01 Jan 2023

# Motivators And Inhibitors For Business Analytics Adoption From The Cross-Cultural Perspectives: A Data Mining Approach

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Information Systems Frontiers
https://doi.org/10.1007/s10796-023-10399-1

# Motivators and Inhibitors for Business Analytics Adoption from the Cross-Cultural Perspectives: A Data Mining Approach

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Accepted: 20 April 2023


**Abstract**
In the increasingly knowledge-based world economy, the multinational firm's success often hinges on its business intelligence capability nurtured by business analytics (BA). Despite the growing recognition of BA's role in enhancing the firm's intellectual capital and subsequent competitiveness, it is still unknown what truly motivates and inhibits BA adoption. This study aims to identify key influencing factors for BA adoption such as organizational characteristics, information security/privacy, and information technology maturity (knowledge level). In so doing, this study employed data mining and data visualization techniques to develop specific patterns of BA adoption practices based on a combined sample of 224 Korean firms and 106 U.S. firms representing various industry sectors. This study is one of the first attempts to develop practical guidelines for the successful implementation of BA based on the cross-national study of BA practices among both Korean and U.S. firms.

**Keywords** Business analytics · Business intelligence · Data mining · Data visualization · Cross-cultural study

## 1 Introduction

Business analytics (BA) can give an organization a broader perspective and important aids in rational decision-making by converting available data to valuable information and then generating deep insights into business environments and customer behavior. According to Zion Market Research (2019), the global business analytics market was approximately $63.3 billion in 2018 and was expected to reach approximately $97.3 billion by 2025, at a compound annual growth rate (CAGR) of around 6.4% between 2019 and 2025. This trend was echoed by the survey of 495 business executives conducted by Lavastorm Analytics reporting that approximately 65% of the respondents invested more in analytics in 2014, with one-fifth (20.5%) of them indicating their companies increased investment in analytics significantly (Rockwell, 2014). Reflecting this trend, the recent survey conducted by NewVantage Partners (2019) indicated that 91.6% of Fortune 1000 companies were increasing big data and artificial intelligence (AI)-related investments to stay current and competitive in the global market. Despite these rosy outlooks and the growing popularity of BA, many firms are still skeptical about its face value. In particular, the acceptance of BA to tackle big data-related issues such as data integration, manipulation, and integrity would take a considerable amount of time until its benefit potentials are fully realized with many success stories. Nearly three fourth (73%) of analysts (business analysts and data analysts) surveyed by Lavastorm Analytics did not use big data tools including BA as of 2014 (Rockwell, 2014). The plausible rationale for a lack of BA adoption is that BA can be meaningless unless its use facilitates the incorporation of big data into complex decision-making processes. Also, there may be many other implementation challenges such as the lack of organizational readiness, cultural incompatibility, technical expertise/infrastructure, and financial resources for BA investment that discouraged the implementation of BA. As such, it is important to develop business strategies that help the firm overcome those challenges while fully exploiting the benefits of BA.

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Published online: 08 May 2023

Business analytics (BA) generally refers to the broad use of various quantitative techniques such as statistics, data mining, optimization tools, and simulation supported by the query and reporting mechanism to assist the decision-maker in making more informed and well-thought decisions within a closed-loop framework seeking continuous process improvement through monitoring and learning (Min, 2016). In a broader sense, BA cuts across multiple disciplines including AI (e.g., machine learning), operations research (OR), data sciences, and information systems (Hindle & Vidgen, 2018; Mortenson et al., 2015). As such, the BA concept is broader and more inclusive than the concept of data or big data analytics (BDA) in that the former leverages a multitude of business intelligence tools including AI whereas the latter primarily refers to information technologies and processes that support data reporting, data storage, statistical analyses, and data mining in big data (high in volume, velocity, and variety) environments. BDA is generally referred to as the process of using advanced technologies to examine big data to uncover useful information (e.g., hidden patterns, unknown correlations) to help with making better decisions across business processes (Chen et al., 2015; Russom, 2011; Zakir et al., 2015). Despite subtle differences between those two, both of them are crucial for making better, more informed, and timely decisions. The increased attention paid to BA is due to the multitude of managerial benefits it can bring to everyday business practices. Examples of these benefits are: improved customer services resulting from a better understanding of customer behaviors through customer/demand data visualization; enhanced security and risk mitigation resulting from faster fraud detection and quick identification of vulnerability through the data integration across the company; shorter order cycle time and the subsequent inventory reduction resultant from increased transparency into current and planned inventory positions; increased cost savings resulting from the higher operating and supply chain efficiency achieved by a unified view and the subsequent visibility improvement across the supply chain (Ahmad, 2017; Min, 2016; Min et al., 2021; Trkman et al., 2010).

Other noted benefits of BA include the higher likelihood of innovation success through improved information processing capability (Yanquing & Guangming, 2015); the improved firm performance and competitive advantages through the accurate estimation of customer values, and the accurate costing and pricing of products and services (Klatt et al., 2011; Shanks & Sharma, 2011); the effective allocation and orchestration of company resources through organized decision-making processes enabled by more accurate and timely business intelligence (Sharma et al., 2014). Despite these potential benefits, many firms are still hesitant to adopt BA. Therefore, there is a need to explore the differences between adopters and non-adopters of BA and then provide guidance for those who may consider using BA in the future.

## 2 Literature Review

### 2.1 Application of Business Analytics

Davenport et al.'s study (2007) is one of the first BA studies that developed consumer analytics to examine the relationship between condom sales and HIV claims. Their study, however, was based on fictitious scenarios and thus did not reflect real-world situations. Trkman et al. (2010) proposed supply chain (SC) analytics to assess the impact of BA on supply chain performance with respect to supply chain operations reference (SCOR) model metrics. They found that firms with good analytical capability and information systems fared better with BA. Following suit, Chae et al. (2014) developed SC analytics based on the GMRG round survey and partial least square analysis. They viewed SC analytics as an IT-enable resource and assessed the positive impact of BA on SC performance. They argued that data management resources should be considered a key building block of manufacturers' BA initiatives for SC planning. Chen et al. (2015) employed a technology-organization-environment (TOE) framework to identify factors affecting the actual usage of big data analytics (BDA) based on a survey of 161 U.S.-based companies. They found that technological factors directly influenced organizational BDA usage, while organizational and environmental factors indirectly influenced organizational BDA usage through top management support. Akter et al. (2016) developed a big data analytics capability (BDAC) model to examine the impact of BDA on firm performance. Based on two rounds of the Delphi study, they validated the logic of how people, systems, data, and management were entangled to influence firm performance and then recognized the importance of the complementarities among humans, technology, and management for the firm's high-level operational efficiency and sustained competitive advantages.

Ghasemaghaei et al. (2017) assessed the impact of data analytics on firm agility by surveying 215 senior IT professionals. They found that at higher levels of fit between data analytics tools, tasks, people, and data, firms were more likely to respond to threats and opportunities in a timely manner and thus improved firm agility (capability to adjust to dynamic market environments) through the use of data analytics.

Vidgen et al. (2017) introduced data analytics and identified challenges of becoming a data-driven organization based on the semi-structured interviews of BA managers. They identified key BA challenges such as analytics skill shortages, data quality problems, and misaligned information technology and human resource strategies. Srinivasan and Swink (2018) conducted an empirical analysis of data gathered from 191 global firms to investigate what complemented supply chain analytics. They discovered that both demand and supply visibility were associated with the development of analytics capability. They also observed that analytics capability and organizational flexibility were more valuable as complementary capabilities for firms that operated in volatile markets, rather than in stable ones.

More recently, Aydiner et al. (2019) assessed the impact of BA on firm performance based on a survey of Turkish executives. They found that business process performance fully mediated the relationship between BA adoption and firm performance. Predicated on the resource-based view and institutional theory, Dubey et al. (2019) examined the role of external institutional pressures on the resources of the organization to build big data capability and then evaluated the impact of such capability on the firm's cost and operational performance. Analyzing the result of a cross-sectional e-mail survey of 195 manufacturing companies located across India, they found that institutional pressures have significant effects on the selection of tangible resources and big data culture had significant and positive moderating effects on the paths leading from BDA. They also discovered that BDA had significant and positive effects on cost and operational performance. Drawing on the resource-based view (RBV), dynamic capability theory (DCT), Akter et al. (2020a) developed and operationalized a service system analytics capability (SSAC) model. They conducted two rounds of Delphi studies, they illuminated the importance of service system analytics management capability, technology capability, and personnel capability in developing overall analytics capabilities for a service system. In addition, they confirmed the strong mediating effects of those three dynamic capabilities in establishing competitive advantages. Similar to Akter et al. (2020a, b) proposed a dynamic service analytics capabilities (DSAC) framework consisting of management, technology, talent, data governance, model development, and service innovation capability. Using the thematic analysis of 30 in-depth interviews, they investigated how BDA could enhance the customer experience in the digital marketplace.

As discussed above, a vast majority of the prior BA or BDA studies (e.g., Trkman et al., 2010; Shanks & Sharma, 2011; Klatt et al., 2011, Davenport et al., 2012; De Oliveira et al., 2012; Chae & Olson, 2013; Sharma et al., 2014; Akter et al., 2016; Côrte-Real et al., 2017; Ramanathan et al., 2017; Vidgen et al., 2017; Popovič et al., 2018; Srinivasan & Swink, 2018; Aydiner et al., 2019; Dubey et al., 2019; Akter et al., 2020a, b) have focused on the assessment of its benefit potentials or business outcomes or competitive advantages and have not identified key determinants of BA adoption decisions (Hindle et al., 2020; Mikalef et al., 2020). Furthermore, many earlier studies (e.g., Akter et al., 2016, 2020a, b; Chen et al., 2015; Dubey et al., 2019; Ghasemaghaei et al., 2017; Vidgen et al., 2017) narrowly focused their attention to data analytics or BDA rather than the big picture of BA. As summarized in Table 1, much of these earlier efforts also rarely explored contextual variables that may affect the successful adoption of BA. Other drawbacks of these earlier BA studies are their reliance on a single country's data that only reflected a particular business culture and national trend in utilizing emerging technology. To fill the void left by prior studies that were well summarized by Ajah and Nweke (2019) and Mikalef et al. (2020), this study investigates overlooked contextual variables that influence a firm's decision to adopt BA. Herein, contextual variables are proxies reflecting firm characteristics, resources, environments, and cultures. Examples of such variables include privacy concerns, security concerns, risk concerns, information technology (IT) capability, and the perceived value of BA. In other words, this study aims to identify what truly motivates BA adoption. In addition, this study conducted cross-cultural studies to better reflect different perspectives and cultural aspects of BA adoption.

### 2.2 Factors Influencing Business Analytics Adoption

The technology acceptance model (TAM) originally proposed by Davis (1989) and its underlying theories identified variables influencing IT adoption. These variables include perceived usefulness, perceived ease of use, user training, end-user support, social influence (subjective norm), objective usability, system quality, compatibility, self-efficacy, and so forth (Granić & Marangunić, 2019; King & He, 2006; Lee et al., 2003; Legris et al., 2003; Scherer et al., 2019). In addition to including variables used in the TAM model, given the plethora of TAM research focusing on the aforementioned variables, this study further sheds light on rarely studied variables such as organizational characteristics and organizational readiness for the following reasons.

According to the diffusion on innovation (DOI) theory, organizational characteristics are important antecedents to organizational innovativeness such as the adoption of IT (Oliveira & Martins, 2011). These organizational characteristics include the size of the organization (e.g., number of employees, amount of sales revenue, the volume of resources). Generally speaking, firm size can influence the firm's willingness to innovate because the firm needs to invest more to innovate (Camisón & Villar-López, 2014; Forés & Camisón, 2016; Shefer & Frenkel, 2005). In particular, the IT literature has demonstrated that larger organizations are likely to facilitate the innovative adoption of IT due to their financial capacity, infrastructure, and organizational power.

