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Attribute of Big Data Analytics Quality Affecting Business Performance

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Abstract: With an accelerating increase of business benefits produced from big data analytics (if used appropriately and intelligently by businesses in the private and public sectors), this study focused on empirically identifying the big data analytics (BDA) attributes. These attributes were classified into four groups (i.e., value innovation, social impact, precision, and completeness of BDA quality) and were found to influence the decision-making performance and business performance outcomes. A structural equation modeling analysis using 382 responses from a BDA related to practitioners indicated that the attributes of representativeness, predictability, interpretability, and innovativeness as related to value innovation greatly enhanced the decision-making confidence and effectiveness of decision makers who make decisions using big data. In addition, individuality, collectivity, and willfulness, which are related to social impact, also greatly improved the decision-making confidence and effectiveness of the same decision makers. This shows that the value innovation and social impact, which have received relatively less attention in previous studies, are the crucial attributes for BDA quality as they influence the decision-making performance. Comprehensiveness, factuality, and realism, which are linked to completeness, also have similar results. Furthermore, the higher the decision-making confidence of the decision makers who used big data was, the higher the financial performance of their companies. In addition, high decision-making confidence using big data was found to improve the nonfinancial performance metrics such as customer satisfaction and quality levels as well as product development capabilities. High decision-making effectiveness with big data was also shown to improve the nonfinancial performance metrics.

Key words: big data analytics (BDA); attribute of BDA quality; decision-making confidence; decision-making effectiveness; financial business performance; nonfinancial business performance

1 Introduction

The development of information and communication technologies (ICT) and the fourth industrial revolution have enabled the creation of an enormous amount of data from diverse sources, such as social media and Internet of Things (IoT), which are unstructured and unrefined in nature[1, 2]. This has led to a strong demand for big data analytics (BDA) technologies that can be applied to smart decision making in diverse business contexts[3−12]. For instance, the global annual cellular data usage has been predicted to reach roughly 650 thousand petabytes (PB). This amount is projected to increase by 2025, potentially reaching 1.9 million PB annually[13]. Based on a report by Zion Market Research[14], the global big data analytics market was forecasted to reach around 37.34 billion US dollars in 2020 and is predicted to arrive at approximately 147.17 billion US dollars by 2027, growing at a compound annual growth rate (CAGR) of around 22.3% between 2021 and 2027.

Technological, organizational, and environmental

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factors all affect the adoption of BDA among small-sized enterprises as well as the financial performance and market performance of small and medium-size enterprises (SMEs)[15]. In a similar vein, various big data attributes, such as data quality (which is related to how much value is extracted from the data analysis) and data security (which is related to precision and completeness) can affect big data adoption[16, 17]. Positive and negative valence factors such as data accessibility and security can also influence big data analytics usage[18]. Based on studies on the data quality attributes related to big data, it is necessary to acquire a large volume of data at a high velocity with the attributes of variety and veracity.

The quality of data-driven decisions depends on the data analysis attributes employed for data collection and analysis. The diverse attributes of the relationships hidden in datasets demand expertise from different disciplines, leading to a chain of activities known as a big data chain. This chain encompasses steps such as data collection, data preparation, data analysis, and decision-making[19]. One of the promising ways to explain the positive association between the use of BDA and firm outcomes can be explained by various BDA attributes when using big data technologies. Most studies in the literature have addressed big data analytics capabilities and big data decision-making capabilities[9]. While data science has evolved greatly, the ultimate achievement of extracting valuable insight has been largely limited by the extent to which crucial data analysis quality issues related to reliability, inconsistencies, accuracy, and incompleteness can be overcome[20]. For instance, users must ensure that cloud computing servers correctly allow for the checking of the data’s completeness by means of a data integrity verification technique[21]. These challenges are directly related to the fourth dimension of big data: Veracity.

Our study suggests data attributes or data analysis attributes that can better ensure the accomplishment of BDA objectives. Our study had three objectives based on the literature on data attributes of big data adoption, as follows. Firstly, our study determined a diverse set of data analysis attributes for BDA, which were classified into four categories: value innovation, social impact, precision, and completeness of BDA quality. While previous studies have concentrated on the data attributes or management factors that affect the adoption and usage of big data[18, 20, 22–24] as well as big data management[25], value innovation and social impact have received relatively less attention in previous studies compared to other factors influencing decision-making performance. Furthermore, previous studies of information attributes based on the processing of structured and refined information may not be applicable to investigations on the attributes of BDA. In addition, given that previous studies on data analysis attributes were rather fragmented, as they focused on the specific context of studies, our study intended to provide an integrated model for BDA attributes that encompass value innovation, social impact, precision, and completeness. Thus, our study focused on suggesting a coherent model for specific data analysis attributes to ensure the quality of a BDA.

Secondly, this study investigated whether the existence of BDA attributes can ultimately lead to better business performance. Given the lack of studies of the attributes of information analyses, it was necessary to investigate the relationships among the attributes of BDA and decision-making performance outcomes and satisfaction levels[26]. In addition, business performance was examined based on the research gap in the attributes of data analyses affecting the adoption and usage of big data[7]. Big data management exerts an importance effect on decision-making capabilities[9], and data quality has been a crucial factor in affecting the big data performance[27]. Our study investigated the BDA attributes that affect decision-making performance outcomes. While the use of big data has significantly supported leaders in their efforts to obtain better firm outcomes, indicators continue to show that the growth curve of business performance using big data is flattening out[28]. Thus, it was necessary to examine the effects of BDA attributes on business outcomes in terms of financial and nonfinancial aspects.

2 Research Background

2.1 Big data technology

Amazon maintains a database on the patterns of customer purchasing behaviors and utilizes business analytics to customize their marketing campaign strategy according to customer interests. The United

States manages a website (https://.data.gov) that provides data search and utilization functions for every interested person. The website also offers all data, except for data related to national or diplomatic interests or data restricted for personal privacy reasons. The United Kingdom operates a website (https://www.data.gov.uk) that facilitates the sharing of information and statistics for business purposes. This website is supported by people who consider data as public goods despite the negative view on possible privacy and anonymity infringements[23]. There exists a risk of information distortion from a monopoly or from exclusivity of data management, as well as unbalanced information sharing in an accelerated manner[24]. It is crucial to establish social recognition and policies that consider information as assets, which create future national competitiveness utilize these assets transparently[26]. It is also necessary to suggest information quality attributes and the criteria for BDA to realize effective information acquisition, thereby ensuring decision-making performance and satisfaction outcomes based on previous studies of data analysis frameworks, big data quality characteristics and attributes, decision-making performance and overall performance outcomes, and business cases in the public sector and financial, logistics, retail, IT, health big data platform technologies, and service utilization sectors.

Big data are defined as a large amount of complicated data with business values that requires IT and methods to enable collection, storage, refinement, and value creation[29, 30] as well as to analyze unstructured data. These data comprise 90% of all data for smart decision-making, which are not possible using traditional relational database systems[31] that are based on component technologies such as sensors for collecting diverse data, cloud computing for data storage and sharing, data mining software for analyzing data, and Hadoop and parallel data processing systems. BDA technology is one of ten strategic technologies, and one of the most notable technologies for business growth[32]. Big data have 3V traits given the large volume, great variety, and high velocity[33]. The forms of data are diverse in that they include structured data such as numeric and textual data and semi-structured or unstructured data such as audio, video, image, HTML, and XML data. An increasing number of service providers are offering data-based analysis to fulfill specific customer requirements. For instance, businesses analyze online texts posted on Facebook and Twitter (now X) to determine customer responses to their products and services.

2.2 Attribute of BDA

The attributes of big data can be derived from studies on the attributes or dimensions of data quality aspects such as accuracy, reliability, timeliness, and precision[34–36]. As big data show diverse and unstructured characteristics with regard to the types of data along with a large volume and high velocity of data preprocessing, a revised list of attributes for big data is necessary for the existing attributes of structured information.

