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Big data and business analytics enabled innovation and dynamic capabilities in organizations: Developing and validating scale

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ABSTRACT

In recent years, innovation and competitive advantages have been built through information systems (IS); in particular, big data and business analytics (BDA) capabilities are being highlighted as essential enablers in creating innovation. This research focused on developing a big data scale using the Dynamic Capabilities View (DCV). DCV is based on an organization's ability to sense, seize, and transform capabilities to transform organizations and leverage innovations to remain competitive in the changing business environment. This study is based on convergent and discriminant validity using PLS-SEM with a sample of 191 firms. The proposed model includes twelve traits connected to sensing, seizing, and transforming attributes. The research outcome validates the scale and demonstrates that BDA enables dynamic capabilities and can achieve innovation in organizations when coupled with strategic management practices and IT resources that can be used to measure IT-business value.

1. Introduction

The current economic environment presses firms to build dynamic capabilities to meet the challenges of market globalization, hyper-competition, and complex environmental factors to create innovation and leverage sustainable competitive advantage (Jantunen, Tarkiainen, Chari & Oghazi, 2018; Li et al., 2023; Mikalef, Pappas, Krogstie & Pavlou, 2020; Dwivedi et al.,2021).

Competition in the information age is challenging, and achieving innovation, competitive advantage, and business value is difficult for organizations across industries and sectors (Chen & Liang, 2023; Gupta, Bag, Modgil, Jabbour & Kumar, 2022; Modgil, Gupta, Sivarajah & Bhushan, 2021). To remain competitive, organizations often explore and exploit technologies to innovate and create organizational capabilities to sustain and survive in a dynamic business environment.

Big data and business analytics is an emerging technology, and emerging technologies serve as a principal resource to drive transformation in the organization (Bharadwaj, El Sawy, Pavlou & Venkatraman, 2013; Luftman et al., 2015; Chatterjee, Chaudhuri, Vrontis & Jabeen, 2022) of sustainable viable advantage by innovation under hyper-turbulent environments (Nan & Tanriverdi, 2017). Emerging technologies are technological resources that enable firms to build capabilities to leverage digital transformation in their activities and decision-making in order to affect adjacent and distal outcomes (Chiu, Liu, Muehlmann & Baldwin, 2019; Nadeem, Abedin, Cerpa & Chew, 2018; Saha et al., 2022).

Artificial intelligence, machine learning, blockchain, cloud computing, big data analytics, and other internet technologies (Saha et al., 2022) are some examples of emerging technologies. This study examines how big data analytics (BDA) enables dynamic capabilities in innovation as a critical organizational resource to create business value (Mikalef & Krogstie, 2020; Wamba, Dubey, Gunasekaran & Akter, 2020).

Big data analytics play a vital role as catalysts in innovation and performance for organizations (Chen & Liang, 2023; Lozada, Arias-Pérez & Henao-García, 2023; Modgil et al., 2021). BDA can help businesses acquire richer and deeper data about business processes, operations, competitors, and markets, which can be helpful in the innovation of products, services, and strategies, and to satisfy stakeholders' requirements. Therefore, BDA can help organizations generate business value and dynamic capabilities by changing and transforming their ways of doing business (Elia, Raguseo, Solazzo & Pigni, 2022; Grover, Chiang, Liang & Zhang, 2018).

BDA is useful for organizations to make strategic decisions,

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customize products to targeted markets, conduct potential risk assessments, innovate, and manage complex stakeholder networks (Hussinki, 2022; Wamba et al., 2020). However, the value of customer and competition data is not guaranteed and depends on various factors, such as the speed at which insight from big data can be incorporated, potential for improvements, and lasting value (Mikalef & Krogstie, 2020; Steininger, Mikalef, Pateli & Ortiz-De-guinea, 2022). Therefore, it has immense potential for organizations that can navigate, adopt, use, and exploit it strategically.