**Table 1** A summary of key literature on BA adoption

| Author(s) | BA Type | Research methodology | Research features | Application area/Key findings |
|---|---|---|---|---|
| Davenport and Harris (2007 ) | Descriptive (Consumer analytics) | Case study based on fictitious scenarios | Study the relationship between condom sales and HIV claims | Analyze loan card use patterns in the grocery chain |
| Trkman et al. (2010) | SC analytics | Descriptive and exploratory (PLS, executive survey) | Assess the impact of BA on supply chain performance (w.r.t. SCOR Model metrics) | Firms with good analytical capability and information systems fared better with BA |
| Chae et al. (2014) | SC analytics-prescriptive analytics | An empirical study based on the GMRG round survey _PLS | Viewed SC analytics as an IT-enable resource and assessed the positive impact of BA on SC performance | Data management resources should be considered a key building block of manufacturers' BA initiatives for SC planning |
| Chen et al. (2015) | Big data analytics (BDA) | An empirical study based on a survey of US companies_PLS | Examined how organizational-level BDA usage affects organizational value creation | The firm's BDA use, reflecting its IT processing capability, has a positive influence on both the firm's asset productivity and business growth |
| Akter et al. (2016) | Big data analytics (BDA) | An empirical study based on a survey of US IT professionals_PLS | Regarded BDA as the company resource and assessed the impact of BDA on firm performance | BDA management capability has a significant impact on the firm's competitive advantage |
| Vidgen et al. (2017) | Data analytics | Case study based Delphi method (Semi-structured interviews) | Use the diamond framework to study the challenges in becoming a data-driven organization | Identified BA challenges such as analytics skill shortages, data quality problems, and misaligned ICT & HR strategies |
| Aydiner et al. (2019) | Generic BA | Empirical (based on the survey of Turkish executives) _SEM | Examined the impact of BA on firm performance | Business process performance fully mediates the relationship between BA adoption and firm performance |
| Dubey et al. (2019) | BDA and predictive analytics | A cross-sectional e-mail survey of Indian manufacturing firms | Examined the role of external institutional pressures on the resources of the organization to build big data capability | The institutional pressure of the manufacturing firms directly influenced the firm's adoption of BDA and predictive analytics |
| Akter et al. (2020a, b) | BDA in service systems | Thematic analysis of 30 in-depth interviews | Analyzed the nature of service analytics to identify its capability dimensions | A dynamic service analytics capabilities framework consisted of management, technology, talent, data governance, model development, and service innovation capability |
| Proposed Study | Multiple forms with broad categories | Data mining (Decision tree) and cluster analysis) | Develop profiles of BA adopters to identify BA motivating factors or prerequisites for BA adoption (while assessing the organizational readiness for BA adoption) from the cross-cultural perspective | Identified key influencing factors for BA adoption such as BA familiarity, organizational resistance, big data collection capability, IT expertise, IT budget, etc. using the cross-national data (US and Korea data) |

(Bakos, 1991; Dewar & Dutton, 1986; Galbraith, 1977; Min & Galle, 1999; Min et al., 2021; Moch & Morse, 1977; Thong, 1999). In addition, Bharadwaj et al. (1999) found that the growth of IT assets through IT investment contributed to firm performance and the future growth potential of firms including a greater investment in innovative initiatives. This finding implied that the firm's financial (or investment) capacity could contribute to the adoption of innovative tools such as BA. The rationale is that a firm with a larger IT unit and budget (e.g., financial resources for software and hardware investment including upgrades, IT staff salaries, and equipment maintenance and repair) is likely to adopt BA because it has greater information processing capacity and organizational power than its smaller counterpart. In other words, a firm with a large IT unit is likely to possess the financial resources and bargaining power large enough to achieve the economies of scale necessary to absorb the cost of BA implementation.

In addition, the adoption of BA will trigger managerial changes and thus requires system redesign including changes in staffing, workflow, communication, and decision-making process. As such, a lack of organizational readiness for such changes can increase organization resistance to BA adoption. Organizational readiness for change is viewed as a function of how much organizational members value the change and how favorably they appraise the organization's technical capability, resource availability, and situational factors including organizational culture (Weiner, 2009, 2020; Weiner et al., 2008; Wraikat et al., 2017). In particular, some companies such as K-Mart, which failed to integrate BA into the organizational culture, ultimately failed to deliver on positive BA expectations (Liu et al., 2018; Rathore et al., 2014). When organizational readiness for change is high, organizational members are more likely to initiate change, exert greater effort, exhibit greater persistence, and display more cooperative behavior (Weiner, 2009, 2020). In other words, higher organizational readiness would increase the chances of BA adoption and implementation success.

Specifically, the decision process leading to the institutionalization of IT usage can be conceptualized as a sequence of steps through which a firm passes with the knowledge of IT. These steps may include (1) the formation of either a favorable or unfavorable attitude toward IT; (2) the decision to adopt or reject it; (3) the implementation of IT for certain application areas; (4) the reinforcement of the adoption decision (Rogers, 1983). One of the important constructs in these steps is the perceived benefit of IT that is communicated to the potential adopter by his/her peers, trading partners, and own employees (Karahanna et al., 1999). That is to say, the preconceived notion of BA benefits may have a profound effect on the adoption of BA. Triandis (1971) indicates that well-known social norms will have a more pronounced effect in determining the adoption behavior when such behavior is new and innovative. A significant body of research also showed that the perceived usefulness (or value) of IT was closely linked to IT adoption decisions (e.g., Davis, 1989; Mathieson, 1991; Venkatesh & Morris, 2000).

Furthermore, Attewell (1992) observed that the adoption and diffusion of IT were inversely related to the extent of knowledge barriers. That is to say, many firms tend to postpone the adoption of IT until they develop sufficient IT technical skills and expertise. Likewise, many prior IT studies such as Ettlie (1990), Thong and Yap (1995), Thong (1999), Nguyen et al. (2015), Tarhini et al. (2015), and Min et al. (2021) discovered that firms with employees who have more knowledge of IT were likely to adopt IT more.

In light of the above literature review and discussions relevant to BA adoption, key variables of interest for data mining were identified and used to develop survey questions for the collection of empirical data as summarized in Table 2.

## 3 Research Methodology

This study explores the following research questions to identify why some firms utilize BA more than others to uncover whether there are any significant cross-national differences in BA adoption practices between Korean and U.S. firms:

(1) How significantly do the organizational characteristics (nationality, industry classifications, size measured by sales revenue, or workforce size) of a firm influence its decision to adopt BA?
(2) How significantly does the IT investment (IT employee size, IT budget, BA familiarity level) of a firm influence its decision to adopt BA?
(3) How significantly do organizational readiness and implementation challenges of a firm influence its decision to adopt BA?
(4) What factors are most likely to hinder or motivate the potential adoption of BA?

### 3.1 Research Sample

To seek feedback on the number of BA implementation issues specified in the literature review section, an eight-page questionnaire consisting of 25 questions was mailed to 700 randomly selected Korean firms from August 1 through September 15, 2018. The same questionnaire was sent to 300 randomly selected U.S. firms from October 30 through December 20, 2019. The primary survey targets included Korean firms which were listed in the Korea Securities Dealers Association (KOSDAQ) and the Korea Composite Stock Price Index (KOSPI). In addition, to diversify the sample with smaller and medium-sized firms which were not listed on the Korean Stock Exchange, we included firms

**Table 2** Variables considered for the decision tree analysis

| Variable dimension | Measures used in this Study and the Number of Questions raised by the Survey Instrument |
|---|---|
| Organizational characteristics<br>(Camisón & Villar-López, 2014; Forés & Camisón, 2016; Shefer & Frenkel, 2005) | • Nationality<br>• Industry classifications (one question)<br>• Total workforce size (one question)<br>• Annual sales revenue (one question) |
| IT investment<br>(Bakos, 1991; Bharadwaj et al., 1999; Dewar & Dutton, 1986; Galbraith, 1977; Min & Galle, 1999; Min et al., 2021; Moch & Morse, 1977; Thong, 1999) | • IT employee/workforce size (one question)<br>• Annual IT budget (in total volume) (one question)<br>• Annual IT budget allocation (in the percentage of the total annual budget) (one question)<br>• Familiarity with BA (one question) |
| Organizational readiness<br>(Weiner, 2009; Weiner et al., 2008; Wraikat et al., 2017) | • Information security (one three-item question)<br>• Information Privacy (one four-item question)<br>• Analytics Intention (one three-item question)<br>• Business Analytics risk assessment (one three-item question)<br>• Perceived Business Analytics value (one four-item question)<br>• Perceived Business Analytics simplicity (ease of BA use) (one four-item question)<br>• Perceived Business Analytics costs ((one five-item question))<br>• Organizational resistance (one six-item question)<br>• Confidence in Business Analytics (one four-item question)<br>• Technical capability (IT infrastructure) (one four-item question) |
| Implementation challenges<br>(Attewell, 1992; Ettlie, 1990; Thong & Yap, 1995; Thong, 1999; Nguyen et al., 2015; Tahini et al., 2015) | • Perceived Business Analytics benefits (one six-item question)<br>• The seriousness of obstacles to BA adoption (one ten-item question)<br>• Application potentials (one fourteen-item question) |

that belonged to the Korean manufacturers association and Korean retailers association. The primary survey targets of the U.S. firms represent both manufacturing, service (including healthcare, retail, and education), and government sectors (including utility providers).

### 3.2 Data Collection and Preprocessing

The raw data were collected using a structured questionnaire described in Sect. 3.1. Since the input to the data mining model affects the choice of a data mining algorithm and the resultant rules, we attempted to remove polluted data such as missing input, incorrectly coded input, redundant input, and inconsistent input (e.g., outliers) from the database through visualization and explorations using Microsoft Excel, SAP Predictive Analytics and SAS Visual Analytics. This data cleaning process was followed by the data pre-processing step that involves converting categorical variables into a numerical representation. For instance, we encoded the responding firm's IT workforce size categories as: 1 = 1–2 IT professionals; 2 = 3–4 IT professionals; 3 = 5–10 IT professionals; 4 = 1–20 IT professionals; 5 = 21–49 IT professionals; 6 = 50 or more IT professionals.

### 3.3 Dimension Reduction and Cluster Analysis

The quality of a decision tree depends on the classification accuracy (Chen et al., 1996). Factor analysis and cluster analysis were used to improve classification accuracy to derive more meaningful rules and profiling. As multiple survey items were used to assess each aspect of implementation challenges and organizational readiness based on literature summarized in Table 2, confirmatory factor analysis followed by exploratory factor analysis were conducted using SPSS to derive latent factors and reliability tests were performed on dimensions of each latent factor. There are nine latent factors representing organizational readiness and three latent variables representing implementation challenges. The resulting twelve latent factors with their dimensions/characteristics are shown in Table 3. For example, the latent factor "Perceived Business Analtyics Value" with the reliability of Cronbach's $\alpha = 0.905$ is described in terms of "improve business intelligence," "improve the competitiveness of the organization," "increase the productivity of the organization," and "reduce business risk and uncertainty" dimensions/characteristics.