The integration of product and service perspectives can be adopted to describe data quality attributes (which can be considered similar to data attributes)[37]. A semiology-based theoretical framework can be used to evaluate data forms, semantics, and usage quality[20]. Data quality attributes can be described by classifying the ontological essentials of quality attributes based on the difference between representation and real-world information systems[35]. These categories include accuracy, correctness, currency, completeness, and relevance. Theories describing data quality attributes include communication theory, which deals with the delivery of signals, and information economic theory, which investigates the economic value of signal usage. These theories evaluate information systems that induce specific users' activities or processes through signal delivery and usage. Another theoretical approach includes design-oriented methods that investigate data attributes focusing on system design contexts such as the designs of entities, fields, values, and the corresponding executions in information systems. These approaches are data-centric methods and indicate that the specifications of data quality attributes are dependent upon the specific design of the data.

The present study adopted data quality attributes based on the premise that data are types of products or services[38] and are evaluated by those who demand the data in terms of the extent to which they consider the data appropriate for use[39–42]. Furthermore, social impact influences the formation of categories for data quality attributes within the organizational boundary. The internal systems perspective for building data quality attributes focus on the effects of the design, implementation, and operation of the system, and on the steps of the data creation cycle, such as acquisition, maintenance, and delivery of data. This perspective is limited, as the social impact through collecting data from social media and online systems is more crucial for suggesting data quality attributes. Our study encompassed data quality attributes based on both the internal information systems environment and the design and external social impact based on a diverse range of user requirements. This will help systems designers understand the required data quality attributes for better system performance.

Data quality attributes refer to attributes that contribute to generic quality, user satisfaction, information systems success, and proper audit and accounting outcomes. The data attributes related to generic quality include timeliness, accuracy, consistency, and completeness[43, 44] as well as reliability, traceability, and validity[45, 46]. Numerous generic data qualities are based on data attributes in relational databases, which can still be partially applied to big data. The data attributes for information systems success are important for systems performance[34] and include reliability, usefulness, relevance, accuracy, precision, timeliness, and completeness[47]. Data attributes that are important for user satisfaction include precision, timeliness, accuracy, completeness, and reliability. For accounting and audits, the data attributes include the relative and absolute attributes as well as internal reliability[47]. Moreover, a logical basis for general and concrete attributes was also suggested.

Big data infrastructure taxonomy is composed of the source type, source site, volume, velocity, variety, veracity, data management, computation, control, and archival needs, which provide 50 attributes for big data[48]. This suggests the importance of veracity such that the filtering out of noise is crucial to integrate semantics with the data attributes. The data type or quality attributes related to culture, deception detection, trust, privacy, and reliability have been considered as among the top-ranked issues in big data research[49, 50]. For instance, the quality of information is crucial when determining the trust of “informediaries”, and the decision-making performance plays an important role in improving trust[9]. The factors of trust and recommendation agents can increase or decrease trust in decision-making support technologies[51].

Quality checking of autonomous data from social media or data from IoT has become a major concern related to the quality of big data. The veracity of big data can be ensured by using automatic quality controls applied to a large amount of data collected from diverse sensors and Internet-connected devices. As data from social media accumulate, the data attributes required by social media participants are deception, subjectivity, and encapsulation[52]. The uncertainty of big data increases due to diverse sources, and veracity is a crucial factor for creating value from data with a high velocity of processing, a large volume, and a great variety. Many businesses have difficulty finding general methods to evaluate and define the veracity of big data[53]. Veracity represents the uncertainty of the data and the level of reliability, which can encompass truthfulness, accuracy, precision, and correctness[53]. The veracity of data can be ensured by utilizing and merging contextual information such as locations. Our study used veracity as a qualitative attribute of big data quality and investigated its effects on decision-making performance outcomes.

2.3 Decision-making performance and business performance

Decision-making performance is the extent to which the capability of information systems supports decision-making and problem solving[54]. The aspects that comprise decision-making performance include decision-making efficiency and confidence, as well as time[49]. Our study employed decision-making efficiency and confidence as sub-constructs of decision-making performance by analyzing data from transportation, climate, insurance, finance, and social media sources. The quality attributes of information and systems affect the decision-making performance[55]. The value of the information system is determined by the information quality, which is dependent upon user recognition[56]. These relationships among input resources such as the decision-making duration, effort, and use of group-decision support systems (GDSS) as well as outputs such as decision satisfaction and quality can be examined through a data envelopment analysis.

Information quality, information presentation, and system quality are determinants of the decision-making performance in a web-based decision support system[56]. The measurement of decision-making performance is based on items such as the number of decision alternatives, the perceived level of confidence in related subjects, the time spent completing the decision-making process, the amount of data considered during the decision-making process, the appropriateness of decision alternatives, and the financial and economic aspects of decision making. The decision-making quality is based on increases in sales and net profits from software systems, and decision confidence is based on suggestions of decision alternatives that can be accomplished by organizational members.

The business performance from big data quality is composed of internal business performance factors such as the productivity of employees, manufacturing costs, and inventory costs, as well as external business performance metrics such as the market ratio. Internal business performance can be increased by corporate responsibility, as it pertains to product quality, innovations in work process and statistical process control, and teamwork, all of which improve corporate productivity and reduce quality management costs. External management is increased by customer-oriented management activities and satisfaction of customer requirements, which improve the corporate image and customer loyalty. Quality management activities can affect financial performance metrics such as the annual sales growth rate and the return on assets, as well as operational performance metrics such as productivity, employee satisfaction, and the employee turnover rate[57]. In our study, we encompassed financial and nonfinancial performance outcomes for business performance, which can be affected directly by the decision-making performance and indirectly by BDA attributes.

The financial measures for assessing the outcomes that the BDA system can produce through better decision making include increases in the market ratio, sales increase, and return on investment. For instance, improved quality management can lead to improvements in production and operation processes, increases in the sales of products, and an increased market ratio based on an improved brand image and stronger customer satisfaction[41, 58].

Financial measures involve assessing the past outcomes, possibly leading to errors in these measurements. In order to overcome the drawbacks of financial measures, nonfinancial measures such as customer satisfaction, internal process efficiency, corporate innovation and learning, quality improvements, customer retention, and production lead times should also be considered[41, 59, 60]. It is necessary to assess the potential for profitability beyond past performance.

3 Research Model

The significant barriers associated with big data include poor data quality and poor data management[61]. Data analytics capability and output quality are important factors affecting the perceived usefulness of BDA[62]. Data quality attributes include accuracy, timeliness, precision, representability, innovativeness, interpretability, accuracy, and reliability, all of which affect the decision-making process and business performance outcomes. We organized the attributes of BDA quality into four groups (value innovation, social impact, precision, and completeness of BDA quality) that influence the decision-making performance and business performance outcomes. While previous studies focused on data attributes or management factors that influence the adoption and use of big data[20, 22–24, 26] as well as big data management[25], value innovation and social impact have received relatively less attention in previous studies as influences on the decision-making performance. Furthermore, given that previous studies on data analysis attributes have been rather fragmented in examining the specific context of studies, our study intended to offer an integrated model for BDA attributes that encompasses value innovation, social impact, precision, and completeness. Thus, our study focused on suggesting a coherent, specific model for data analysis attributes to ensure the quality of BDA.

BDA attributes can be derived from the literature on data quality[11, 34–36]. While precision and completeness have been well suggested in previous studies, value innovation and social impact have been studied less. Value innovation can be an attribute based on how much BDA obtains meaningfulness, value added, and relevance from BDA, which have been suggested in previous studies[63, 64]. Social impact can be explained in terms of alignment and relevance in the social context of BDA as data quality attributes. The importance of social impact can be deduced from the role of individual motivations and social capital with social apps on the relationship quality, which encompass trust toward mobile social apps and satisfaction with mobile social apps[65]. The first two groups of BDA quality are closely related to the extent to which data are beneficial and offer advantages from their use and the extent to which data are helpful or applicable for the task at hand, which is mostly individual and social. Our study suggests a research model based on the relationships among data quality attributes, decision-making performance, and business performance, as shown in Fig. 1.