Previous researchers have investigated how BDA can be useful for building dynamic capabilities using a Resource-Based View (RBV) (Table 1) (Barney, 2001; Božič & Dimovski, 2019; Ciampi, Demi, Magrini, Marzi & Papa, 2021; Dubey, Gunasekaran & Childe, 2018; Shuradze, Bogodistov & Wagner, 2018; Wamba et al., 2017) in terms of resources and competencies, which may be appreciated, scarce, difficult to replicate, and non-substitutable in unique situations (Amit & Schoemaker, 1993; Eisenhardt & Martin, 2000; Helfat & Winter, 2011; Winter, 2003). The RBV literature in the IS field posits that firms possessing IT and organizational resources (Melville, Kraemer & Gurbaxani, 2004) can be valuable, rare, inimitable, and non-substitutable and sustain their agility over a consistent duration (Bharadwaj, 2000). The literature also shows that the RBV may have limitations in addressing rapid and unpredictable market conditions (Eisenhardt & Martin, 2000). The DCV compensates for these shortcomings by emphasizing firms' ability to leverage internal resources and external capabilities to sustain agility in a dynamically unpredictable environment (Teece, 2018).

Moreover, these empirical studies demonstrated how the adoption of organizational IT resources as ordinary capabilities (present: zero-order) enables DC (as first-order) to reconfigure and transform routines in response to changing environments and customers' needs to turn innovation into competitive advantage.

However, while organizations can adopt rare and valuable IT resources that support operational routines to be inimitable and non-substitutable by competitors, the influence cannot be exerted to leverage dynamic capabilities to create and adapt changes under novel situations (Chan, Denford & Wang, 2019; Daniel, Ward & Franken, 2014).

Table 1
Big data analytics ordinary capabilities.

Study	BDA construct	Effects on Dynamic Capabilities (DC)
Wamba et al. (2017)	BDA capabilities related to management capabilities, IT infrastructure flexibility, and personnel IT expertise.	Strong BDA has positive effects on process-oriented DC to leverage firm performance.
Dubey et al. (2018)	BDA resources include advanced data visualization techniques, dashboards, and integration tools.	Superior BDA influences DC in supply chain agility to allow innovation and competitive advantage.
Shuradze et al. (2018)	BDA capabilities related to the infrastructure of data analytics, marketing-oriented analytical expertise in social capital, and IT marketing.	Marketing BDA has a positive effect on DC in organizational agility.
Božič and Dimovski (2019)	BI&A assets define related to technology, humans, and relationships.	BI&A contributes to enabling DC in absorptive capabilities through acquisition, assimilation, transformation, and exploitation.
Mikalef et al. (2020)	BDA capabilities related to tangibles, human skills, and intangible resources.	Strong BDA enables dynamic capabilities in the sensing, seizing, and transforming of routines.
Ciampi et al. (2021)	BDA capabilities related to tangibles, human skills, and intangible resources.	BDA influences dynamic capabilities in business model innovation through the sensing of opportunities, development of innovation, and reconfiguring of internal processes.

Hence, as stated, ordinary capabilities could be insufficient. Therefore, available novel avenues to conduct future research investigating how IT embeds firms' dynamic capabilities (as first-order) are required in order to enable firms to acclimate to novel situations. Moreover, higher-order enabled organizational capabilities through IT resources embedded in dynamic capabilities are increasingly adopted in IT studies (Wamba et al., 2020; Yoshikuni, 2022; Yoshikuni & Dwivedi, 2023) and support the elimination of tautological aspects (Li & Chan, 2019; Priem & Butler, 2001).

Therefore, a few IS studies have developed and validated the second-order dynamic capabilities empowered through BDA; further, they have galvanized overall firm-wide sensing, seizing, and reconfiguring as first-order capabilities. An exceptional empirical study by Wamba et al. (2020) investigated how BDA-enabled DC (BDA-DC as second-order) affects supply chain ambidexterity, but the scale of BDA was not developed and validated in that study.