Cluster analysis can be a useful data-mining tool for any organization that needs to identify discrete groups of objects for classification or segmentation. In cluster analysis, objects are separated into groups so that each object is more similar to other objects in its group than to objects outside the group (Aboni & Feil, 2007; Aldenderfer & Blashfield, 1984; King, 2015). As such, cluster analysis offers ways to discover certain patterns in data by reducing the data complexity and is useful for singling out the distinguishing features of data. In other words, as

**Table 3** Factor reliability and cluster size of twelve latent factors

| Category | Latent factor | Description and items |
|---|---|---|
| Organizational Readiness | **Information Security & Privacy** (Cronbach's α= 0.931; clusters = 3) | An Organization's emphasis on **security and privacy of information**.<br>• It is important not to release sensitive information to any entity.<br>• The release of personal information to individuals with whom I have a high comfort level is unacceptable.<br>• The release of personal information to entities where I feel as though I am anonymously providing the information is unacceptable.<br>• The use of personal information that has been released by me but is used in a manner not intended by me is unacceptable<br>• The safekeeping of informational assets (such as financial records, etc.) contained in digital or paper format is important<br>• The security of personal information contained in digital or paper format is important.<br>• The safekeeping of information provided to a corporation or other entity is important. |
| Organizational Readiness | **Perceived BA Adoption Cost** (Cronbach's α = 0.842; clusters =3) | Organization's **perception** of the **cost** associated with business analytics.<br>• The implementation costs are expensive.<br>• The equipment costs are expensive.<br>• The user training costs are expensive.<br>• The transaction costs are expensive.<br>• The support/maintenance/update are expensive. |
| Organizational Readiness | **Confidence in BA** (Cronbach's α = 0.851; clusters =3) | Organization's confidence in business analytics.<br>• has a tendency to trust business analytics is high.<br>• has faith that business analytics will function as expected.<br>• has a high degree of confidence that business analytics will work when it is implemented properly |
| Organizational Readiness | **Analytics Intention** (Cronbach's α =0.902; clusters =3) | Organization's intentions with respect to business analytics<br>• intends to use business analytics.<br>• is willing to use business analytics.<br>• is willing to recommend business analytics to other organizations (esp. trading partners). |
| Organizational Readiness | **Perceived BA Value** (Cronbach's α =0.905; clusters =3) | Organization's perceived value of business analytics to your organization.<br>• improves business intelligence.<br>• improves the competitiveness of the organization.<br>• increases the productivity of the organization.<br>• reduced business risk and uncertainty. |
| Organizational Readiness | **Analytic simplicity** (Cronbach's α = 0.91; clusters =5) | The degree of simplicity in using business analytics in your organization.<br>• Learning to use business analytics should be easy.<br>• Becoming skillful in using business analytics should be easy.<br>• Business analytics should be easy to use |
| Organizational Readiness | **Organizational Resistance** (Cronbach's α = 0.889; clusters =5) | The resistance to adopting business analytics in your organization.<br>• would be among the last to try business analytics even if it appeared promising.<br>• Meaningful change and innovation are often curtailed.<br>• is reluctant to adopt new technology.<br>• hesitates to try new technology.<br>• finds reasons not to implement new technology. |
| Organizational Readiness | **Technical Capabilities** (Cronbach's α =0.891 clusters = 3) | Organization's capability to implement business analytics<br>• Has the IT infrastructure to support business analytics.<br>• Has the Big Data to support business analytics.<br>• Can integrate business analytics tools into the existing IT systems with little or no difficulty.<br>• Has the IT expertise to support business analytics. |
| Organizational Readiness | **Risk Assessment** (Cronbach's α =0.841; clusters = 4) | Organization's assessment of risk associate with business analytics.<br>• There is a significant risk of using business analytics.<br>• There is a significant risk of potential failure. |
| Implementation Challenges | **Business Analytics Obstacle** (Cronbach's α = 0.905; clusters = 4) | Rate the seriousness of the following obstacles in using business analytics.<br>• Big data collection<br>• Lack of data standardization<br>• Insecure data transmission<br>• Data reporting<br>• High maintenance cost<br>• High (start-up) investment cost<br>• Difficulty in data screening/ filtering<br>• Lack of information exchange mechanism<br>• Government regulation (e.g., on privacy)<br>• User training cost |
| Implementation Challenges | **Application Potentials** (Cronbach's α = 0.856; clusters =3) | The likelihood of business analytics usage for the following business practices.<br>• Demand planning/ forecasting<br>• Pricing<br>• Business risk assessment<br>• Credit risk assessment<br>• Market research<br>• Market segmentation<br>• Foreign direct investment<br>• Customer purchasing behavior<br>• Portfolio analysis<br>• Supplier evaluation/selection<br>• Modal/Carrier selection<br>• Locational analysis<br>• Employee screening/hiring<br>• New product development |
| Implementation Challenges | **Perceived BA Benefits** (Cronbach's α = 0.93; clusters =3) | Potential benefits of business analytics.<br>• Gaining insights into business practices<br>• Gaining insights into customer behavior<br>• Enhance operating/supply chain efficiency<br>• Identify potential business risks<br>• Improve communication efficiency<br>• Improve predictability |

compared to popular data analysis techniques such as a structural equation model (SEM), cluster analysis can be an effective tool for searching for significant patterns and trends that can provide valuable information and insights for BA adoption decisions and thus is more suitable for developing detailed profiles of BA adopters than SEM that was designed to test a series of hypotheses with the preconceived notion. Since hypothesis testing aims to either substantiate or disapprove the preconceived notion, it cannot explain subtle nuances somewhere in-between the acceptance and rejection of that preconceived notion (or premise). That is to say, causal inferences made by hypothesis testing may not be sufficient for us to accurately predict behavioral patterns and trends of BA adopters and/or non-adopters. In addition, hypothesis testing can be inconsistent unless the level of significance decreases as the sample size increases (Glamour et al., 1996). In particular, Okazaki (2006) noted that cluster analysis could be effective for developing profiles of IT adopters. Considering the relevancy of cluster analysis to data mining, we employed cluster analysis as one of the data mining tools for profiling the distinctive organizational characteristics of BA adopters. As one of the research objectives is to provide profiling of BA adoption firms, cluster analysis was conducted to group firms into a smaller set of clusters based on dimensions/characteristics of an organizational readiness factor or an implementation challenge factor.

As the k-means clustering algorithm is very sensitive to the choice of a starting point for partitioning the items into an initial group of clusters (Hussein 2018), the two-step cluster analysis was used in this study. In step 1, the number of clusters between 1 and 15 was developed with their respective Schwarz's Bayesian Criterion (BIC), BIC change, Raito of BIC changes, and Ratio of distance measures. For each of the twelve latent factors, the elbow method is then used to identify the most ideal number of clusters that balance interpretability and complexity to conduct the k-mean clustering. The ideal number of clusters for each latent factor is shown in Table 3.

Using the same latent factor "Perceived Business Analytics Value" example, we identified three clusters. These three profile clusters derived from k-mean cluster analysis are shown in Fig. 1. Firms in the "Productivity and Competitiveness" cluster perceived BA values in increased productivity and improved competitiveness while firms in the "High Perceived Analytics Values" cluster perceive high BA values in all four dimensions/characteristics (i.e., "improve business intelligence," "improve the competitiveness of the

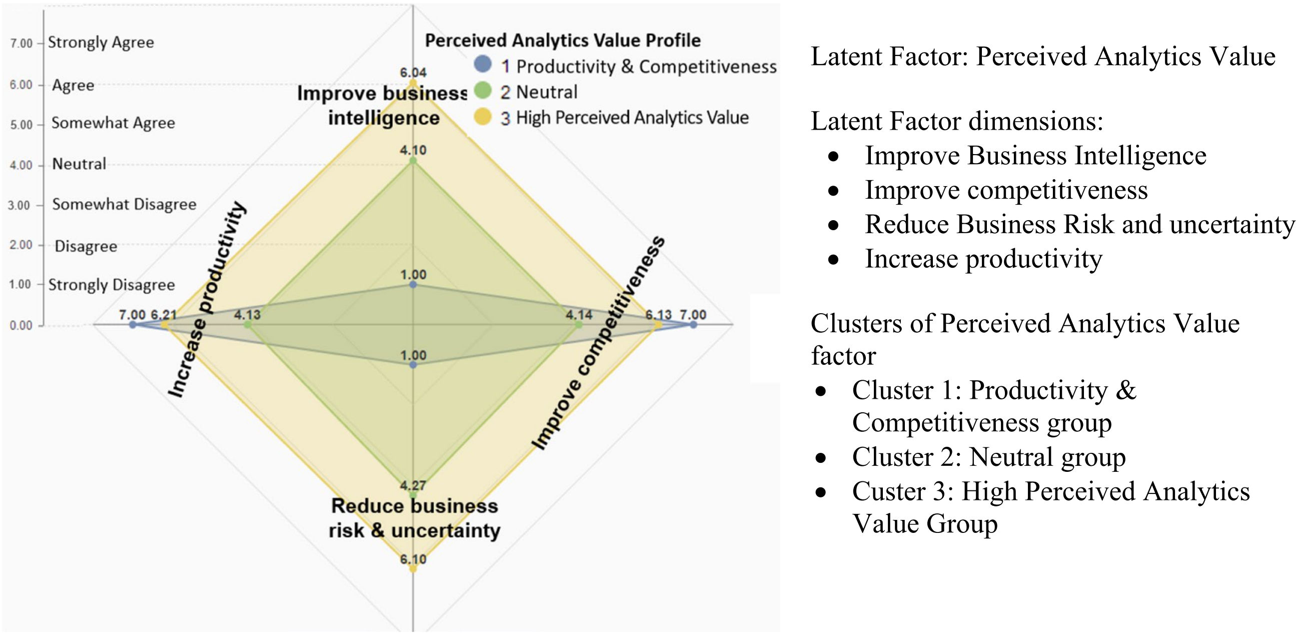



**Fig. 1** Perceived analytics value profiles

organization," "increase the productivity of the organization," and "reduce business risk and uncertainty").

### 3.4 Rule Induction Using Decision Tree Analysis

Decision trees are intended to generate sets of rules that can be easily understood by a decision-maker (e.g., top management, BA project team) and can be replicated in other BA adoption decision settings. These rules may give important clues as to which firms are likely to adopt BA and, consequently help the firm formulate an effective BA implementation strategy while aiding BA vendors in identifying their potential clients. The R scripts and IBM SPSS Statistics were used to build the decision tree. The Chi-squared Automatic Interaction Detection (CHAID) method with k-fold cross-validation (k = 10 in this study) was used to build the decision tree because of its ability to work with categorical targets, prevent overfitting, reduce confounding (or biased in variable selection) issues, and produce a less deep tree for interpretation purposes. The accuracy of the decision tree was computed based on the 10-fold cross-validation results. The Bonferroni adjustment was employed to control tree size (Milanović & Stamenković, 2016; Ritschard, 2013).

### 3.5 Data Visualization

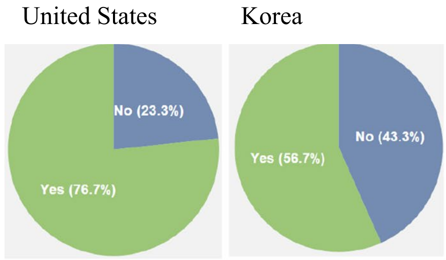
To make sense of data mining results, we used data visualization techniques in the form of tables, charts, histograms, and multi-dimensional plots. By presenting data analysis results in a pictorial format, data visualization enables us to interpret results simply. Generally, data visualization is intended to provide a qualitative overview of complex big data, summarize those data, assist the decision-maker in identifying regions of interest for more focused quantitative analysis and make communication of information to others easier (Grinstein & Ward, 2002; Keller et al., 1994).

## 4 Data Mining Results and Discussions

Based on the identification of potential variables (factors) that may influence the BA adoption decision, we conducted both cluster and decision tree analyses and then tested the extent of influences of those variables on the BA adoption decision. The following subsections provide details of such test results.

