information Management*, *26*(3), 250–275. https://doi.org/10.1108/17410391311325225

Awa, H. (2016). A model of adoption determinants of ERP within T-O-E framework. *Information Technology & People*, *29*(4), 901–930. https://doi.org/10.1108/ITP-03-2015-0068

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*. https://doi.org/10.1177/014920639101700108

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information and Management*, *57*(2), 1–16. https://doi.org/10.1016/j.im.2019.05.003

Boonsiritomachai, W., McGrath, G. M., & Burgess, S. (2016). Exploring business intelligence and its depth of maturity in Thai SMEs. *Cogent Business & Management*, *3*(1), 1–17. https://doi.org/10.1080/23311975.2016.1220663

Bozic, K., & Dimovski, V. (2019). Business intelligence and analytics for value creation : The role of absorptive capacity. *International Journal of Information Management*, *46*(February 2018), 93–103. https://doi.org/10.1016/j.ijinfomgt.2018.11.020

Chin, W. (2010). How to write up and report PLS analyses. In *Handbook of Partial Least Squares* (pp. 655–690). Berlin Heidelberg: Springer-Verlag.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Science,* Second Edition. Lawrence Erlbaum Associates.

Cohen, W., & Levinthal, D. (1990). Absorptive Capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–152. https://doi.org/10.2307/2393553

Cristescu, M. P. (2016). Traditional enterprise business intelligence software compared to software as a service business intelligence. *Informatica Economica*, *20*(1), 39–47. https://doi.org/10.12948/issn14531305/20.1.2016.04

Davis, F. (1986). A technology acceptance model for empirically testing new end-user information systems. Ph.D. thesis - Massachusetts Institute of Technology. https://doi.org/10.1016/S0378-7206(01)00143-4

Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

DePietro, R., Wiarda, E., & Fleischer, M. (1990). The context for change: Organization, technology, and environment. In *The Process of Technological Innovation* (pp. 151–175). Lexington, MA: Lexington Books.

DICT. (2017). Philippine digital strategy. Retrieved from http://www.dict.gov.ph/philippine-digital-strategy/

DTI. (2018). 2018 MSME Statistics. Retrieved from https://www.dti.gov.ph/dti/index.php/2014-04-02-03-40-26/news-room/179-workshop-on-market-access-for-MSMe-set

Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Massachusetts: Addison-Wesley Publishing Company, Inc.

Flynn, L. R., & Goldsmith, R. (1993). A validation of the Goldsmith and Hofacker Innovativeness Scale. *Educational and Psychological Measurement*. https://doi.org/10.1177/0013164493053004023

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing*, *18*(1), 39–50.

Ghobakhloo, M., Arias-aranda, D., Benitez-Amado, J., Arias-Aranda, D., Benitez-Amado, J., Arias-aranda, D., & Benitez-Amado, J. (2011). Adoption of e-commerce applications in SMEs. *Industrial Management & Data Systems, 111* (8), 1238-1269. https://doi.org/10.1108/02635571111170785

Goodhue, D. (1995). Understanding user evaluations of information systems. *Management Science*, *41*(12), 1827–1844.

Gov Ph. (2008). Republic Act No. 9501: Guide to the magna carta for micro, small and medium enterprises. Bureau of Micro, Small and Medium Enterprises Development (BMSMED), Department of Trade & Industry, Philippines.

Hair, J., Hult, T., Ringle, C., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Los Angeles: SAGE Publication, Inc.

Harman, H. H. (1976). *Modern Factor Analysis*. Chicago and London: The University of Chicago Press.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Iacovou, C., Benbasat, I., & Dexter, A. S. (2013). Electronic data interchange and small organizations: Adoption and impact of technology. *MIS Quarterly*, *19*(4), 465–485.

Ifinedo, P. (2011). Internet/e-business technologies acceptance in Canada's SMEs : An exploratory investigation. *Internet Research, 21*(3), 255–281. https://doi.org/10.1108/10662241111139309

Kock, N., & Lynn, G. S. (2010). Lateral collinearity and misleading results in variance-based SEM : An illustration and recommendations. *Journal of the Association of Information Systems*, *13*(7), 546–580.

Kulkarni, U., Robles-Flores, J. A., & Popovič, A. (2017). Business intelligence capability: The effect of top management and the mediating roles of user participation and analytical decision making orientation. *Journal of the Association for Information Systems*, *18*(7), 516–541.

Kumar, D., Samalia, H. V., & Verma, P. (2017). Exploring suitability of cloud computing for small and medium-sized enterprises in India. *Journal of Small Business and Enterprise Development*, *24*(4), 814–832. https://doi.org/10.1108/JSBED-01-2017-0002

Lai, H. M., Lin, I. C., & Tseng, L. T. (2014). High-level managers' considerations for RFID adoption in hospitals: An empirical study in Taiwan. *Journal of Medical Systems*, *38*(2). https://doi.org/10.1007/s10916-013-0003-z

Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management*, *50*(October 2018), 57–70. https://doi.org/10.1016/j.ijinfomgt.2019.04.003

Liang, H., Saraf, N., Hu, Q., & Xue, Y. (2014). Assimilation of enterprise systems: The effect of institutional pressures and the mediating role of top management. *MIS Quarterly*, *31*(1), 59–87.