Moreover, BDA growth is approximately 13% per year. As per Fortune Business Insight, it will be $308 billion in 2023 and about three quarter trillion dollars in the year 2030 (Fortune Business Insight, 2023). Salesforce uses CRM analytics in every area and sector to provide its clients with predictive insight and enable them to enter the marketplace (Davenport, Harris & Morison, 2010). Apple, Amazon, Walmart, Target, Costco, Facebook, Google, UPS, FedEx, etc. are using big data analytics to analyze structured and unstructured datasets and recognize and supply insights based on patterns and correlations that help them understand market, customer, and competition requirements to innovate, maintain, and achieve sustainable innovation and competitive advantage (Bean, 2017).

In the same direction, previous studies have questioned the value of BDA investments because only a few percent of organizations can develop true BDA business value (Mikalef, Krogstie, Pappas & Pavlou, 2020). Günther, Mehrizi, Huysman and Feldberg (2017) posited that, despite rigorous efforts at an individual level, organizations might not derive value from big data if work practices, organizational structures, and stakeholder interests lack alignment. Woerner and Wixom (2015) contend that the value derived from big data may be compromised if organizations are hindered from combining diverse data sources in new ways, potentially restricting analysts and decision-makers at the work-practice level from unveiling insights that could spearhead new lines of business. In a trade press, Marr (2016) emphasizes that many firms have not achieved a competitive edge from their big data investments. These findings from research and practice suggest that many companies need help understanding and harnessing performance benefits from big data investments in a rapidly evolving environment.

Many studies have investigated the business value of big data and business analytics through the lens of an RBV (Božič & Dimovski, 2019; Ciampi et al., 2021; Dubey et al., 2018; Shuradze et al., 2018). In these studies, it is assumed that these resources are efficiently orchestrated to achieve the desired performance outcomes. Nevertheless, aspects such as integrating big data and business analytics into business processes and leveraging dynamic capabilities that promote organizational innovation through analytics solutions are frequently neglected (Mikalef, Pappas, Krogstie & Pavlou, 2020). Moreover, according to Steininger et al. (2022), previous studies have investigated IT-embedded dynamic capabilities in sensing, seizing, and transforming, but not ones that were integrated with the big data and analytics capabilities of an enabler. They argue that this is an exciting avenue for further research.

Hence, this empirical study to fill knowledge gaps proposes a consistent and effective scale to measure the usefulness of dynamic capabilities to influence innovation through BDA. Thus far, this issue still needs to be addressed, developed, and communicated in the literature. Therefore, we have a research question.

RQ: How do big dataanalytics-enabled **dynamic capabilities contribute to innovation in organizations?**

To the best of the authors' knowledge, this empirical work conceptualizes and validates a novel construct of BDA-DC through sensing, seizing, and transforming firms' routines in innovation. Hence, this study fills gaps mentioned by practitioners and scholars and contributes to strategic management and BDA literature.

The introduction section covers the background of the study. Section two covers contemporary literature related to the topic from major journals and magazines. Section three covers the research approach for BDA scale development and validation. The scale development process comprises five phases: (1) conceptualization of the scale, (2) measurement of scale development, (3) specification of the scale model, (4) scale evaluation and refinement of the scale, and (5) scale validation. Section four covers results and findings from empirical work. Sections six and seven cover discussions and conclusions. Therefore, the remainder of the article is organized into the following sections: theory background, scale development, scale testing, discussion, conclusion, hypothetical and managerial consequences, as well as limitations and upcoming research.

2. Literature review

2.1. Big data analytics

This study examines emerging technologies that focus on big data analytics associated with the dynamic capabilities approach in innovation.

Volume, velocity, veracity, and variety are the major characteristics of big data (Akter, Wamba, Gunasekaran, Dubey & Childe, 2016; Mikalef et al., 2020). The term analytics consists of managing, analyzing, and extracting the value from data, i.e., creating knowledge to enable better decision-making through statistical techniques, data-mining models, data visualization, and other associated tools (Grossman & Siegel, 2014).