### 4.1 Influence of Organizational Characteristics

Research question one seeks insights on the influence of organizational characteristics (nationality, industry classifications, size measured by sales revenue, and workforce size) of a firm on its decision to adopt BA. After eliminating incomplete and inconsistent responses, we received a total of 328 valid responses (32.8 response rate) used in this research that including 224 valid responses received (32% response rate) from Korean firms and 104 valid responses receive (34.7% response rate) from US firms. A majority (76.7%) of U.S. responding firms adopted BA as their decision-aid tool, while 56.7% of Korean responding firms indicated their BA




Tests of Between-Subjects Effects

Dependent Variable: Analytics_in_Decision_1

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 2.823[a] | 1 | 2.823 | 12.499 | .000 |
| Intercept | 125.551 | 1 | 125.551 | 555.888 | .000 |
| Country1 | 2.823 | 1 | 2.823 | 12.499 | **.000** |
| Error | 73.403 | 325 | .226 | | |
| Total | 206.000 | 327 | | | |
| Corrected Total | 76.226 | 326 | | | |

**Fig. 2** Business analytics adoption level by the country

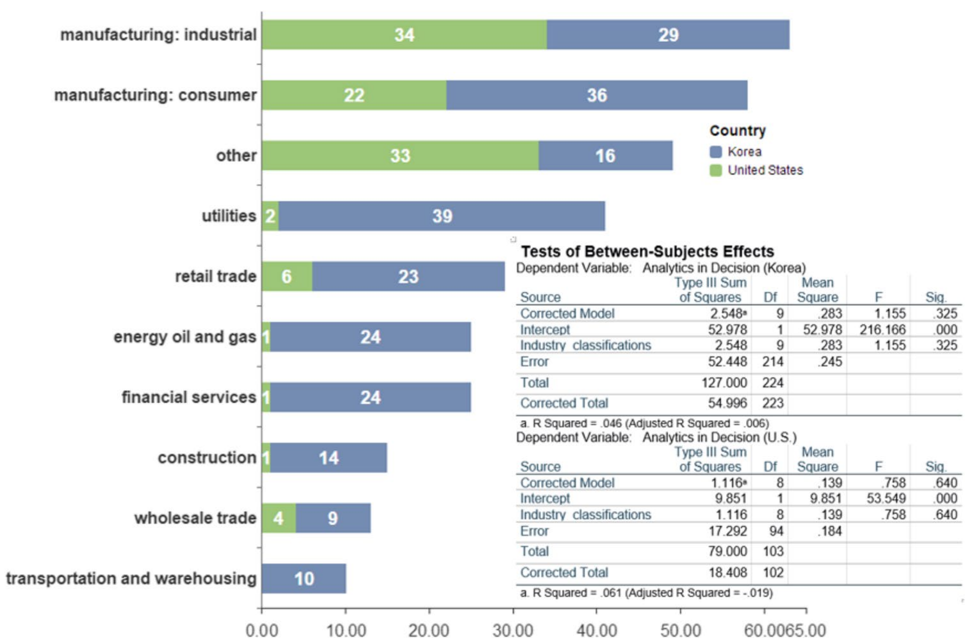
adoption as shown in Fig. 2. The ANOVA analysis reveals that the adoption level of BA differs significantly between the two countries at α = 0.05.

The industry profile of 328 research participants and its breakdown by country is provided in Fig. 2. The manufacturing-industrial products industry and manufacturing-consumer products industry account for 35.9% and 53.8% of participants for overall and U.S., respectively. Approximately 46.4% of Korean respondents are from three industries, manufacturing-industrial products, manufacturing-consumer products, and utilities. However, the adoption level of BA does not differ significantly concerning industry types in both U.S. and Korea as shown in the ANOVA test results in Fig. 3.

The size of a firm can be measured by annual sales or employee size. The firm size measured by the annual sales does affect the adoption of BA in decision making and the adoption patterns are different by country, as shown in Fig. 4. The larger-sized firms are more likely than the smaller-sized firms to adopt BA in decision-making in both Korean firms and U.S. firms. The use of BA in decision-making is also influenced by the firm size measured by employee size, as shown in Fig. 5. The majority of firms with more than 1,000 employees are more likely to use BA in their decision while most of the firms with less than 100 employees did not adopt BA in decision making.

## 4.2 IT Investment

The second research question investigates the influence of IT investment (IT employee size, IT budget, the familiarity of BA) of a firm on its decision to adopt BA. IT investment is often assessed through the IT employee/workforce size, IT budget, and the level of BA familiarity. The ANOVA test to investigate if there was any statistical significance of IT workforce to BA adoption and found a statistical significance at α = 0.05. The larger the IT workforce, the greater the chance the firm would adopt BA regardless of its nationality, as shown in Fig. 6. A majority (64.3%) of the responding firms with fewer than three IT professionals did not use BA, whereas more than two-thirds (68.3%) of the responding firms with three or more IT professionals used BA.




**Tests of Between-Subjects Effects**

Dependent Variable: Analytics in Decision (Korea)

| Source | Type III Sum of Squares | Df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 2.548[a] | 9 | .283 | 1.155 | .325 |
| Intercept | 52.978 | 1 | 52.978 | 216.166 | .000 |
| Industry_classifications | 2.548 | 9 | .283 | 1.155 | .325 |
| Error | 52.448 | 214 | .245 | | |
| Total | 127.000 | 224 | | | |
| Corrected Total | 54.996 | 223 | | | |

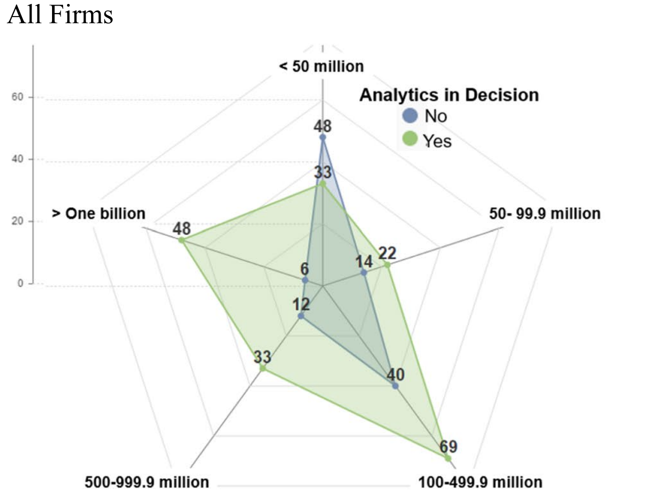
a. R Squared = .046 (Adjusted R Squared = .006)

Dependent Variable: Analytics in Decision (U.S.)

| Source | Type III Sum of Squares | Df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 1.116[a] | 8 | .139 | .758 | .640 |
| Intercept | 9.851 | 1 | 9.851 | 53.549 | .000 |
| Industry_classifications | 1.116 | 8 | .139 | .758 | .640 |
| Error | 17.292 | 94 | .184 | | |
| Total | 79.000 | 103 | | | |
| Corrected Total | 18.408 | 102 | | | |

a. R Squared = .061 (Adjusted R Squared = -.019)

**Fig. 3** Industry profile of responding firms




**Tests of Between-Subjects Effects**

Dependent Variable: Analytics_in_Decision_1

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 10.670a | 9 | 1.186 | 5.743 | .000 |
| Intercept | 95.004 | 1 | 95.004 | 460.247 | .000 |
| Annual_sales | 6.550 | 4 | 1.637 | 7.933 | .000 |
| Country | 1.084 | 1 | 1.084 | 5.254 | .023 |
| Annual_sales* Country | 1.739 | 4 | .435 | 2.106 | .080 |
| Error | 65.022 | 315 | .206 | | |
| Total | 205.000 | 325 | | | |
| Corrected Total | 75.692 | 324 | | | |

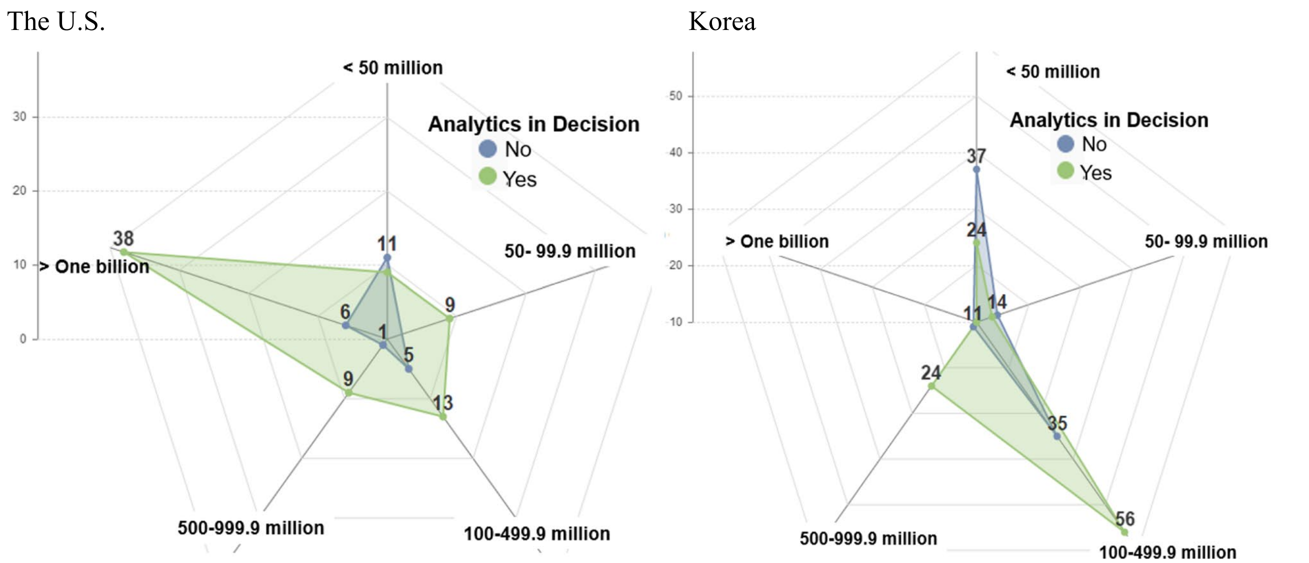
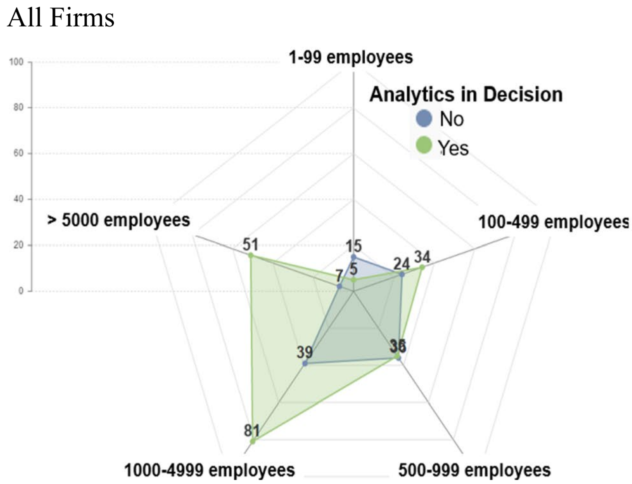



**Fig. 4** Firm size and BA in decision

However, the influence of IT employee size and adoption pattern are different between U.S. firms and Korean firms and the ANOVA test results are shown in Fig. 7a and b. The U.S. firms are more likely to adopt BA regardless of IT staff size, while Korean firms with more than 10 IT professionals have a higher chance to adopt BA. Furthermore, the impact of IT employee size is not significant among U.S. firms, as shown in Fig. 7b.