3.1 Value innovation in BDA and decision-making performance

Our study suggests that the first group of BDA quality is value innovation, which comprises representativeness, predictability, interpretability, and innovativeness. Big data have various effects on decision making according to cognitive biases and overload[66]. In terms of the effects on decision making, previous studies have suggested the importance of attributes of veracity, such as representativeness and predictability. Interpretability and innovativeness are crucial attributes of big data quality when big data are consolidated from diverse sources in terms of semantics and meaning[48]. Representativeness is the extent to which it is possible to describe, explain, and represent the identity and meaning of objects or phenomena. Predictability is the extent to which it is possible to predict phenomena and provide meaning and insights in relation to them. Interpretability is the extent to which it is possible to interpret relationships among specific events, objects, and groups[64]. In a similar vein, Feki and Mnif[63] suggested meaningfulness as a data quality dimension. Innovativeness is the extent to which it is possible to bring value and meaning continuously by identifying and understanding specific objects and phenomena. The group of attributes related to value innovation can include representativeness, predictability, interpretability, and innovativeness, which are indicative of the capability to search out the identities and meanings of objects and phenomena using diverse interpretation and diagnosis tools and to predict

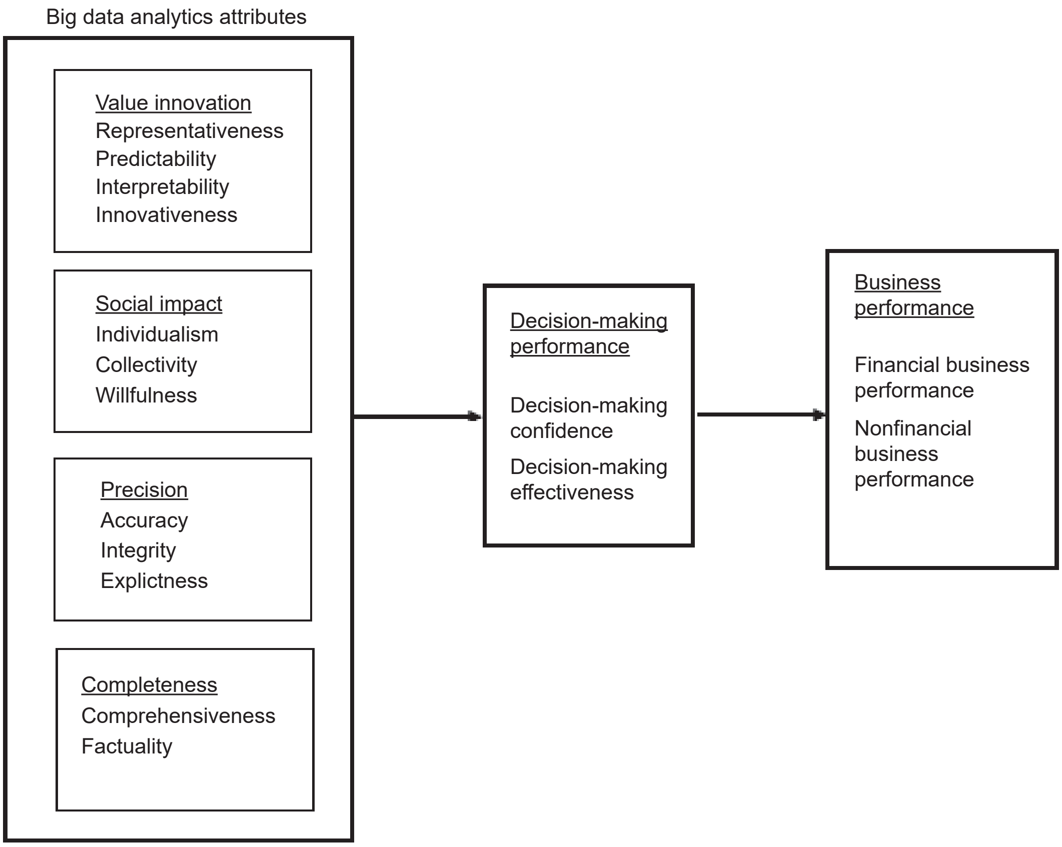

Fig. 1 Research model.

specific situations. These attributes can be suggested by analyzing the ontological essence of data quality based on the representativeness of information systems[35] or with statistical process control and evaluations of data forms and meanings using semiotics. These attributes can provide guidelines for the condition of the data analysis design to ensure the satisfaction of the BDA system's designers according to a design-oriented approach toward a proper level of data quality.

Based on previous studies of data quality attributes[34−36], our study suggests that the attributes of value innovation, which include representativeness, predictability, interpretability, and innovativeness, have a positive effect on the decision-making confidence and effectiveness.

Hypothesis 1: The representativeness of BDA quality has a positive effect on decision-making confidence.

Hypothesis 2: The representativeness of BDA quality has a positive effect on decision-making effectiveness.

Hypothesis 3: The predictability of BDA quality has a positive effect on decision-making confidence.

Hypothesis 4: The predictability of BDA quality has a positive effect on decision-making effectiveness.

Hypothesis 5: The interpretability of BDA quality has a positive effect on decision-making confidence.

Hypothesis 6: The interpretability of BDA quality has a positive effect on decision-making effectiveness.

Hypothesis 7: The innovativeness of BDA quality has a positive effect on decision-making confidence.

Hypothesis 8: The innovativeness of BDA quality has a positive effect on decision-making effectiveness.

3.2 Social impact in BDA and decision-making performance

Another group of BDA quality is social impact, which encompasses individualism, collectivity, and willfulness. Individualism is the extent to which one is oriented toward one's routine, subjective status, and tendency. Moges et al.[64] suggested alignment as a similar concept to individualism. Collectivity is the extent to which empathy and interaction exist in social relationships. Willfulness is the extent to which emotional, political, or economical tendencies are purposefully represented, and this provides more ramification in the context of data analysis from social networks, as social capital is having a great effect on their continuous usage. Attributes of social impact include individualism, collectivity, and willfulness, which are indicative of the extent that shared social values are pursued. The structure of big data is created from the social relationship, and the analysis of such data has a different effect on decision-making performance outcomes. The attributes of big data quality can depend on the perspectives of demanders, who consider the data as products or services in specific situations and evaluate whether the data are appropriate for their use[39−41].

Our study extended the attributes of big data quality, which represents the impact of social media, beyond the attributes for customer requirements such as timeliness and reliability[45]. The attributes of big data quality include both the organizational data's generic attributes of quality and attributes based on the social impact from social media. The attributes created from social impact are established in a real manner[35], and attributes such as individualism, collectivity, and willfulness should be considered when big data are mainly collected through social media[35, 36]. Thus, our study suggested that the attributes of social impact, which include individualism, collectivity, and willful representativeness, have a positive effect on decision-making confidence and effectiveness.

Hypothesis 9: Individualism of BDA quality has a positive effect on decision-making confidence.

Hypothesis 10: Individualism of BDA quality has a positive effect on decision-making effectiveness.

Hypothesis 11: Collectivity of BDA quality has a positive effect on decision-making confidence.

Hypothesis 12: Collectivity of BDA quality has a positive effect on decision-making effectiveness.

Hypothesis 13: Willfulness of BDA quality has a positive effect on decision-making confidence.

Hypothesis 14: Willfulness of BDA quality has a positive effect on decision-making effectiveness.

3.3 Precision in BDA and decision-making performance

The category of BDA quality precision describes the standards, and the forms of data are consistent and without errors, including accuracy, integrity, and explicitness. Accuracy is the extent to which data are presented in a factual manner, requiring no corrections[67]. Explicitness is the extent to which data are difficult to describe in terms of specific characteristics. Data integrity verification is crucial for outsourced big data in the cloud environment[21]. The IoT enables automatic collection through distributed remote sensors, and this requires an automatic data quality control system to ensure the veracity of the data[68]. Big data are not built by a deliberate design and development process. Instead, they are mainly created through voluntarily participation by users via social media or Internet web browsing. As a result, diverse machine sensors and the quality management and refinement of these unstructured and diverse data have become of concern. Accuracy, integrity, and explicitness are the attributes required for a structured relational database. They also represent the required attributes for big data quality; these factors can affect both the decision-making performance and business performance[34−36]. Thus, the following hypotheses were suggested:

Hypothesis 15: The accuracy of the BDA quality has a positive effect on decision-making confidence.

Hypothesis 16: The accuracy of the BDA quality has a positive effect on decision-making effectiveness.

Hypothesis 17: The integrity of the BDA quality has a positive effect on decision-making confidence.

Hypothesis 18: The integrity of the BDA quality has a positive effect on decision-making effectiveness.

Hypothesis 19: Explicitness of the BDA quality has a positive effect on decision-making confidence.

Hypothesis 20: Explicitness of the BDA quality has a positive effect on decision-making effectiveness.