Dynamic capabilities (DC) denote the ability of organizations to change, adjust, transform, and reconfigure their organizational abilities and build new capabilities to respond to business necessities (Helfat & Winter, 2011). Helfat and Raubitschek (2018) argue that firms survive and thrive under stormy market conditions and build dynamic capabilities in innovation by sensing, seizing, and transforming to maintain competitive advantage amidst changes to technologies, competitors, and customers.

2.2. Big data analytics influence dynamic capabilities

Recent studies have examined BDA resources as ordinary capabilities (zero-order) in their association with dynamic capabilities, as well as first- and second-order capabilities to impact innovation and competitive advantage (CA). For example, Wamba et al. (2017) examined the direct impact of BDA capabilities on corporate performance mediated by process-oriented DC. According to Dubey et al. (2018), the effects on CA through BDA capabilities are mediated by DC as supply chain agility. Shuradze et al. (2018) investigated how BDA in marketing influences DC (by organizational agility) in order to understand customer requirements and generate innovation and business success (Collis, 1994). In a similar spirit, Božič and Dimovski (2019) examined how BDA assets influence higher-order DC (such as an absorptive capacity for knowledge creation and innovation ambidexterity) to promote corporate performance gains. In another study, Mikalef et al. (2020) investigated how BDA capabilities allow organizations to create insight to support their DC, influence marketing capabilities and technological capabilities, and improve firm performance in an uncertain environment. Similarly, Ciampi et al. (2021) observed the impact of BDA on DC as a business model invention through the mediative role of entrepreneurial orientation. Table 1 summarizes the studies on BDA's influence on DC.

From Table 1, the previous BDA studies only address the operational capabilities. Operational capabilities refer to the organization's operational functioning that enterprises make in their value chain, i.e., "in what way we earn an existence now" capabilities (Cepeda & Vera, 2007; Collis, 1994). Dynamic capabilities relate to how firms "assimilate, shape, and reconfigure internal and external competencies to address changing business atmospheres" (Teece, Peteraf & Leih, 2016).

Hence, this study updates the recent BDA studies (Table 1) that access ordinary capabilities through the initial resource configuration and operational processes to achieve DC. It investigates how DCs are embedded through BDA in the innovation routines of the firm's strategic knowledge resources and activities.

2.3. Big data analytics-enabled dynamic capabilities

This study conceptualizes and measures big data analytics-enabled dynamic capabilities in innovation through the dynamic capabilities approach (Teece et al., 2016).

The formal description of the novel construct of BDA-DC was precisely and concisely developed and declared by MacKenzie, Podsakoff and Podsakoff (2011) as follows:

> *"…BDA-enabled dynamic capabilities are defined as a firm's abilities to sense, seize, and transform capabilities enabled through big data and business analytics, in orchestration with other organizational resources and capabilities, to leverage innovation and respond to business environmental challenges…".*

As a result, in this study, firms' ability to effectively use big data analytics along with other organizational resources and capabilities to sense, seize, and transform opportunities, leading to innovation and the capacity to respond to business challenges, is referred to as BDA-enabled dynamic capabilities.

As stated, dynamic capabilities are the abilities of a firm to develop strategies for challenges imposed by environmental changes (Teece, 2018; Teece et al., 2016) through complex activities that include sensing emerging opportunities, challenges, and threats (Mikalef & Pateli, 2017; Mikalef et al., 2020), seizing opportunities for development and survival (Wamba et al., 2020; Yoshikuni, 2022), and transforming existing operational capabilities to address market and customer needs (Helfat & Raubitschek, 2018; Mikalef et al., 2020).