IT budget does affect the use of BA in the decision and the impact is different by country, as shown in the ANOVA test results in Fig. 8. The higher the IT budget, the more likely that a firm will use BA in the decision-making process. The majority of firms with more than one million IT budgets adopt BA in the decision. In the U.S., more firms are using BA in their decision than those that do not, and that difference increase as the size of the IT budget increases. In Korea, firms with an IT budget of 20 million or greater are more likely to adopt BA in the decision than those with a lesser than 20 million IT budget as shown in Fig. 8.

As shown in the ANOVA test results in Fig. 9, the level of familiarity with BA plays a role in adopting BA in the decision and the impact is different by country. The majority of firms do not adopt BA in their decision when they know nothing or are somewhat unfamiliar with BA for Korean firms. However, the majority of U.S. firms adopt BA in the decision even though the firms know nothing or are somewhat unfamiliar with BA, and that adoption rate increases as the level of BA familiarity increases, as shown in Fig. 9.




**Tests of Between-Subjects Effects**

Dependent Variable: Analytics_in_Decision_1

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 10.352a | 9 | 1.150 | 5.535 | .000 |
| Intercept | 53.891 | 1 | 53.891 | 259.338 | .000 |
| Employee size | 7.190 | 4 | 1.798 | 8.650 | .000 |
| Country | .514 | 1 | .514 | 2.472 | .117 |
| Employee size* Country | 1.021 | 4 | .255 | 1.228 | .299 |
| Error | 65.874 | 317 | .208 | | |
| Total | 206.000 | 327 | | | |
| Corrected Total | 76.226 | 326 | | | |

a. R Squared = .136 (Adjusted R Squared = .111)

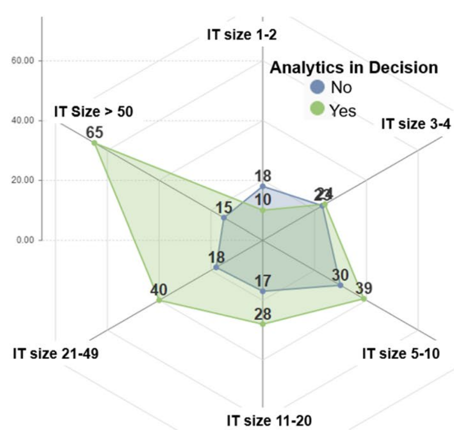
**Fig. 5** Employee size and BA in decision

## 4.3 Influence of Organizational Readiness and Implementation Challenges

Research questions three and four seek insights on the influence of organizational readiness and implementation challenges of a firm on its decision to adopt BA and factors that are most likely to hinder or motivate the potential adoption of BA to uncover if there are cross-national differences in BA adoption practices between Korean and U.S. firms. Research questions one to three reveal the influence of organizational characteristics and IT investment while the factor analysis and cluster analysis result in twelve latent variables and each has its own set of characteristics. With consideration of the number of variables, the complexity of each variable, interdependencies among variables, and interpretability and practicality of research results, to effectively interpret the BA adoption behavior by identifying specific characteristics of the BA adopters and non-adopters through their profiling, a decision tree analysis is conducted to investigate the nine latent factors of organizational readiness (Information Security & Privacy, Perceived Business Analytics Cost, Confidence in BA, Analytics Intention, Perceived BA values, Analytics Simplicity, Organizational Resistance, Technical Capabilities, Risk Assessment), three latent factors of implementation challenges (BA Obstacles, Application Potentials, Perceived BA Benefits), four organizational characteristics (nationality, industry classifications, firm size by annual sales revenue, firm size by total workforce size), and three IT investment variables (IT budget, IT workforce, BA familiarity) that were identified in Table 2.

As shown in Fig. 10, the resultant decision tree using the Chi-squared Automatic Interaction Detection (CHAID) method with 10-fold cross-validation has a classification accuracy of 0.908, a sensitivity of 0.913, a specificity of 0.901, and a precision of 0.940. Thus, this model is useful for making a correct prediction of BA adoption behavioral patterns (Patil et al., 2010). Overall, as shown in Fig. 10, when all variables are considered, familiarity with BA was the most influential (overriding) variable for BA adoption. Three latent variables, the privacy and security risk, the

**Fig. 6** BA adoption level by IT workforce (Combined)

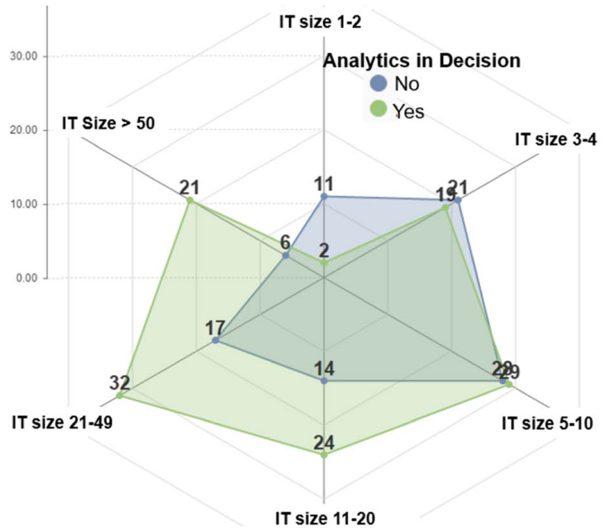



**Tests of Between-Subjects Effects**

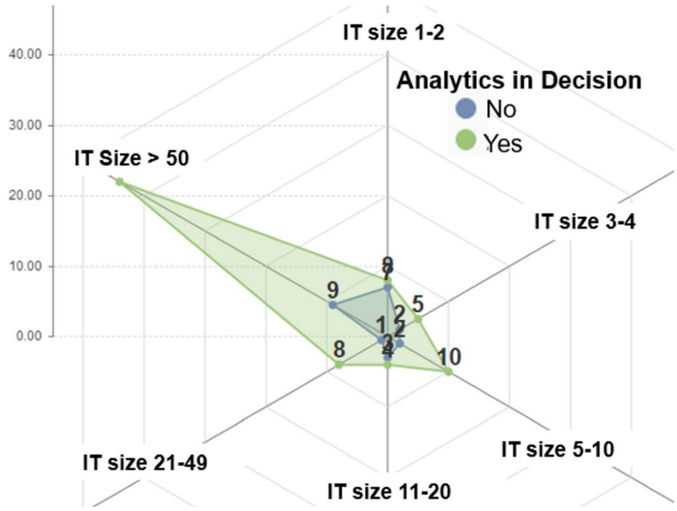
Dependent Variable: Analytics_in_Decision_1

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 8.799a | 11 | .800 | 3.737 | .000 |
| Intercept | 74.556 | 1 | 74.556 | 348.303 | .000 |
| Country | 1.785 | 1 | 1.785 | 8.337 | .004 |
| IT employee size | 4.809 | 5 | .962 | 4.493 | .001 |
| Country * IT employee size | 1.161 | 5 | .232 | 1.085 | .369 |
| Error | 67.427 | 315 | .214 | | |
| Total | 206.000 | 327 | | | |
| Corrected Total | 76.226 | 326 | | | |

a Korean firms




b U.S. firms




**Tests of Between-Subjects Effects**

Dependent Variable: Analytics_in_Decision_1

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 4.472[a] | 5 | .894 | 3.859 | .002 |
| Intercept | 50.388 | 1 | 50.388 | 217.414 | .000 |
| IT_employee_size_1 | 4.472 | 5 | .894 | 3.859 | .002 |
| Error | 50.524 | 218 | .232 | | |
| Total | 127.000 | 224 | | | |
| Corrected Total | 54.996 | 223 | | | |

**Tests of Between-Subjects Effects**

Dependent Variable: Analytics_in_Decision_1

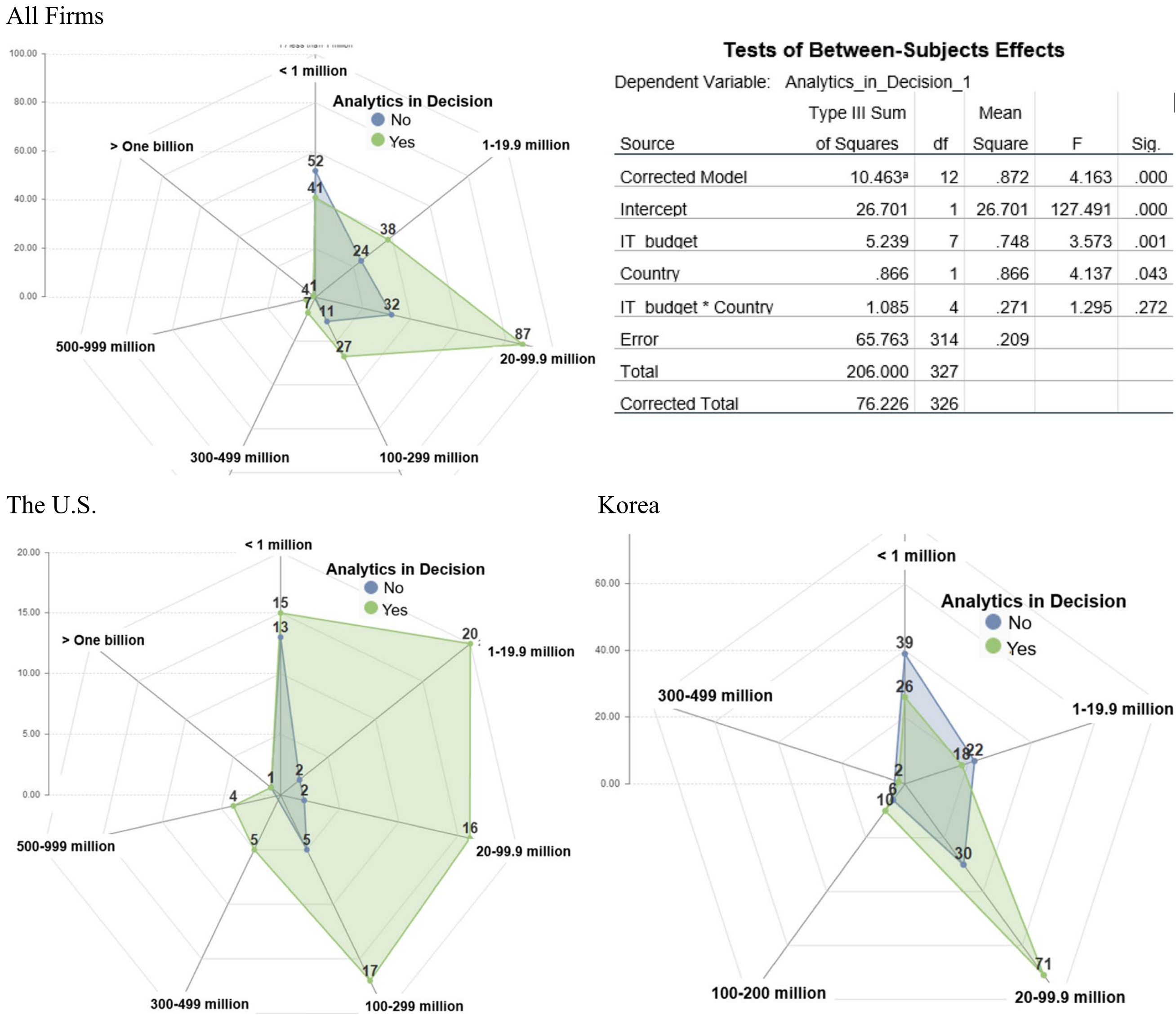
| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 1.504[a] | 5 | .301 | 1.727 | .136 |
| Intercept | 33.781 | 1 | 33.781 | 193.851 | .000 |
| IT_employee_size | 1.504 | 5 | .301 | 1.727 | .136 |
| Error | 16.903 | 97 | .174 | | |
| Total | 79.000 | 103 | | | |
| Corrected Total | 18.408 | 102 | | | |

**Fig. 7** BA adoption level by IT

perceived BA adoption costs, and the perceived BA adoption obstacles played significant roles in splitting nodes in the decision tree, so their profile characteristics will be reviewed before extracting decision rules.