3.4 Completeness in BDA and decision-making performance

The comprehensiveness group of BDA quality represents the extent to which data represent phenomena or objects to a certain depth and scope. It also includes comprehensiveness and factuality. Factuality is the extent to which data are based on trustworthy and reliable facts on a specific aspect. The group of attributes of completeness represents how big data are based on facts and are fully accessible, providing adequate amounts of details and contents. These attributes in previous studies on data quality are consistency, traceability, timeliness, reliability, and completeness[11, 36, 44, 46, 47, 51, 64, 69]. As the generic crucial criteria for user satisfaction and information systems success, these attributes of completeness can positively affect the decision-making performance and business performance outcomes[34−36]. Thus, the following hypotheses were suggested:

Hypothesis 21: Comprehensiveness of the BDA quality has a positive effect on decision-making confidence.

Hypothesis 22: Comprehensiveness of the BDA quality has a positive effect on decision-making effectiveness.

Hypothesis 23: Factuality of the BDA quality has a positive effect on decision-making confidence.

Hypothesis 24: Factuality of the BDA quality has a positive effect on decision-making effectiveness.

Big data have been posited to have an effect on firm performance[18, 70]. Decision-making performance is described as the extent to which BDA systems can support the decision makers' decision-making and problem-solving processes. Decision-making confidence and effectiveness have been suggested as two of the most important aspects of decision making[49]. Our study considered decision-making reliability and effectiveness as two factors that comprise decision-making performance in analyzing data from transportation, insurance, financial businesses, and social media sources. Information quality and system quality both affect the decision-making performance[55, 56], as decision makers consider information and system quality attributes as important aspects of an information system[48]. Decision-making outcomes can be derived from the fitness or financial economics of decision alternatives[55]. Sales and net profits as the decision-making quality and decision-making performance represent the confidence that a decision analysis system can provide the best possible solution[56].

Quality management activities can improve financial (i.e., sales, return on investment, and return on assets) and operational (i.e., productivity, employee satisfaction, and employee turnover) performances[57]. For instance, geospatial big data management algorithms can affect a big-data-driven smart urban economy[2, 71], and knowledge acquisition through affiliations with online knowledge networks that affect business performance[72, 73]. Business performance in this sense can include internal performance metrics such as employee productivity, manufacturing costs, and inventory costs, as well as external performance metrics such as the corporate brand image, market ratio, and customer loyalty. Business performance can encompass financial performance aspects such as the return on marketing, sales, profitability, and total assets, as well as nonfinancial performance metrics such as customer satisfaction, customer retention ratio, product development capabilities, and quality improvements. Our study posited that decision-making confidence in decisions related to problems and the effectiveness of decision-making[55, 56] have an effect on financial and nonfinancial business performance outcomes.

Hypothesis 25: Decision-making confidence has a positive effect on financial business performance.

Hypothesis 26: Decision-making confidence has a positive effect on nonfinancial business performance.

Hypothesis 27: Decision-making effectiveness has a positive effect on financial business performance.

Hypothesis 28: Decision-making effectiveness has a positive effect on nonfinancial business performance.

4 Method

4.1 Measurement of research variables

The conceptual definitions of the research variables are presented in Table 1. The measurement items are given in Table 2. The measurement items consist of 66 items for the BDA attributes and 6 items for decision-making performance, along with 16 items for business performance. All items were measured on a five-point Likert-type scale.

4.2 Data collection

The data were collected from employees of public and

Table 1 Conceptual definitions of attributes for research variables.

Group of variables		Variable	Operational definition
Value innovation	Attributes that indicate the extent that data analysis quality is continuously pursuing diverse diagnosis, interpretation, and prediction about objects and phenomena for understanding identity and meaning.	Representativeness	Extent that the identity and meanings of objects are able to be described or explained.
		Predictability	Extent that phenomena are fully explainable and predictable.
		Interpretability	Extent that objects are interpretable in terms of causal relations.
		Innovativeness	Extent that it is very fast in capturing the meanings and values of objects and continuous in consecutively creating meanings.
Social influence	Attributes that indicate the extent that data analysis quality is pursuing shred values of individuals, regions, and nations.	Individualism	Extent that it is oriented to individual routines and tendency if whatsoever.
		Collectivity	Extent that social empathy exists in relations if whatsoever.
		Willfulness	Extent that it is intentionally leading to represent emotional, political, and economical tendency if whatsoever.
Precision	Attributes that indicate the extent that data analysis quality is pursuing the exact format, standard according to designed structure.	Accuracy	Extent that correction for errors is not required.
		Integrity	Extent that standards and formats are represented without errors.
		Explicitness	Extent that it is easy to characterize the traits.
Completeness	Attributes that indicate the extent that data analysis quality is pursuing the complete volume, depth, and scope of information.	Comprehensiveness	Extent that it is possible to represent specific matter in appropriate scope and depth.
		Factuality	Extent that data are converged into specific meaningful facts.
Decision-making performance	Extent that data analysis is supporting decision making and problem solving.	Decision-making confidence	Extent that decision-making is targeting decision goals and is preferred by decision-making, and re-applicable in the future.
		Decision-making effectiveness	Extent that decision-making effectiveness is increased.
Business performance	Extent that data analysis is producing financial and nonfinancial business performance.	Financial business performance	Extent that financial measures such as return to marketing, total assets, productivity, or market ratio are increased.
		Nonfinancial business performance	Extent that customer satisfaction, development capability, or product (or service) quality increased or error rate in products is reduced.

Table 2 Measurement items for the research variables.

Variable	Item	Reference
Representativeness	BDA shows embedded meanings.	[34]
	BDA can describe phenomena.	
	BDA can explain objects or phenomena.	
	Keywords extracted from BDA are representative.	
	BDA shows identity of individuals or objects.	
	BDA shows trends of phenomena.	
	BDA enables data visualization.	
Predictability	BDA can be used to forecast objects.	[51]
	BDA can provide predictive capability for specific situation at specific time.	
	BDA can be used to improve specific situation at specific time.	
	BDA can be used to obtain new meanings.	
	BDA can be used to provide insights to the situation.	
	BDA can be used to make diagnosis for phenomena.	
Interpretability	BDA can be used to show the difference between groups.	[51, 74]
	BDA can be used to show the relationship among objects or events.	
	BDA can be used to match causes and effects.	
	BDA can be used to show the reasons for specific phenomena.	
Innovativeness	BDA can be used to create meanings sequentially if whatsoever.	[51, 75]
	BDA can be used to create meanings continuously if whatsoever.	
	BDA can be used to identify specific objects or phenomena if whatsoever.	
	BDA can be used to investigate specific objects or phenomena if whatsoever.	
	BDA can be used to alert specific objects or phenomena if whatsoever.	
	BDA can be used to signal extraordinary objects or phenomena if whatsoever.	
	BDA can be used to create diverse values of specific objects or phenomena if whatsoever.	
	BDA can be used to enable rapid review of results at wanted time.	
Individualism	BDA can be used to show individual life.	[74]
	BDA can be used to show individual status.	
	BDA can be used to show individual routines.	
	BDA can be used to show subjective information.	
	BDA can be used to show individual tendency.	
	BDA can be used to show time sensitive information.	
Collectivity	BDA can be used to show empathy in social relationships.	
	BDA can be used to provide recommendation data by others.	
	BDA can be used to show the influence from others.	
	BDA can be used to show empathy by a majority of others.	
Willfulness	BDA can be used to show the national tendency of people if whatsoever.	[74, 76]
	BDA can be used to show emotional tendency if whatsoever.	
	BDA can be used to show the lead by specific trends if whatsoever.	
	BDA can be used to show hidden intentions if whatsoever.	
	BDA can be used to show publicity information if whatsoever.	
	BDA can be used to show intentional information if whatsoever.	
	BDA can be used to show political information if whatsoever.	
	BDA can be used to show political tendency if whatsoever.	
	BDA can be used to show personal emotional information if whatsoever.	
	BDA can be used to show the traits of information sources if whatsoever.	
	BDA can be used to show irresponsible information if whatsoever.	