"Sensing" dynamic capabilities enabled by big data analytics is used to generate insights to analyze and identify emerging conditions to position or reposition the firm accordingly (Wamba et al., 2017). As per strategic management literature (Mintzberg, Ahlstrand & Lampel, 2009; Porter, 1998; Wolf & Floyd, 2017), enterprises must frequently scan external environments, including cultural, social, governmental, policy-related, rules and regulatory, legal, demographic, political, energy-related, and technological factors, among others, to identify opportunities and threats.

The business trends and micro factors of the business environment, such as stakeholders, customers, suppliers, regulatory authorities, and governments, may affect organizations by changing people's thinking, perceptions, behaviors, and attitudes, such as values and lifestyles (Babafemi, 2015; Porter, 1998).

Thus, the insights generated by big data and business analytics work as an enabler of dynamic capabilities, which has been investigated in the strategic management literature. Based on this view, organizations can use BDA to generate insights that expand the notion of decision-making performance (Jantunen et al., 2018; Yoshikuni, Galvão & Albertin, 2022) and provide data and information to create strategic knowledge which was previously unavailable for decision-making to the firm (Mikalef et al., 2020; Wamba et al., 2020, 2017).

"Seizing" dynamic capabilities denotes how quickly an organization develops business processes to respond to prospects and mitigate threats once they have been mapped and identified as important (Teece, 2018). This ability includes activities that develop, design, update, and implement BDA-DC to achieve possible business value through products, services, and business models (Helfat & Raubitschek, 2018; Porter, 1998).

Previous studies of IS strategies have demonstrated that organizations use strategic information systems to scan external factors to foster incremental and radical innovation to improve firm performance (Marabelli & Galliers, 2017; Merali, Papadopoulos, & Nadkarni, 2012; Yoshikuni & Jeronimo, 2013; Yoshikuni, Lucas & Albertin, 2019). Recent studies investigated how BDA technologies, through the power of processing raw data, allow actionable insight and improve response speed to develop possible business resolutions to see trends in the external situation and seize opportunities (Jantunen et al., 2018; Mikalef et al., 2020; Nisar et al., 2020; Tandon, Revankar, Palivela & Parihar, 2021).

Thus, strong BDA can not only enable organizations to scan and identify opportunities and threats but also enable activities that capture opportunities using empirical evidence to create incremental or radical innovation (Agrawal, Wankhede, Kumar, Luthra & Huisingh, 2022; Dubey et al., 2020; Dwivedi, Nerur & Balijepally, 2023). Thus, seizing dynamic capabilities allows firms to build potential business solutions to meet the organization's target market and customer needs (Wamba et al., 2017; Yoshikuni et al., 2022).

"Transforming" dynamic capabilities refers to firms' ability to keep the resources of the organizational system aligned with their strategy and other elements (Teece, 2018). These capabilities are critical to an organization's capability to orchestrate its capital through reconfiguring its business processes (Jantunen et al., 2018; Yoshikuni & Dwivedi, 2023) and optimizing the use of current practices to new extents with new purposes in response to changes in business priorities (Mikalef & Pateli, 2017; Porter, 1998).

While an organization can transform its resources processes and existing approaches to operation without solely depending on the technology (Davenport et al., 2010; Mikalef et al., 2020; Sakas, Reklitis, Terzi & Glaveli, 2023), Nisar et al. (2020) found that the quality and efficiency of decision-making performance depends upon the level to which organizations have established their BDA capabilities to build and align new know-how with the company's existing data, information, and knowledge. Thus, transforming capabilities enabled by BDA capabilities refer to the skill to firmly orchestrate tangible and intangible resources and IT-enabled organizational resources to influence proximate and distal outcomes.

Wamba et al. (2020) demonstrated that BDA-enabled reconfiguring through data visualization techniques and dashboard applications/information from communication devices (e.g., smartphones, computers) allows users or decision-makers to gain supply chain agility and adaptability under the challenges of the external environment. Thus, this empirical study recognizes that firms' DC enables organizational capabilities to respond to prospects and threats by varying, encompassing, adjusting to, or creating resource configurations, and transforming operational routines (Helfat & Raubitschek, 2018; Teece, 2018).