Llave, M. R. (2017). Business Intelligence and Analytics in Small and Medium-sized Enterprises: A Systematic Literature Review. *Procedia Computer Science*, *121*, 194–205. https://doi.org/10.1016/j.procs.2017.11.027

Maduku, D. K., Mpinganjira, M., & Duh, H. (2016). Understanding mobile marketing adoption intention by South African SMEs: A multi-perspective framework.

International Journal of Information Management, *36*(5), 711–723. https://doi.org/10.1016/j.ijinfomgt.2016.04.018

McLuhan, M. (2020). Barrier and Strategies for Enterprise ICT Adoption in SMEs. In L. Rao-Graham, M. McNaughton, & G. Mansingh (Eds.), *Business Intelligence for Small and Medium-Sized Enterprises* (1st ed., pp. 9–15). Boca Raton: CRC Press Taylor & Francis Group.

MSMED Council. (2017). Micro, small, and medium enterprise development plan 2017-2022. Department of Trade & Industry, Philippines. https://www.dti.gov.ph/sdm_downloads/msme-development-plan-2017-2022/

Negash, S. (2004). Business intelligence. *AMCIS 2008 Proceedings*, *11*(4), 161. https://doi.org/10.1007/978-3-642-36318-4

Olszak, C. C. M. C., & Ziemba, E. (2012). Olszak, C. M., & Ziemba, E. (2012). Critical success factors for implementing business intelligence systems in small and medium enterprises on the example of upper Silesia, Poland. *Interdisciplinary Journal of Information, Knowledge, and Management*, *7*(September 2015), 129–150.

Paydar, S., Endut, I. R., Yahya, S., & Rahman, S. H. A. (2014). Environmental factors influencing the intention to adopt RFID technology in retail industry: An empirical study. *Asia-Pacific Journal of Management Research and Innovation*, *10*(1), 13–26. https://doi.org/10.1177/2319510x14529490

Podsakoff, P. M., Mackenzie, S. B., Lee, J., & Podsakoff, N. P. (2003). Common method biases in behavioral research : A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Popovic, A., Puklavec, B., & Oliveira, T. (2018). Justifying business intelligence systems adoption in SMEs. *Industrial Management & Data Systems*. https://doi.org/10.1108/IMDS-02-2018-0085

Puklavec, B., Oliveira, T., & Popovic, A. (2017). Understanding the determinants of business intelligence system adoption stages : An empirical study of SMEs. *Industrial Management & Data Systems Article Information*.

Ramayah, T., Ling, N. S., Taghizadeh, S. K., & Rahman, S. A. (2016). Factors influencing SMEs website continuance intention in Malaysia. *Telematics and Informatics*, *33*(1), 150–164. https://doi.org/10.1016/j.tele.2015.06.007

Ramdani, B., Chevers, D., & Williams, D. A. (2013). SMEs' adoption of enterprise applications: A technology-organisation-environment model. *Journal of Small Business and Enterprise Development*, *20*(4), 735–753. https://doi.org/10.1108/JSBED-12-2011-0035

Rogers, E. M. (1962). *Diffusion of Innovations* - 3rd Edition. New York: Free Press of Glencoe.

Ryans, A. B. (1974). Estimating consumer preferences for a new durable brand in an established product class. *Journal of Marketing Research, 11*(4), 434-443.

Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy*, *5*(1), 105–115. https://doi.org/10.1016/j.jfbs.2014.01.002

Tan, C.-S., Sim, Y.-W., & Yeoh, W. (2011). A maturity model of enterprise business intelligence. *Communications of the IBIMA*, *2011*, 1–9. https://doi.org/10.5171/2011.417812

Teo, H., Wan, W., Wang, X., & Wei, K. (2003). Effects of absorptive capacity on organizational predisposition toward information systems. In *International Conference on Information Systems 2003*.

Thong, J. (1999). An integrated model of information systems adoption in small businesses. *Journal of Management Information Systems*, *15*(4), 187–214. https://doi.org/10.2307/40398410

Thong, J., & Yap, C. (1995). CEO characteristics, organizational characteristics and information technology adoption in small businesses. *Omega*, *23*(4), 429–442. https://doi.org/10.1016/0305-0483(95)00017-I

Thong, J., Yap, C. C. ., & Raman, K. . (1996). Top management support, external expertise and information systems implementation in small businesses. *Information Systems Research*, *7*(2), 248–267. https://doi.org/10.1287/isre.7.2.248

Tutunea, M. F., & Rus, R. V. (2012). Business intelligence solutions for SME's. *Procedia Economics and Finance*, *3*(12), 865–870. https://doi.org/10.1016/S2212-5671(12)00242-0

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: toward a unified view. *MIS Quarterly*, *27*(3), 425–478.