(To be continued)

Table 2 Measurement items for the research variables. (Continued)

Variable	Item	Reference
Accuracy	BDA can be used to show adherence to standards or formats. BDA can be used to show right or wrong information. BDA can be used to show freedom from error. BDA can be used to show precise information on specific area.	[74]
Integrity	BDA can be used to show regularity of information. BDA can be used to show consistency of information. BDA can be used to show no defects of information.	[77−79]
Explicitness (inversely rated)	BDA can be used to show rough information. BDA can be used to show semantic limitations of information. BDA can be used to show difficulty in determining trends.	[51, 74, 80]
Comprehensiveness	BDA can be used to show enough depth of information. BDA can be used to show enough scope of information. BDA can be used to show diverse sources of information.	[36, 74, 80]
Factuality	BDA can be used to show honest information. BDA can be used to show trustful information. BDA can be used to show consistency between thoughts and presentation. BDA can be used to show the convergence into specific meanings. BDA can be used to show accurate information following facts.	[53, 68, 80]
Decision-making Confidence	BDA can be trusted to help choosing the best alternative according to analysis goals or intentions. BDA can be trusted to be used for choosing the most wanted alternative. If I would have to make decision making again, BDA can be trusted to be used. BDA can be trusted to be used to select the best operable alternative within the allocated budget.	[55, 74, 80]
Decision-making effectiveness	The corporate decision making process effectiveness is increased due to BDA. The corporate decision making process is improved by obtaining objectives using a smaller amount of resources due to BDA. The corporate decision making process time is decreased due to BDA.	[56, 80]
Financial business performance	The corporate sales amount is increased due to BDA-based decision making. The corporate market ratio is increased due to BDA. The corporate return to marketing is increased due to BDA. The corporate business productivity is increased due to BDA. The corporate total assets are increased due to BDA. The corporate ratio of value added is increased due to BDA.	[59, 81, 82]
Nonfinancial business performance	The customer satisfaction is increased due to BDA-based decision-making. The defects rate in products is reduced due to BDA. The corporate business lead time is increased due to BDA. The quality level of products is increased due to BDA. The product development capability is increased due to BDA. The customer repurchasing rate is increased due to BDA.	[59, 81, 82]

private organizations that used big data analyses to support their public or private business activities in Republic of Korea. The target sample was obtained from a public list of organizations provided by the Big Data Association in Republic of Korea. The questionnaire was reviewed by interviewing ten experts in BDA in academia and business to improve the overall composition of the items and the comprehensibility of the sentences. The Google online survey method was utilized during June and July of 2020 after solicitation and confirmation calls were delivered by the Big Data Association in Republic of Korea. The final received sample was 412, and 30 responses were excluded due to incomplete or unfaithful answers, leaving the final sample of 382 responses used in our study.

The distribution of the final sample is presented in Table 3. The majority of respondents were male (78.8%), in their 40s or 50s (54.6%), college graduates (58.6%), working in the ICT industry (35.1%) or in the public sector (23.0%), and had less than or equal to two years of experience with big data technology (75.4%).

5 Result

5.1 Measurement properties of variables

This study conducted a confirmatory factor analysis to test the measurement model using AMOS 26.0. An exploratory factor analysis was conducted to examine whether the items for each variable belonged to the same factor (see Tables 4 and 5). Items with factor loadings of less than 0.5 were excluded. The items intended to measure each variable were factored into the same factor group and had factor loadings greater than 0.5 to establish convergent and discriminant validity of the variables. The Cronbach alphas were all greater than 0.7, which established reliability of the variables.

The confirmatory analysis results are presented in Tables 6 and 7. The fitness of the measurement model was within the appropriate range. Composite construct

Table 3 Distribution of sample (*N*=382).

Category	Item	Frequency	Percentage (%)
Gender	Male	301	78.8
	Female	81	21.2
Age	20−29	11	2.9
	30−39	84	22.1
	40−49	92	24.0
	50−59	117	30.6
	Older than 60	78	20.4
Education	High school graduate	12	3.1
	Community college degree	15	3.9
	Undergraduate degree	224	58.6
	Graduate degree	131	34.4
Industry sector	Public	89	23.0
	Finance/insurance	27	7.0
	Medical/health	28	7.0
	ICT	134	35.1
	Logistics/retail	20	5.1
	Tourism	26	6.8
	Research/manufacturing	20	5.1
	Others	38	9.9
Position	Employee	71	18.6
	Assistant manager	35	9.1
	Manager	56	15.5
	Assistant team head	49	14.6
	Team head	76	19.9
	Executive	74	19.4
	CEO	21	5.5
Usage experience of BDA	Less than one year	126	32.9
	1 year ⩽ usage experience ⩽ 2 years	162	42.5
	2 years < usage experience ⩽ 3 years	41	10.7
	3 years < usage experience ⩽ 4 years	20	5.3
	4 years < usage experience ⩽ 5 years	18	4.7
	More than 5 years	15	3.9

Table 4 Exploratory factor analysis results for the BDA attributes.

Group of variables	Variable	Item	Factor loading	Eigen value	Variance explained	Cronbach alpha
Value innovation	Representativeness	REP1	0.921	4.102	24.117	0.926
		REP3	0.917			
		REP4	0.912			
		REP5	0.846			
		REP6	0.795			
		REP7	0.776			
	Predictability	EXP2	0.846	3.851	17.924	0.874
		EXP1	0.822			
		EXP3	0.797			
		EXP5	0.768			
		EXP4	0.753			
		EXP6	0.751			
	Interpretability	INT1	0.878	2.286	14.435	0.739
		INT3	0.866			
		INT2	0.861			
		INT4	0.764			
	Innovativeness Performance	INN1	0.940	2.527	13.917	0.815
		INN4	0.918			
		INN2	0.906			
		INN5	0.792			
		INN7	0.775			
		INN6	0.761			
Social Influence	Individualism	IND1	0.916	2.579	23.612	0.916
		IND4	0.835			
		IND3	0.730			
		IND2	0.723			
		IND5	0.712			
		IND6	0.710			
	Collectivity	COL3	0.915	2.387	21.548	0.778
		COL2	0.901			
		COL1	0.836			
		COL4	0.722			
	Willfulness	WIL2	0.908	2.615	19.296	0.710
		WIL1	0.897			
		WIL5	0.874			
		WIL6	0.832			
		WIL8	0.776			
		WIL7	0.764			
		WIL9	0.755			
Precision	Accuracy	ACC1	0.846	2.282	33.015	0.701
		ACC3	0.767			
		ACC2	0.713			
		ACC4	0.685			
	Integrity	INT2	0.804	2.016	27.167	0.714
		INT1	0.789			
		INT3	0.730			
	Explicitness (inversely rated)	EXP1	0.916	2.119	20.163	0.721
		EXP2	0.902			
		EXP3	0.865			

(To be continued)

Table 4 Exploratory factor analysis results for the BDA attributes. (Continued)

Group of variables	Variable	Item	Factor loading	Eigen value	Variance explained	Cronbach alpha
Completeness	Comprehensiveness	COM2	0.790	2.287	23.414	0.926
		COM1	0.768			
		COM3	0.756			
	Factuality(factual)	FAC2	0.792	2.868	21.635	0.784
		FAC1	0.788			
		FAC3	0.766			
		FAC4	0.741			
		FAC5	0.704			

Table 5 Exploratory factor analysis results for decision-making performance and business performance.

Group of variables	Variable	Item	Factor loading	Eigen value	Variance explained	Cronbach alpha
Decision-making performance	Decision-making confidence	DECO1	0.775	2.563	27.849	0.876
		DECO3	0.756			
		DECO2	0.738			
		DECO4	0.732			
	Decision-making effectiveness	DEEF2	0.863	2.852	25.873	0.738
		DEEF1	0.786			
		DEEF3	0.778			
Business performance	Financial business performance	FIPE3	0.863	2.929	28.680	0.721
		FIPE2	0.832			
		FIPE1	0.767			
		FIPE4	0.745			
		FIPE6	0.721			
		FIPE5	0.716			
	Nonfinancial business performance	NFPE1	0.915	2.806	33.298	0.872
		NFPE2	0.907			
		NFPE6	0.894			
		NFPE4	0.867			
		NFPE5	0.820			
		NFPE3	0.773			

reliability rates for all variables were greater than 0.7, which established reliability of the variables. The factor loadings of the items and the average variance extracted were all greater than 0.5, indicating convergent validity of the variables. The squares of the correlations among the variables were smaller than the average variance extracted, which established the discriminant validity of variables (Table 8). Furthermore, the ± 2 × standard deviation correlations among the variables did not include one, which also established discriminant validity[83].