Therefore, this research incorporated BDA into organizational capabilities as a novel construct; that is, dynamic capabilities are enabled by BDA techniques as second-order latent variables rooted in sensing, seizing, and transforming.

3. Research design

Creating and validating scale is a critical challenge in the field of information systems. Empirical research must contribute and fill knowledge gaps in the literature and have practical implications (Boateng, Neilands, Frongillo, Melgar-Quiñonez & SL, 2018; Jarvis, Mackenzie, Podsakoff, Giliatt & Mee, 2003; MacKenzie et al., 2011).

Past studies have demonstrated the steps of the process in scale development (Boateng et al., 2018; Devellis & Thorpe, 2021; Lewis, Templeton & Byrd, 2005). The empirical research is based on the guidelines recommended by Mackenzie et al. (2011) in IS research. The scale development process is divided into five phases: (1) conceptualization of the scale, (2) measurement of scale development, (3) specification of the scale model, (4) scale evaluation and refinement, and (5) scale validation (Fig. 1.)

3.1. Scale conceptualization

The first step consists of explaining and predicting phenomena through theoretical propositions to instruments that develop measurement of the novel concept and construct domain Boateng et al. (2018). The hypothetical definition of the novel construct refers to determining theoretical intentions and the dimensions that cover them (Devellis & Thorpe, 2021).

3.2. Development of measures

This part of the process consists of developing a novel construct for the measurement instrument.

3.3. Items generation to characterize the construct

This section describes the steps used to develop the measures of the

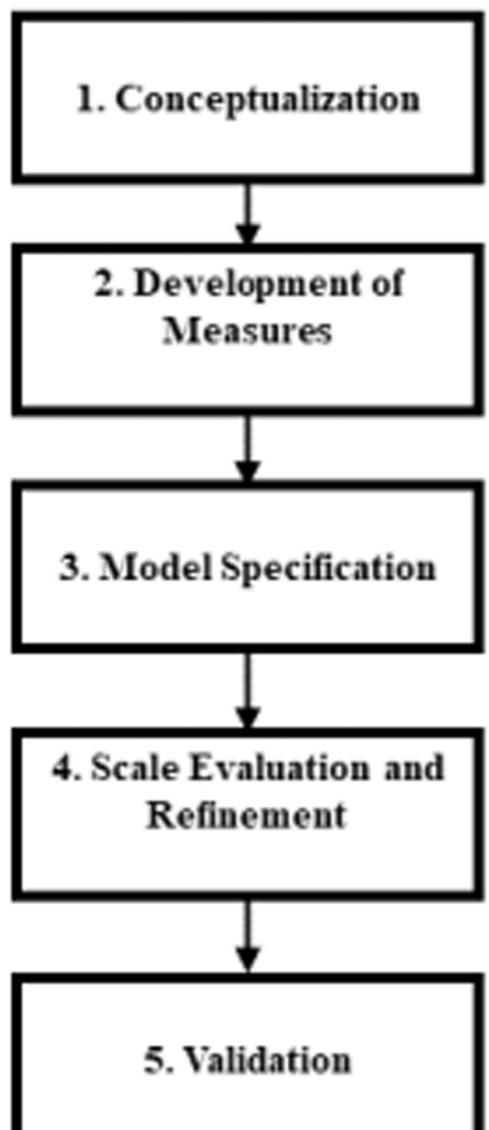

Fig. 1. The scale development process was adapted from Mackenzie et al. (2011).

construct of BDA-enabled dynamic capabilities through the conceptualization and validation of their dimensions by specialists (Lewis et al., 2005). Hence, based on the grounding of previously published resources about the process of scale development (Jarvis et al., 2003; MacKenzie et al., 2011), this empirical work assumed the contemporary of empirical and theoretical literature grounding, feedback, and ideas from experts in the fields of information systems and strategic management.