Wang, S., Yeoh, W., Richards, G., Fan, S., & Chang, Y. (2019). Harnessing business analytics value through organizational absorptive capacity. *Information and Management*, *56*(7), 103152. https://doi.org/10.1016/j.im.2019.02.007

Williams, S., & Williams, N. (2007). *The Profit Impact of Business Intelligence*. San Francisco, CA: Morgan Kaufman (pp. 5–10).

Appendix A
Measurement items

Construct	Item ID
Relative Advantage (Ghobakhloo *et al.*, 2011; Maduku *et al.*, 2016)	
Business intelligence and analytics would enable our employees to save time in preparing reports.	PRAV1
Business intelligence and analytics would help our company access business information quickly.	PRAV2
Business intelligence and analytics would help our company access business information efficiently.	PRAV3
Business intelligence and analytics can aid top management in decision-making.	PRAV4
Complexity (Ghobakhloo *et al.*, 2011; Maduku *et al.*, 2016)	
Learning to use business intelligence and analytics would require much time.	PCMP1
Learning to use business intelligence and analytics is difficult.	PCMP2
Business intelligence and analytics would be difficult to implement in our company.	PCMP3
Business intelligence and analytics would be difficult to integrate into our current work.	PCMP4
Cost (Ghobakhloo *et al.*, 2011; Maduku *et al.*, 2016)	
The cost of business intelligence and analytics would be greater than the expected benefits.	PCST1
The cost of maintaining business intelligence and analytics would be very high for the company.	PCST2
The cost involved in providing a support system for business intelligence and analytics would be too high for the company.	PCST3
The amount of money to be invested in the training of employees for business intelligence and analytics would be too high.	PCST4
Top management support (Lai, Lin, & Tseng, 2014; Maduku *et al.*, 2016)	
Top management would be enthusiastic about adopting business intelligence and analytics.	TMSP1
Top management would provide training opportunities to employees in using business intelligence and analytics.	TMSP2
Top management would provide the necessary tools for exploring the capabilities of business intelligence and analytics.	TMSP3

Top management would encourage employees to explore the capabilities of business intelligence and analytics.	TMSP4
Absorptive Capacity (Liang, Saraf, Hu, & Xue, 2014; Teo, Wan, Wang, & Wei, 2003)	
Our employees have extensive training in using computer-based applications in their work.	ACAP1
Our company can provide adequate technical support in using business intelligence and analytics.	ACAP2
Our company knows who can help solve business intelligence and analytics problems.	ACAP3
Our company can provide training for business intelligence and analytics to employees regularly.	ACAP4
Organizational Resource Availability (Boonsiritomachai *et al.*, 2016)	
Our company has sufficient technological resources for adopting business intelligence and analytics.	ORAV1
Our company has sufficient financial resources for adopting business intelligence and analytics.	ORAV2
Our company can provide training and IS support for adopting business intelligence and analytics.	ORAV3
Our company has sufficient time for learning business intelligence and analytics.	ORAV4
Information intensity (Ghobakhloo *et al.*, 2011; Thong & Yap, 1995)	
Our company needs to have access to reliable information for decision making.	IINT1
The company's daily operations rely on accurate information.	IINT2
Our company needs to have access to relevant information for decision making.	IINT3
The company's daily operations rely on up-to-date information.	IINT4
Our company needs to have quick access to information when needed.	IINT5
Competitive pressure (Maduku *et al.*, 2016; Thong & Yap, 1995)	
Our decision to adopt business intelligence software would be strongly influenced by our competitors in the industry.	CPRE1
I am aware that our competitors were already using business intelligence and analytics.	CPRE2
Our company needs business intelligence and analytics to gain competitiveness in the market.	CPRE3

Adopting business intelligence is a strategic necessity for the company.	CPRE4
Vendor support (Al-Qirim, 2005; Ifinedo, 2011)	
Vendors of business intelligence and analytics should provide appropriate technical support.	VNSP1
Vendors of business intelligence and analytics help SMEs must understand the benefits and risks of adopting the technology.	VNSP2
Vendors of business intelligence and analytics should provide free training for our employees.	VNSP3
Vendors of business intelligence and analytics should actively promote the technology for SMEs.	VNSP4
Innovativeness (Agarwal & Prasa, 1998; Thong & Yap, 1995)	
If I heard about new information systems for business, I would look for ways to experiment with them.	INNO1
I am one of those who first tried out new information systems for business.	INNO2
In general, I am hesitant to try out new information systems for business. (Reverse code)	INNO3-
I like to experiment with new information systems for business.	INNO4
Intention to use (Venkatesh *et al.*, 2003)	
I intend to use business intelligence and analytics in the next 6 months.	IADP1
I predict that I will use business intelligence and analytics in the next 6 months.	IADP2
I plan to use business intelligence and analytics in the next 6 months.	IADP3

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Author Credits Declaration

RBS: Conceptualization, methodology, software, model solution, data curation, writing- original draft preparation.

MTS: Supervision, writing-reviewing, formatting, and editing.