5.2 Hypotheses testing

The estimation of the structural model and test results of the hypotheses are given in Table 9 and Fig. 2. The effects of nine attributes on the decision-making performance were significant. The effects of accuracy, integrity, and explicitness on the decision-making performance were not significant. The effects of the decision-making performance on the business performance were significant, except for the effect of decision-making effectiveness on financial business performance.

6 Discussion

Our study tried to fill the research gap in the attributes of data analyses affecting the adoption and usage of big data since previous studies concentrated on data attributes or management factors that affected the adoption and usage of big data[20, 22−24, 26] as well as big data management[25]. This was done by showing a diverse set of data analysis attributes for BDA, which

Table 6 Confirmatory factor analysis results for the attributes of data analysis quality.

Variable	Item	Standard factor loading	Standard error	Composite reliability	Composite construct reliability	Average variance extracted
Representativeness	REP1	0.935	—	—	0.901	0.784
	REP3	0.921	0.026	42.861		
	REP4	0.810	0.034	26.989		
	REP5	0.805	0.029	33.510		
	REP6	0.749	0.037	22.037		
	REP7	0.693	0.105	9.178		
Predictability	EXP2	0.787	—	—	0.819	0.612
	EXP1	0.776	0.081	9.380		
	EXP3	0.697	0.100	9.816		
	EXP5	0.690	0.081	9.520		
	EXP4	0.689	0.089	12.535		
	EXP6	0.618	0.083	13.536		
Interpretability	INT1	0.825	—	—	0.847	0.653
	INT3	0.752	0.076	12.947		
	INT2	0.694	0.089	12.643		
	INT4	0.683	0.083	12.722		
Innovativeness	INN1	0.885	—	—	0.835	0.637
	INN4	0.777	0.076	13.062		
	INN2	0.760	0.085	12.575		
	INN5	0.691	0.089	11.961		
	INN7	0.684	0.079	12.575		
	INN6	0.609	0.087	13.524		
Individualism	IND1	0.892	—	—	0.907	0.765
	IND4	0.858	0.058	23.936		
	IND3	0.808	0.057	22.863		
	IND2	0.774	0.048	17.806		
	IND5	0.747	0.053	33.037		
	IND6	0.652	0.038	32.328		
Collectivity	COL3	0.808	—	—	0.835	0.568
	COL2	0.742	0.102	12.297		
	COL1	0.679	0.085	12.005		
	COL4	0.584	0.105	11.123		
Willfulness	WIL2	0.831	—	—	0.932	0.824
	WIL1	0.827	0.049	27.364		
	WIL5	0.825	0.051	27.310		
	WIL6	0.813	0.046	28.718		
	WIL8	0.787	0.069	23.976		
	WIL7	0.768	0.042	22.811		
	WIL9	0.758	0.054	21.046		
Accuracy	ACC1	0.811	—	—	0.861	0.591
	ACC3	0.783	0.071	19.236		
	ACC2	0.758	0.026	17.372		
	ACC4	0.707	0.058	18.058		
Integrity	INT2	0.819	—	—	0.873	0.728
	INT1	0.784	0.057	16.247		
	INT3	0.715	0.061	17.352		

(To be continued)

Table 6 Confirmatory factor analysis results for the attributes of data analysis quality. (Continued)

Variable	Item	Standard factor loading	Standard error	Composite reliability	Composite construct reliability	Average variance extracted
Explicitness (inversely rated)	EXP1	0.837	—	—	0.940	0.863
	EXP2	0.807	0.048	28.081		
	EXP3	0.761	0.052	27.152		
Comprehensiveness	COM2	0.846	—	—	0.836	0.630
	COM1	0.728	0.056	12.935		
	COM3	0.665	0.071	11.940		
Factuality(factual)	FAC2	0.926	—	—	0.942	0.826
	FAC1	0.844	0.035	40.852		
	FAC3	0.812	0.041	28.977		
	FAC4	0.806	0.038	33.518		
	FAC5	0.737	0.037	22.025		

Note: χ^2 (Chi-square statistic) = 2357.178, normed χ^2 = 1.916, goodness of fit index (GFI) = 0.875, adjusted GFI (AGFI) = 0.908, root mean squared error of approximation (RMSEA) = 0.047, normed fit index (NFI) == 0.832, comparative fit index (CFI) = 0.928.

Table 7 Confirmatory factor analysis results for the decision-making performance and business performance.

Variable	Item	Standard factor loading	Standard error	Composite reliability	Composite construct reliability	Average variance extracted	Cronbach alpha
Decision-making confidence	DECO1	0.818	—	—	0.847	0.590	0.897
	DECO3	0.786	0.061	17.256			
	DECO2	0.756	0.06	18.371			
	DECO4	0.747	0.059	17.055			
Decision-making effectiveness	DEEF2	0.859	—	—	0.813	0.635	0.793
	DEEF1	0.737	0.057	12.937			
	DEEF3	0.664	0.051	11.950			
Financial business performance	FIPE3	0.885	—	—	0.838	0.697	0.764
	FIPE2	0.787	0.076	14.034			
	FIPE1	0.776	0.085	13.525			
	FIPE4	0.731	0.070	12.972			
	FIPE6	0.694	0.085	12.528			
	FIPE5	0.609	0.071	12.545			
Nonfinancial business performance	NFPE1	0.926	—	—	0.923	0.805	0.853
	NFPE2	0.917	0.035	34.861			
	NFPE6	0.882	0.041	28.977			
	NFPE4	0.882	0.029	33.528			
	NFPE5	0.734	0.045	24.039			
	NFPE3	0.697	0.106	9.268			

were classified into four groups (value innovation, social impact, precision, and completeness of BDA quality). Our study also further stressed value innovation and social impact, as they have received relatively less attention in previous studies compared to other factors in influencing the decision-making performance.

In regards to value innovation, firstly, the positive effect of representativeness on the decision-making performance indicated that BDA can extract the meanings embedded in data, describe or explain the identity of objects, and represent and visualize the trends of the objects, which increased the decision-making confidence and effectiveness. The effect of predictability on the decision-making performance showed that BDA provided predictions of specific phenomena and derived diagnoses and future directions and insights into certain objects, all of which enhanced the decision-making confidence and effectiveness.

The significant effect of interpretability on decision-

Table 8 Correlations among variables.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Representativeness (1)	0.784	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Predictability (2)	0.324**	0.612	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Interpretability (3)	0.117*	0.228**	0.653	—	—	—	—	—	—	—	—	—	—	—	—	—
Innovativeness (4)	0.235**	0.263**	0.341**	0.637	—	—	—	—	—	—	—	—	—	—	—	—
Individualism (5)	−0.406**	−0.263**	−0.088*	−0.162**	0.765	—	—	—	—	—	—	—	—	—	—	—
Collectivity (6)	0.223**	0.263**	0.317**	0.524**	−0.138**	0.568	—	—	—	—	—	—	—	—	—	—
Willfulness (7)	−0.025	−0.028	−0.016	−0.012	0.016	−0.115*	0.824	—	—	—	—	—	—	—	—	—
Accuracy (8)	−0.679**	−0.246**	−0.061	−0.199**	0.552**	−0.176**	−0.007	0.591	—	—	—	—	—	—	—	—
Integrity (9)	0.475**	0.538**	0.198**	0.276**	−0.289**	0.259**	−0.026	−0.519**	0.728	—	—	—	—	—	—	—
Explicitness (10)	−0.005	−0.021	0.017	0.048	0.032	0.047	0.067	−0.043	−0.041	0.863	—	—	—	—	—	—
Comprehensiveness (11)	0.379**	0.531**	0.406**	0.529**	−0.258**	0.522**	0.013	−0.305**	0.502**	0.008	0.630	—	—	—	—	—
Factuality (12)	0.215**	0.249**	0.287**	0.373**	−0.142**	0.398**	0.045	−0.167**	0.341**	0.048	0.478**	0.826	—	—	—	—
Decision-making confidence (13)	0.169**	0.138**	0.337**	0.457**	−0.112**	0.456**	−0.061	−0.158**	0.174**	0.058	0.365**	0.277**	0.590	—	—	—
Decision-making effectiveness (14)	−0.003	−0.041	0.017	0.048	0.024	0.047	0.067	−0.028	−0.043	0.341**	0.352**	0.048	0.461**	0.635	—	—
Financial business performance (15)	0.179**	0.236**	0.328**	0.367**	−0.070	0.362**	−0.026	−0.112*	0.177**	0.037	0.461**	0.372**	0.338**	0.452**	0.697	—
Nonfinancial business performance (16)	0.228**	0.197**	0.249**	0.386**	−0.086*	0.384**	−0.023	−0.189**	0.256**	0.081*	0.440**	0.398**	0.365**	0.380**	0.267**	0.805

Note: The numbers in the diagonals are average variance extracted. * $p<0.05$ and ** $p<0.01$.

making performance indicated that when BDA showed differences among events as well as objects and relationships between causes and effects, or when it explained the reasons behind certain phenomena, it boosted the decision-making confidence and effectiveness.