Conceptual research and the adaptation of pre-existing elements from empirical research in the areas of IS and strategic management led to the creation of the innovative construct of BDA-enabled dynamic capacities to influence innovation. Hence, the second-order BDA-enabled dynamic capabilities combine the first dimensions of sensing, seizing, and transforming, thereby establishing the organization's ability to achieve strategic change and create innovation through dynamic capabilities.

The attributes and measurement of the innovative construct in Table 2 present the set of objects. For each item, the preceding sentence asks experts to rate "how your business using IS by application of BDA to support the firm for the following purposes" on the scale of one to seven, where one is not at all effective and seven is highly effective.

3.3.1. Evaluate the content validity of the items

The validity of the content was assessed in the next phase. According to Boateng et al. (2018), determining whether each item in an instrument accurately reflects the domain in terms of content relevance, representativeness, and technical excellence is known as content validity. According to the recommendations given by Mackenzie et al. (2011), it was established evaluating content validity is meant to determine (1) whether each item accurately reflects the content domain according to the attributes, and (2) whether the items set as a whole accurately reflect the construct dimension.

The content validity of the empirical results through qualitative and quantitative outcomes is used to validate the content (Almeida, Yoshikuni, Dwivedi & Larieira, 2022; Lawshe, 1975; Lewis et al., 2005). The experts used judgmental and subjective assessments to make qualitative decisions. Experts keep business objectives in mind when commented on the difficulty, as well as made suggestions for improvement (such as adding, altering, or eliminating items). The q-sort method and content validity ratio (CVR) tools were quantitatively evaluated in combination. This study is based on five senior executives at the strategic level from the IT industry and six senior academicians from the IS discipline.

The study used a table with three columns and eighteen assertive items in MS Excel by the expert committee to assess content validity. Each column indicates the attributes of the BDA-enabled dynamic capacities to catalyze innovation, and the eighteen forceful elements (Table 1) were randomly ordered. Industry and academia experts were requested to select the aggressive item measurement that would result in a better construct attribute. When the Excel file was completed, the item placement ratio ("HIT Ratio") was calculated to show how many measurement elements were appropriately placed in the correct attribute. The item placement ratio to the total number of measurements was calculated by dividing the number of measurements appropriately allocated to their corresponding attributes by the total number of items.

Table 3 shows the number of appropriately selected aggressive measurements by all industry and academia experts in diagonal elements. The findings indicate that the three attributes of the unique construct can be tested by an explicit collection of aggressive measurements.

Following the HIT Ratio, industry and academia experts were given another MS Excel file that included a list of measurements from the modified measure items and were asked to rate the significance of each attribute on a one-to-three scale (where 1= essential, 2= important, 3= not appropriate (Lewis et al., 2005). The formula used for content validity ratio (CVR) is CVR= (n-N/2)/(N/2), where "n" is the number of experts from academia and industry and "N" is the total number of respondents who shared their opinion, see Table 4.

Table 2
Items of the BDA-enabled dynamic capabilities construct.