As summarized in Table 3, the factor of Information security and Privacy is described through seven dimensions in terms of sensitive information release, personal information releases anonymously, personal information release, unintended use of personal information, safekeeping of information, security of personal information, and safekeeping of information assets. As shown in Fig. 11a and b, three profile groups and their respective cluster size derived from the two-step k-fold cluster analysis in terms of their degree of perceived security/privacy risk concerns with BA adoption on each of seven dimensions detailed in Table 3: (1) the high alert group who tended to agree strongly (above 6.0 out of a 7-point Likert scale) that information security/privacy was of serious concern for BA adoption on each of seven dimensions; (2) insensitive group who tended to somewhat disagree (ranging from 3.0 to 3.9 on a 7-point Likert scale) that information security/security was of concern for BA adoption on each of the seven dimensions; (3) awareness group who tended to slightly agree (in the range between 4.5 and 5.5 on a 7-point Likert scale) that information security/privacy is of significant concern for BA adoption on each of the seven dimensions. As shown in Fig. 11b, a majority (84.3%) of the U.S. firms recognized the importance of safekeeping of organizational and personal information assets to BA adoption, whereas only a small number (15%) of Korean firms did.

The factor of perceived cost concerns with BA adoption is described using five dimensions such as equipment cost, implementation costs, support/maintenance/update cost, transaction costs, and user training cost as summarized in Table 3. As shown in Fig. 12a, the latent variable of the perceived cost of BA adoption was classified into three profile groups: (1) the "affordable" group who tended to disagree (below 4.0 on a 7-point Likert scale) that costs were of concern for BA adoption. In other words, this group believed that costs were not an inhibitor to BA adoption; (2) the "unaffordable" group tended to strongly agree (above 5.5 out of a 7-point Likert scale) that costs were of primary concern for BA adoption; (3) "recurrent cost concern" group who tended to slightly agree (ranging from 4.0 to 5.5 on a 7-point Likert scale) that recurrent costs such as transaction costs and support/maintain/update costs were of concern for




**Tests of Between-Subjects Effects**

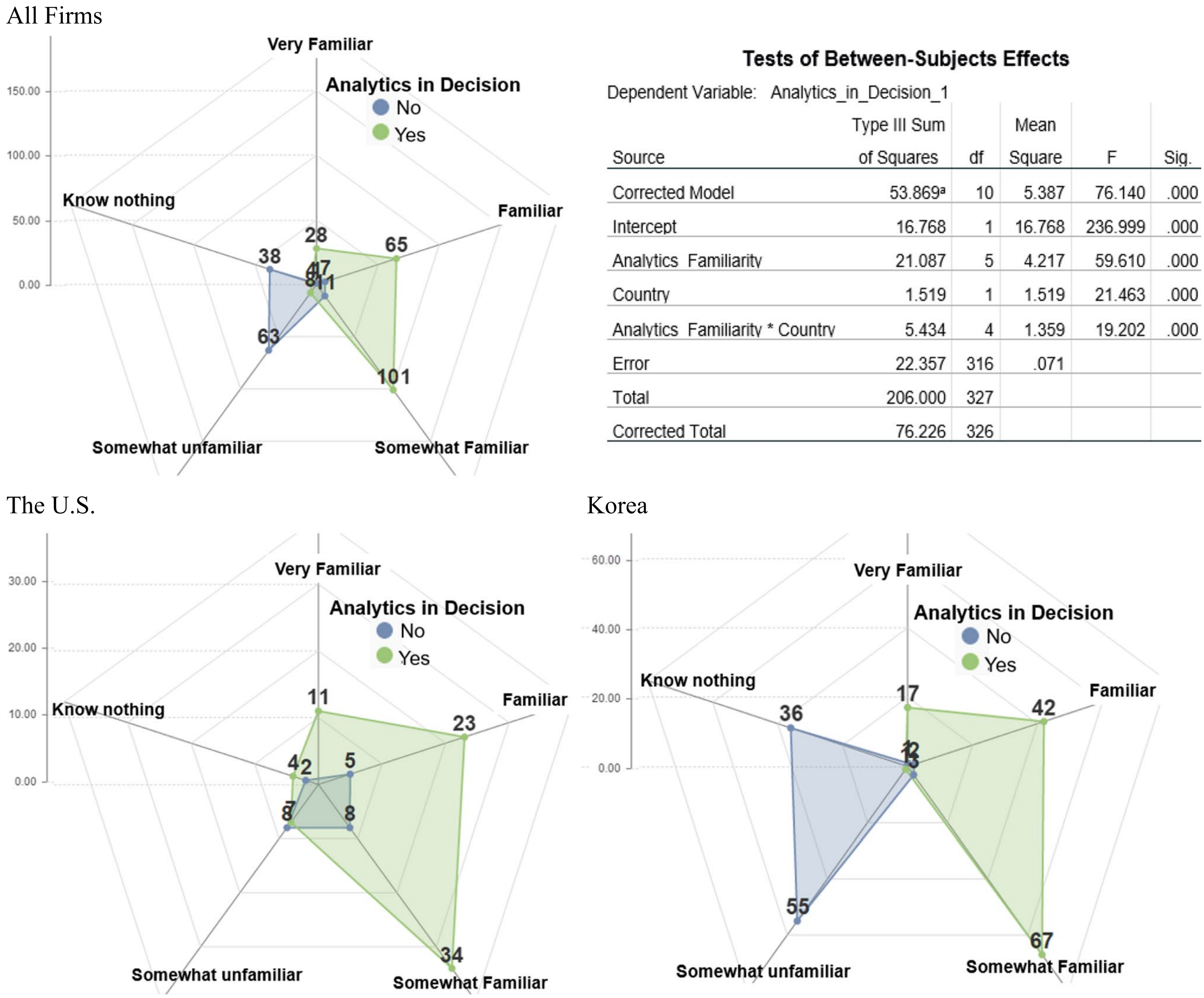
Dependent Variable: Analytics_in_Decision_1

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 10.463[a] | 12 | .872 | 4.163 | .000 |
| Intercept | 26.701 | 1 | 26.701 | 127.491 | .000 |
| IT_budget | 5.239 | 7 | .748 | 3.573 | .001 |
| Country | .866 | 1 | .866 | 4.137 | .043 |
| IT_budget * Country | 1.085 | 4 | .271 | 1.295 | .272 |
| Error | 65.763 | 314 | .209 | | |
| Total | 206.000 | 327 | | | |
| Corrected Total | 76.226 | 326 | | | |

**Fig. 8** IT budget and BA in decision

BA adoption. The cluster size of each profile group is shown in Fig. 12b. It is intriguing to note that a majority (71.92%) of both unaffordable and recurrent cost concern groups were primarily concerned about recurring costs of supporting, maintaining, and updating BA. As shown in Fig. 12b, nearly half (43.3%) of Korean firms and 46% of U.S. firms tended to believe that BA was expensive to adopt.

As summarized in Table 3, the perceived obstacle to BA adoption is described through dimensions of big data collection, data reporting, data screening/filtering, data standardization, start-up investment, insecure data transmission, maintenance cost, lack of information exchange mechanism, regulation, and user training cost. As shown in Fig. 13a, the responding firms were classified into four profile groups in terms of their perceived obstacles with BA adoption: (1) the "no obstacle" group whose degree of seriousness of obstacles was below 3.0 on a Likert scale of 7; (2) "neutral" group whose degree of seriousness of obstacles were in the range of 3.0 to 4.06; (3) group with "serious obstacles" whose degree of seriousness of obstacles were above 5.0; (4) group with "some obstacles" whose degree of seriousness of obstacles were in the range of 4.17 to 4.86. The cluster size of each profile group is shown in Fig. 13b. In particular, both the group with no perceived obstacles and the neutral group did not believe that government regulation posed any barrier to BA adoption, whereas both the group with serious obstacles and the group with some obstacles viewed government regulation as a serious obstacle. Figure 8b also showed that a majority (81.26%) of the Korean firms did not recognize any serious obstacles to BA adoption, whereas more than




**Tests of Between-Subjects Effects**

Dependent Variable: Analytics_in_Decision_1

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 53.869[a] | 10 | 5.387 | 76.140 | .000 |
| Intercept | 16.768 | 1 | 16.768 | 236.999 | .000 |
| Analytics_Familiarity | 21.087 | 5 | 4.217 | 59.610 | .000 |
| Country | 1.519 | 1 | 1.519 | 21.463 | .000 |
| Analytics_Familiarity * Country | 5.434 | 4 | 1.359 | 19.202 | .000 |
| Error | 22.357 | 316 | .071 | | |
| Total | 206.000 | 327 | | | |
| Corrected Total | 76.226 | 326 | | | |

**Fig. 9** BA familiarity and BA in decision

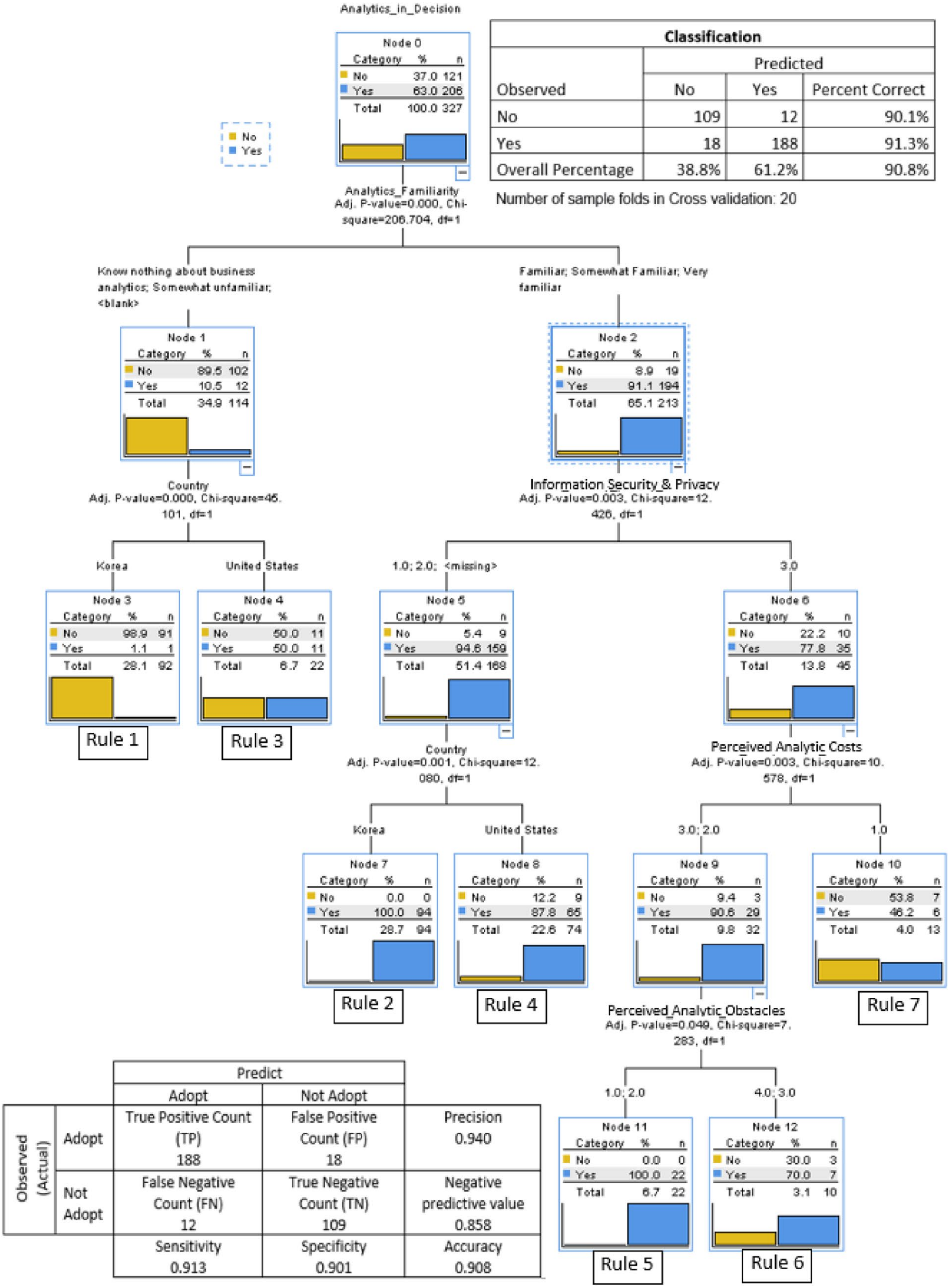
half (59.37%) of the U.S. firms recognized the existence of some obstacles or serious obstacles to BA adoption.