Innovativeness had a positive effect on decision-making performance, indicating that BDA provided sequential and continuous meanings in a short time, provided alerts of specific situations, signaled exceptional situations and objects, and created diverse insights or values from patterns of phenomena, thus increasing decision-making confidence and effectiveness.

Individualism positively affected the decision-making performance, showing that BDA can delve into the patterns of individual behaviors or the routine or subjective trends of individual statuses that vary over time. This in turn positively affected decision-making confidence and effectiveness.

The effect of collectivity on decision-making performance showed that big data collected from communication data with others and BDA can be used to investigate the empathy of belonging to a group and the relationships with other members in groups. Thus, BDA can improve the decision-making confidence and effectiveness.

Willfulness had a positive effect on decision-making performance. This indicates that when BDA provided the emotional skewedness of individuals in a proactive manner and the tendencies of people, and when targeting a goal-oriented investigation of, for instance, political or campaign activities, it increased the decision-making confidence and effectiveness.

The significant effects of representativeness, predictability, interpretability, and innovativeness as related to value innovation, and individuality, collectivity, and willfulness as related to social impact on the decision-making confidence and decision-making effectiveness are in line with or supporting previous studies[7, 9, 26, 27]. This indicates that data quality has been a crucial factor affecting big data performance. This further shows that the value innovation and social impact of the BDA quality, which have received relatively less attention in previous studies, are crucial attribute groups for BDA quality as influencing decision-making performance.

The effect of accuracy on decision-making performance was insignificant, explaining that adherence to standards, formats, or correctness in creating decision alternatives and precision in proving analysis results are not highly important when seeking to increase decision-making confidence and effectiveness. The effect of integrity on decision-making performance was not significant, indicating that the regularity, consistency, and correctness of the

Table 9 Test results of hypothesized paths.

Path	Estimate	Standard error	*t* value	*p*-value	Test result
Representativeness → decision-making confidence	0.298	0.065	3.494	0.000***	Accepted
Representativeness → decision-making effectiveness	0.276	0.052	3.583	0.000***	Accepted
Predictability → decision-making confidence	0.198	0.073	2.298	0.003**	Accepted
Predictability → decision-making effectiveness	0.298	0.042	5.556	0.000***	Accepted
Interpretability → decision-making confidence	0.279	0.046	3.458	0.000***	Accepted
Interpretability → decision-making effectiveness	0.212	0.029	3.126	0.002**	Accepted
Innovativeness → decision-making confidence	0.132	0.043	2.519	0.004**	Accepted
Innovativeness → decision-making effectiveness	0.281	0.058	3.724	0.000***	Accepted
Individualism → decision-making confidence	0.228	0.037	3.142	0.002**	Accepted
Individualism → decision-making effectiveness	0.189	0.051	2.528	0.004**	Accepted
Collectivity → decision-making confidence	0.201	0.112	3.115	0.001**	Accepted
Collectivity → decision-making effectiveness	0.173	0.113	2.091	0.021*	Accepted
Willfulness → decision-making confidence	0.367	0.056	5.213	0.000***	Accepted
Willfulness → decision-making effectiveness	0.147	0.053	2.125	0.018*	Accepted
Accuracy → decision-making confidence	−0.012	0.043	−0.074	0.598	Rejected
Accuracy → decision-making effectiveness	0.092	0.074	1.335	0.176	Rejected
Integrity → decision-making confidence	−0.034	0.035	−0.857	0.353	Rejected
Integrity → decision-making effectiveness	−0.045	0.048	−0.726	0.358	Rejected
Explicitness → decision-making confidence	0.076	0.057	1.347	0.194	Rejected
Explicitness → decision-making effectiveness	0.047	0.062	0.726	0.381	Rejected
Comprehensiveness → decision-making confidence	0.247	0.048	4.852	0.006**	Accepted
Comprehensiveness → decision-making effectiveness	0.204	0.037	3.391	0.001**	Accepted
Factuality → decision-making confidence	0.397	0.047	6.784	0.000***	Accepted
Factuality → decision-making effectiveness	0.227	0.053	3.368	0.002**	Accepted
Decision-making confidence → financial business performance	0.199	0.031	2.860	0.003**	Accepted
Decision-making confidence → nonfinancial business performance	0.215	0.058	3.318	0.002**	Accepted
Decision-making effectiveness → financial business performance	0.072	0.079	1.365	0.193	Rejected
Decision-making effectiveness → nonfinancial business performance	0.326	0.082	3.572	0.000***	Accepted

Note: χ^2 (Chi-square statistic) = 2578.416, normed χ^2 = 1.884, GFI = 0.925, AGFI = 0.908, RMSEA = 0.056, NFI == 0.897, CFI = 0.925. * p<0.05, ** p<0.01, and *** p<0.001.

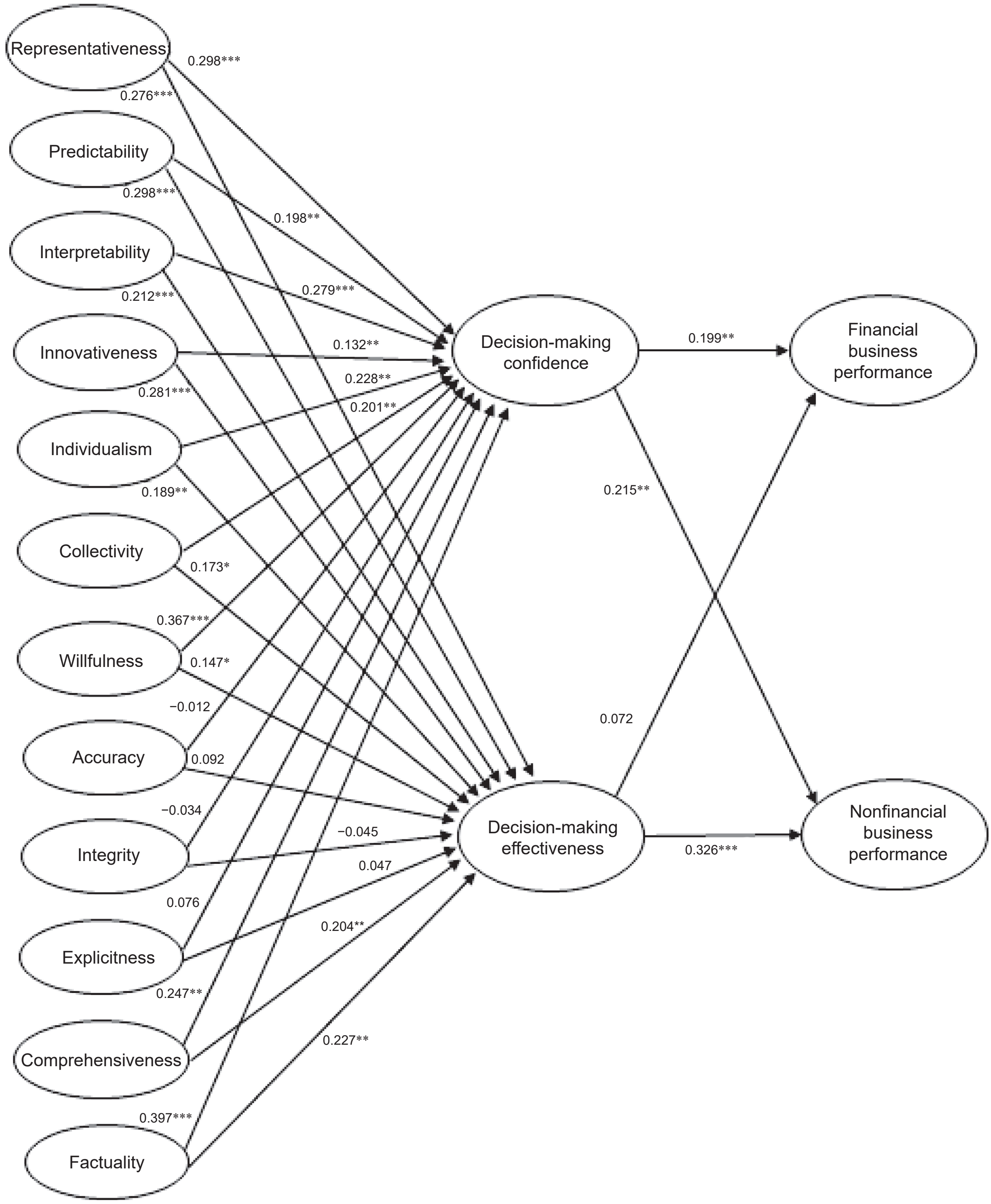

Fig. 2 Estimated structural model.