Seven different sets of "IF–THEN" rules are extracted based on key variables of interest summarized in Table 2 and the decision tree is shown in Fig. 10 and is summarized in Table 4.

## 5 Key Findings and Managerial Implications

One of the main objectives of data mining analysis in this study was to classify the surveyed sample firms into a certain type of segmentation (profile) to identify important variables that significantly influence a firm's BA adoption. In addition, this study examined the influence of responding firms' profiles (e.g., firm size, industry type, BA knowledge or familiarity level, organizational readiness, nationality) on BA adoption patterns. This section summarizes several of the noteworthy findings of this study and their managerial implications for firms that either currently use or plan to use BA in the future.

First, we discovered that firm size itself did not play an influential role in the BA adoption decision when all variables are considered in the decision tree analysis, although the firm size measured by annual sales revenue and by employee size does influence the BA adoption when no other variables are considered. This finding defies the conventional wisdom that large firms with more human and financial resources could leverage their scale economies to amortize the costs of launching and maintaining BA over a period of time and thus their return on investment in BA could be relatively high as compared to smaller firms. This finding is somewhat incongruent with the findings of many earlier studies indicating that large firms tended to invest more in innovation such as




| Classification | | | |
|---|---|---|---|
| | Predicted | | |
| Observed | No | Yes | Percent Correct |
| No | 109 | 12 | 90.1% |
| Yes | 18 | 188 | 91.3% |
| Overall Percentage | 38.8% | 61.2% | 90.8% |

Number of sample folds in Cross validation: 20

| | | Predict | | |
|---|---|---|---|---|
| | | Adopt | Not Adopt | |
| Observed (Actual) | Adopt | True Positive Count (TP) 188 | False Positive Count (FP) 18 | Precision 0.940 |
| | Not Adopt | False Negative Count (FN) 12 | True Negative Count (TN) 109 | Negative predictive value 0.858 |
| | | Sensitivity 0.913 | Specificity 0.901 | Accuracy 0.908 |

**Fig. 10** Decision tree model

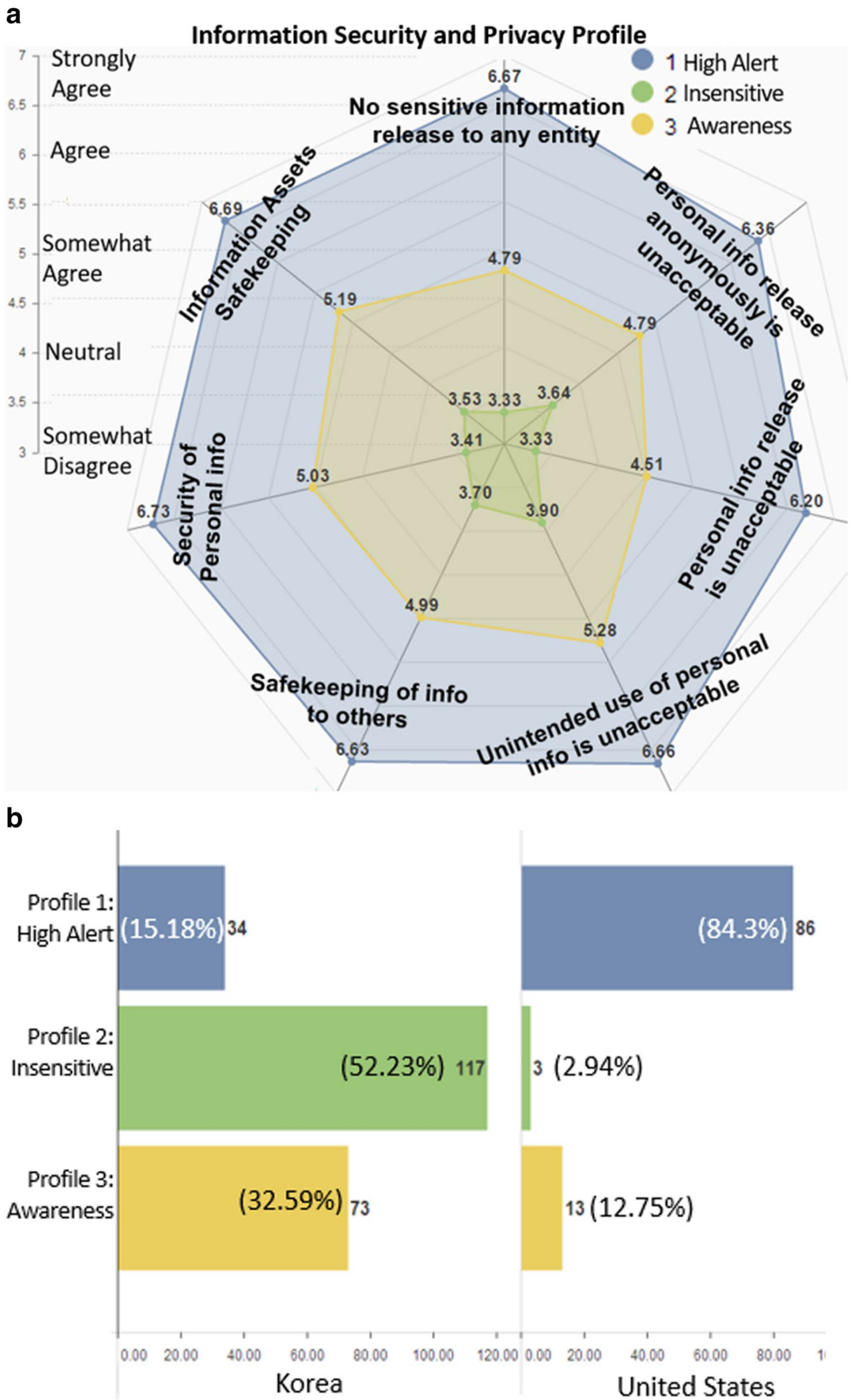



**Fig. 11** **a** Information security and privacy profile characteristics of combined Korean and US firms. **b** Cluster size of information security and privacy profile

BA than did small ones (Kleinknecht, 1989; Schumpeter, 1942; Shefer & Frenkel, 2005). As this research recognized and considered the number of and the interdependency of influential factors in BA adoption decisions, the finding of firm size influence is noteworthy in the process of identifying the most influential factors in BA adoption decisions.

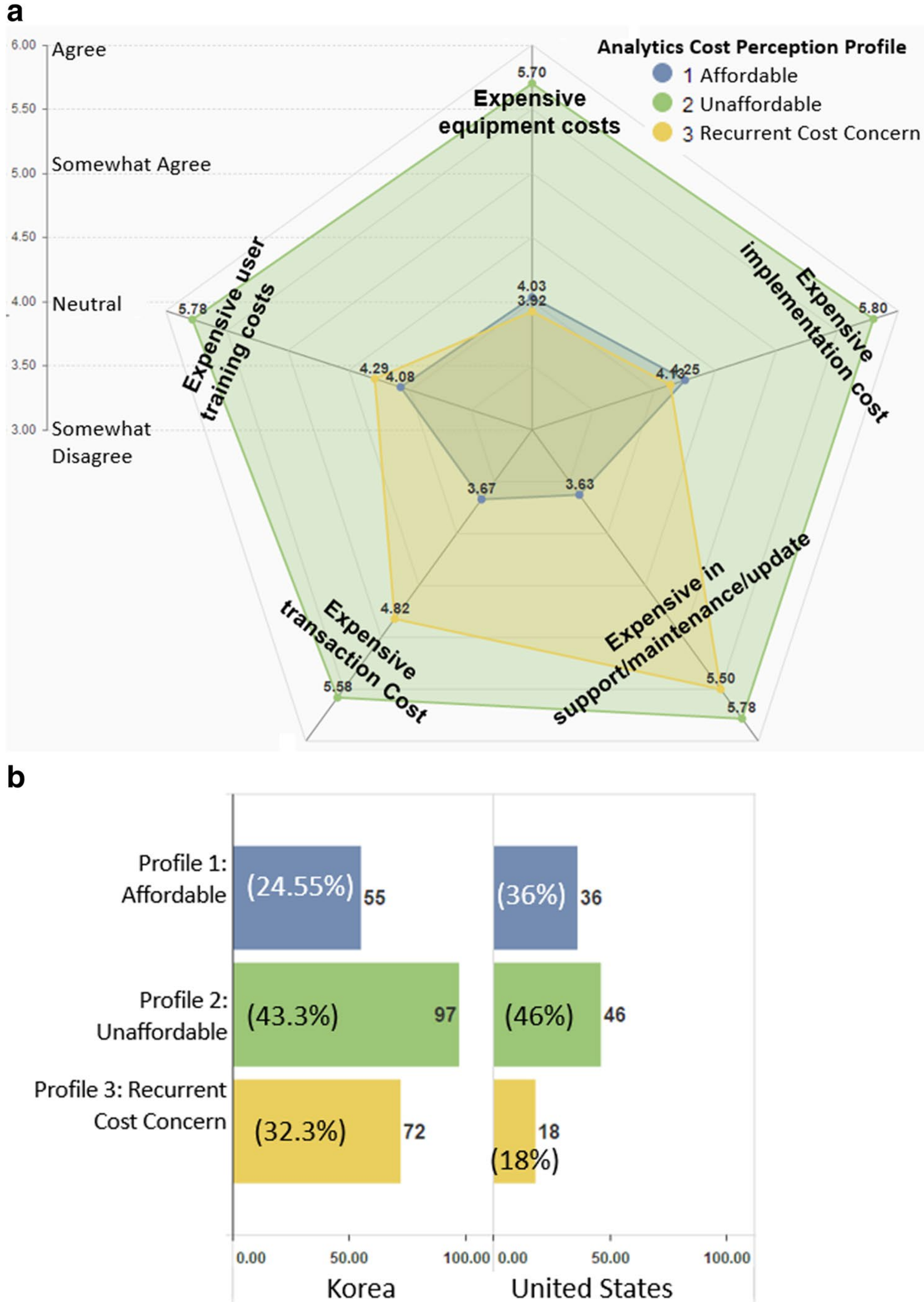



**Fig. 12** **a** Profile characteristics of combined Korean and US firms in terms of their perceived cost concerns with BA adoption. **b** The cluster size of Perceived Cost concerns with BA adoption profile

The firm's level of BA familiarity is identified as the most important influencing (overriding) factor or the biggest motivator for BA adoption from the decision tree analysis. This finding makes sense in that a higher level of BA familiarity can be translated into a greater technology readiness which, in turn, can increase the likelihood of emerging technology such as BA. This finding is not surprising in that familiarity may foster the adoption of innovative technology such as BA. The rationale is that, as the firm's experience with technology increases, its technology capabilities would grow, and subsequently, the firm would be more inclined to adopt that technology (Lefebvre et al., 1991; Min & Galle, 1999). By analogy, Oliveira and Martins (2011) found that the firm's technology readiness influenced its adoption of newer computer-based systems such as e-business. In light of the above discussions, firms that consider adopting BA should first nurture the BA expertise among their employees and ensure the hiring and training of qualified IT staff who can support BA application efforts before BA adoption.

Second, neither information security/privacy concerns nor BA implementation and other related costs were the sole deciding factor for BA adoption when all variables are considered in decision tree analysis. In other words, information security/

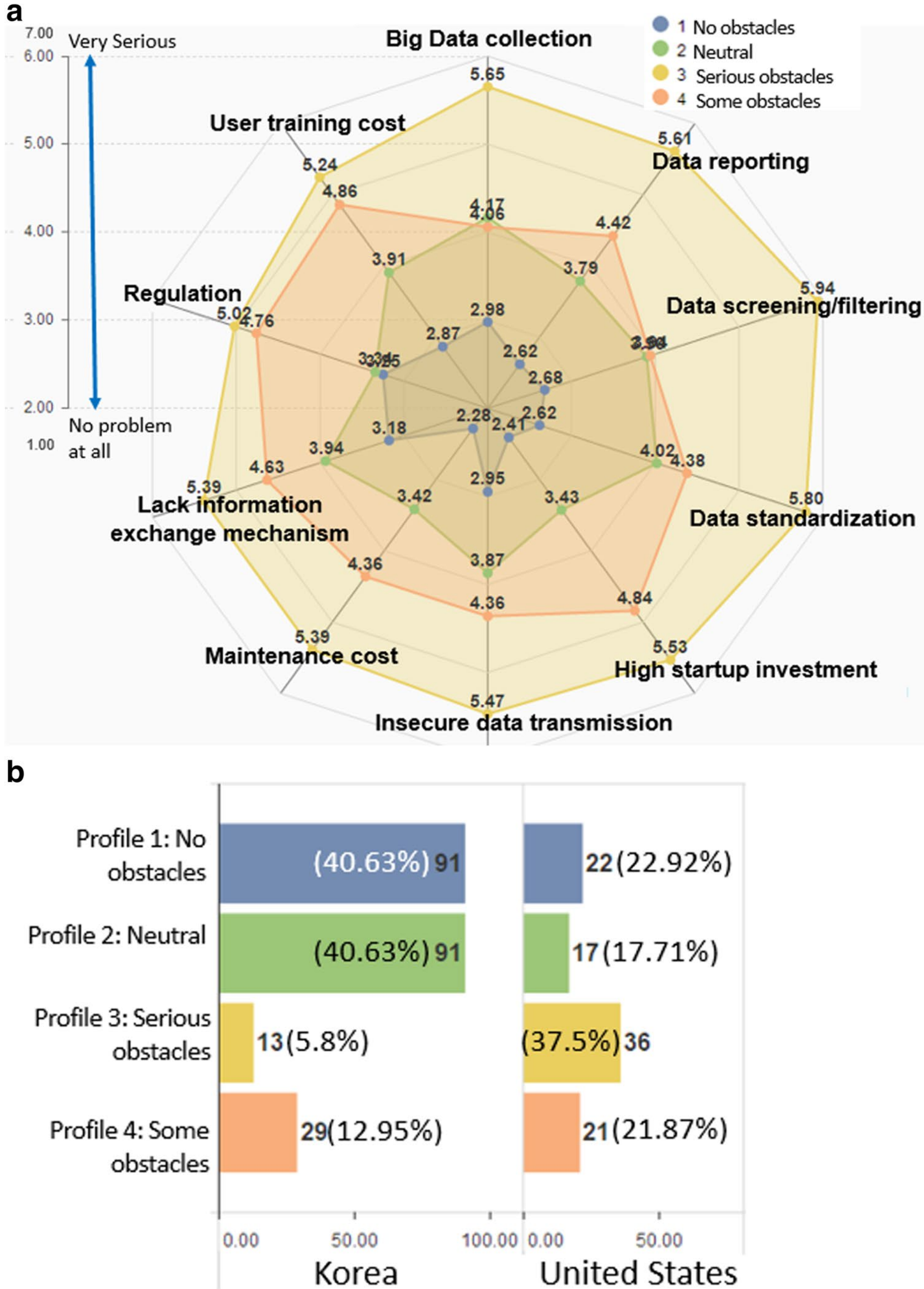



**Fig. 13** **a** Profile characteristics of combined Korean and US firms in terms of their perceived obstacles to BA adoption, **b** Cluster size of perceived obstacles with BA adoption profile

privacy concerns or BA implementation and related costs are not a "deal-breaker" (key inhibitor) for adopting BA. Although sharing information (including the unprecedented scale of big data) with trading or supply chain partners can enrich BA benefits, there were concerns about information sharing practices that might reveal the firm's sensitive or proprietary information to its competitors. However, our findings did not validate those concerns. Other than the interdependencies among variables and variable importance identified during the decision tree analysis process, one of the possible explanations for this finding is that recent advances in data-driven security technology, the Cloud Security Alliance (CSA), and government-induced privacy regulations mitigated information security/privacy risks, and thus information security/privacy concerns would not be a serious deterrent to BA adoption (Cárdenas et al., 2013). Also, a lack of cost concerns for BA adoption can be interpreted in two ways: (1) BA implementation and related costs are perceived to be manageable (not prohibitively high); (2) BA implementation and other related costs (e.g., user training costs, maintenance/upgrade costs) are hard to estimate and thus potential

**Table 4** A summary of IF–THEN rules for BA adoption

Country-specific rules: For Korean firms

**Rule 1**: IF the firm knows nothing about or has limited familiarity *(is somewhat unfamiliar)* with BA, THEN it has a 98.9% chance of not adopting BA

**Rule 2**: IF the firm has at least some degree of familiarity with BA (i.e., *familiar*, *somewhat familiar,* or *very familiar)* AND IF it is in high alert profile (profile 1 in Fig. 11a) OR insensitive profile (profile 2 in Fig. 11a) to information security and privacy risk, THEN it has a 100% chance of adopting BA

**Country-specific rules: For U.S. firms**

**Rule 3**: IF the firm knows nothing about or has limited familiarity (*is somewhat unfamiliar*) with BA, THEN it has only a 50% chance of adopting BA

**Rule 4**: IF the firm has at least some degree of familiarity with BA (i.e., *familiar, somewhat familiar, or very familiar*) AND IF it is in high alert profile (profile 1 in Fig. 11a) OR insensitive profile (profile 2 in Fig. 11a) to information security and privacy risk, THEN it has an 87.8% chance of adopting BA

**Generic rules (based on combined Korean and U.S. data)**

**Rule 5**: IF the firm knows nothing about or has some degree of familiarity with BA (i.e., *familiar, somewhat familiar, or very familiar*) AND IF it is aware of information security and privacy risk (Profile 3 in Fig. 11a) AND (EVEN IF it perceives BA cost as unaffordable (profile 2 in Fig. 12a) OR has a concern about recurrent BA support/maintenance/update costs (profile 3 in Fig. 12a)) AND IF it perceived no serious obstacles (profile 2 in Fig. 13a) OR neutral on obstacle profile (profile 2 in Fig. 13a) for BA adoption, THEN it has a 100% chance of adopting BA

**Rule 6**: IF the firm knows nothing about or has some degree of familiarity with BA (i.e., *familiar, somewhat familiar, or very familiar*) AND IF it is aware of information security and privacy risk (Profile 3 in Fig. 11a) AND (EVEN IF it (perceives BA cost as unaffordable (profile 2 in Fig. 12a) OR has concern of recurrent BA support/maintenance/update costs (profile 3 in Fig. 12a)), AND IF it perceived some obstacles (profile 4 in Fig. 13a) OR serious obstacle (profile 3 in Fig. 13a) for BA adoption, THEN it has a 70% chance of adopting BA (or 30% of chance of not adopting BA)

**Rule 7**: IF the firm has at least some degree of familiarity with BA (i.e., *familiar, somewhat familiar, or very familiar*) AND IF it is aware of information security and privacy risk (Profile 3 in Fig. 11a) AND IF it perceived cost of BA is affordable (Profile 1 in Fig. 12a), THEN it has a 53.8% chance of not adopting BA (or 46.2% of chance of adopting BA)

BA adopters cannot gauge their impact on their BA adoption decision due to a difficulty in BA cost–benefit analysis. This finding is in contrast with some of the findings of prior IT studies indicating that perceived costs could either positively or negatively influence the IT adoption decision (Chau & Hui, 2001; Teo et al., 2006; Zhu et al., 2006). Regardless, it appears that the importance of cost concerns is superseded by that of BA familiarity. In other words, BA project funding and finances are not the most crucial prerequisite to BA adoption.

Lastly, we found that U.S. firms tended to be warier of information security/privacy risk than their Korean counterparts although information security/privacy concerns would not discourage their BA adoption. In particular, after experiencing one of the biggest data breaches of credit card companies in Korea, the Korean government enacted the Personal Information Protection Act in 2014 in addition to the Act on Promotion of Information and Communications Network Utilization and Information in September of 2011 to tighten information security/privacy (IFLR, 2015; Korean Law Blog, 2014). These strict information protection laws eased the Korean firms' fear of information security/privacy risks and might have reduced their perceived security/privacy concerns. Also, U.S. firms recognized the greater seriousness of obstacles to BA adoption and thus felt pressured to overcome more barriers to BA adoption than their Korean counterparts. However, those differences did not affect their actual BA adoption in that 56.7% of the Korean firms already adopted BA, while 76.7% of the U.S. firms adopted BA despite the recognition of greater obstacles to BA among U.S. firms. It is intriguing to note that 59.1% of the U.S. firms that have not adopted BA still plan on adopting it in the future, while 67% of the Korean firms that have not adopted BA still plan on adopting it in the future. That is to say, serious concerns about potential BA obstacles would not hinder the firm's BA adoption decision regardless of national differences in the seriousness of obstacles to BA adoption.

## 6 Concluding Remarks and Future Research Directions

This study has sought to assess the impact of contextual variables such as the industry sectors, organizational characteristics, organizational culture, IT resources, BA familiarity, information security/privacy concerns, and various perceived costs and obstacles associated with BA on the decision to adopt BA. This study is also one of the first attempts to use data mining techniques to develop detailed profiles of BA adopters and non-adopters rather than relying on a series of hypotheses tests using conventional multivariate analyses or confirmatory factor analysis that cannot capture a multitude (multiple combinations) of influencing factors simultaneously for BA adoption.

Future research will need to extend the scope of this study to examine the direction of causality between these variables and the BA adoption decision through multiple periods of longitudinal studies. In addition, future research endeavors should investigate the potential impact of other contextual variables such as industry trends, peer pressures, and the firm's risk orientation (risk aversion versus risk tolerance) on the firm's BA adoption decision.

**Data Availability** Data were collected with a promise to keep the confidentiality of survey respondents.

## Declarations

**Competing Interests** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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