information provided did not have strong effects on the decision-making confidence and effectiveness. Furthermore, explicitness did not affect decision-making performance, showing that BDA had limitations in providing clear semantic implications about specific phenomena and objects and offering apparent presentations of results. This lowered the decision-making confidence and effectiveness.

Comprehensiveness had a significant effect on decision-making performance, and this indicates that BDA provided results in sufficient depth when reporting the content and scope of the domains of a problem, as well as diversity of the sources from which the data were collected. These factors can lead to decision-making confidence and effectiveness. Furthermore, factuality had a positive influence on decision-making performance, indicating that BDA provides results based on facts and transforms any intentions of users into appropriate implementable reports with meaningful directions, thus improving decision-making confidence and effectiveness.

Decision-making confidence had a positive effect on financial and nonfinancial business performance. This shows that as users have greater confidence in decision making, this will result in greater sales, a better return to market, more total assets, a better ratio of value added as well as improvements in customer satisfaction, quality levels, product development capabilities, and customer retention. The significant effect of decision-making effectiveness on nonfinancial business performance and not on financial business performance indicates that decision-making effectiveness is more directly related to nonfinancial than financial business performance outcomes. While decision-making effectiveness represents effectiveness and efficiency in business processes, this does not directly result in an improvement in financial performance. Instead, it increases nonfinancial performance metrics such as customer satisfaction, quality levels, product development capabilities, and customer retention more.

This study investigated whether the existence of BDA attributes can ultimately lead to better business performance. As the studies are lacking regading the attributes of information analyses[7, 26], our study investigated the relationships among the attributes of BDA, decision-making performance outcomes, satisfaction levels, and business performance based on the research gap in the attributes of data analyses affecting the adoption and usage of big data.

7 Conclusion and Implication

This study discussed the BDA attributes, which were classified into four groups (value innovation, social impact, precision, and completeness of BDA quality) and which influenced the decision-making performance and business performance outcomes. A structural equation modeling analysis using 382 responses from practitioners of BDA indicated that the attributes of representativeness, predictability, interpretability, and innovativeness (which were all related to value innovation) greatly enhanced the decision-making confidence and decision-making effectiveness of decision makers who make decisions using big data. Individuality, collectivity, and willfulness, all of which are linked to social impact, greatly improved the decision-making confidence and decision-making effectiveness of decision makers who make decisions using big data. Comprehensiveness, factuality, and realism, which were factors of completeness, greatly improved the decision-making confidence and decision-making effectiveness of decision makers who make decisions using big data. Furthermore, the higher the decision-making confidence of decision makers using big data is, the better the company’s financial performance. In addition, high decision-making confidence using big data was found to improve nonfinancial performance metrics such as customer satisfaction, quality levels, and product development capabilities. Furthermore, high decision-making effectiveness with big data was shown to improve nonfinancial performance outcomes.

There are limitations as well as future research directions here. First, our model is exploratory in nature, as it suggests the attributes for BDA quality. Future studies can expand the list of attributes by adding new attributes or examining the validity and generalizability of our attributes and their groups, or applying conditions of our attributes through an additional empirical study. Second, the sample here was composed of organizations employing BDA, and the results should be viewed with caution with respect to the extent of the BDA capabilities, expertise, and usage experience. Future studies can reexamine the generalizability of our model by using a sample with different BDA capabilities, expertise levels, and usage experiences. Third, the effects of BDA attributes should be different between public and private organizations. Furthermore, the effects of decision-making performance on financial and nonfinancial business performance outcomes should differ between public and private organizations, as public organization can show less of an impact on financial business performance. Thus, studies should investigate how BDA attributes differ between public and private organizations and how the effects of decision-making performance on financial and nonfinancial business performance outcomes differ between public and private organizations.

7.1 Implication for researchers

Although there exists a great demand for studies on BDA quality, previous studies have focused on data attributes or management factors that affect the adoption and usage of big data[20, 22–24, 26]. As a result, studies on BDA attributes are lacking. Furthermore, previous studies of information attributes based on the processing of structured and refined information may not be applicable to investigatingthe attributes of BDA. Thus, it is necessary to suggest specific data analysis attributes to ensure the quality of a BDA.

While there are previous studies of the attributes of information quality contributing to generic quality, user satisfaction, information systems success, and auditing and accounting, as well as studies on the effects of the BDA capabilities or contexts on business performance outcomes[84, 85], studies on the data analysis attributes of big data are lacking. As the studies on the attributes of information analyses regarding the effects of BDA attributes on business perforamnce[7, 9, 26, 27], especially those on value innovation and social impact, have received relatively less attention compared to other factors as influencing decision-making performance, our study provided insights into previous studies on value innovation and social group of BDA quality. We showed the significant effects of representativeness, predictability, interpretability, and innovativeness as related to value innovation, as well as individuality, collectivity, and willfulness related to social impact on the decision-making confidence and decision-making effectiveness.

Our study provided additional insights into related previous studies, as the attributes for value innovation were derived based on how much BDA obtain meaningfulness, value added, and relevance from BDA[63, 64]. In addition, the attributes for social impact can be explained in terms of alignment and relevance in the social context of BDA as well as the role of individual motivations and social capital for social apps[65]. Our study accordingly contributes to expanding the attributes for BDA quality beyond the current set of the most studied data quality attributes. Given that previous studies on data analysis attributes have been rather fragmented in investigating specific contexts of studies, our study intended to offer an integrated model for BDA attributes, including those of value innovation, social impact, precision, and completeness of BDA quality. Thus, our study focused on suggesting a coherent, specific model for data analysis attributes to ensure the quality of BDA. Hence, these diverse aspects of value innovation and social impact, along with precision and completeness, should be considered as important characteristics in order to realize the decision-making confidence and effectiveness. Our study extended earlier work regarding the attributes of information or information systems quality by suggesting the attributes of BDA quality. This will constitute the basis of evaluation studies of BDA to improve the decision-making performances.

Previous studies indicated that the growth curve of businesses that utilize BDA is flattening[28]. Thus, another contribution of our study was investigating the impact of big data on organizational performance. Our study highlighted the path from BDA quality to decision-making performance (i.e., confidence and effectiveness) and finally to business performance, specifically financial and nonfinancial performance outcomes.

7.2 Implication for practitioners

There are several implications for practitioners of our study. First, given the importance of facilitating the analysis attributes of BDA for improving business performance[86, 87], the BDA attributes can be suggested as criteria with which to evaluate BDA to produce decision-making confidence and effectiveness. Big data analysts can evaluate their analyses in terms of whether they are in agreement with the attributes of value innovation, social impact, and completeness. This will lead to greater trust toward BDA for the best decision making or for effectiveness and efficiency during the business process.

Second, as BDA can be trusted to help choose the best alternatives according to the analysis’ goals or intentions, it was found to affect sales, the return on marketing, total assets, the ratio of value added, the market ratio, productivity, customer satisfaction, quality levels, lead time reduction, and customer retention. As corporate businesses process effectiveness or efficiency is increased due to BDA, nonfinancial business performance can also improve. Thus, our study clearly validates the positive impact of BDA on business performance, which can be used to encourage businesses to adopt BDA for their decision-making activities.

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