Dimensions	Assertive items	Source	References
Sensing	SENS1. Scanning trends in the external environment (such as social-cultural, federal, demographic, political, energy-related, technological, etc.) and identifying new business opportunities	Adapted	(Mikalef & Pateli, 2017; Mintzberg et al., 2009; Porter, 1998; Yoshikuni & Dwivedi, 2022)
	SENS2. Identifying changes in the organization's target market	Adapted	(Porter, 1998; Wamba et al., 2020)
	SENS3. Identifying changes in people's behavior and attitudes (values and lifestyles)	Adapted	(Jantunen et al., 2018)
	SENS4. Identifying new business opportunities in the micro-sector environment (such as suppliers, intermediary customers, state and municipal governments, regulatory agencies, etc.)	Created	(Jantunen et al., 2018; Porter, 1998)
	SENS5. Identifying new business practices to create unique customer experiences	Created	(Jantunen et al., 2018; Porter, 1998)
	SENS6. Identifying changes in customer needs	Adapted	(Mikalef & Pateli, 2017)
Seizing	SEIZ1. Developing potential business solutions to meet changes in the micro-operating environment to deal with opportunities and threats	Created	(Jantunen et al., 2018; Porter, 1998)
	SEIZ2. Developing effective routines for creating potential business solutions to deal with opportunities or threats	Adapted	(Mikalef & Krogstie, 2020)
	SEIZ3. Developing potential business solutions to meet trends in the external environment to deal with opportunities and threats	Adapted	(Mikalef & Krogstie, 2018)
	SEIZ4. Developing potential business solutions to actively influence the direction of the sector to which it belongs	Adapted	(Jantunen et al., 2018; Porter, 1998)
	SEIZ5. Developing potential business solutions to meet the organization's target market	Adapted	(Jantunen et al., 2018; Porter, 1998))
	SEIZ6. Developing new ways of conducting business to meet customer needs	Created	(Jantunen et al., 2018; Porter, 1998)
Transforming	TRA1. Adjusting your business processes in response to changes in your business priorities	Adapted	(Mikalef & Pateli, 2017)
	TRA2. Reconfiguring your business processes to generate new productive assets (resources)	Adapted	(Mikalef & Pateli, 2017; A.C. Yoshikuni et al., 2021)
	TRA3. Optimizing the use of existing productive resources in new areas for new purposes	Adapted	(Jantunen et al., 2018; Porter, 1998)
	TRA4. Optimizing the use of existing knowledge in new areas for new purposes	Adapted	(Jantunen et al., 2018; Porter, 1998)

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Table 2 (*continued*)

Dimensions	Assertive items	Source	References
	TRA5. Integrating new know-how with the company's existing knowledge	Adapted	(Jantunen et al., 2018; Porter, 1998)
	TRA6. Developing new business processes to achieve the organization's goals and objectives	Created	(Mintzberg et al., 2009; Porter, 1998)

Source: Adopted from Yoshikuni and Dwivedi's (2022) conference paper Southeast Decision Science Conference 2022 (Authors Work).

Table 3
Ratio of item placement.

Attributes	Sensing	Seizing	Transforming	Total	Item placement ratio
Sensing	68	4	0	72	94%
Seizing	1	61	10	72	85%
Transforming	0	7	65	72	90%

4. Findings of the model

After the model has been constructed, it is required to find out the most valuable constructs through attributes and the best captures of the assertive measurements (Lewis et al., 2005). According to the recommendations of Mackenzie et al. (2011), the innovative construct of BDA-enabled dynamic capabilities was well-defined as a Type II second-order factor demonstrated by a formative construct model with three (sensing, seizing, and transforming) first-order reflecting measurement models.

Thus, reflective assertive items were used to model the three dimensions. They were recorded and quantified in each first-order dimension to quantify the reflective-formative second-order construct (Hair, Hult, Ringle & Sarstedt, 2017). The first-order attributes are logically different and contribute a distinct part to the BDA-enabled dynamic capabilities as a higher-order latent variable.

4.1. Scale assessment and improvement

The next stage was to conduct a pretest to obtain empirical input on the scale's measurement properties using a controlled sample to determine the suitability of testing the convergent, discriminant, and nomological validity (Boateng et al., 2018). According to Mackenzie et al. (2011), problematic indicators have low validity, low reliability, strong and significant measurement error covariances, and strong and significant non-hypothesized cross-loadings .

The findings show that all requirements for the pretest with fifty firms were accepted. Furthermore, the size of the sample exceeded the required pretest sample size of fifteen cases, as suggested by Malhotra (2010).

The common method bias (CMB) was controlled in the research design phase as suggested by Schwarz, Rizzuto, Wolverton and Roldán (2017) such as: choosing respondents with the ability to answer the questionnaire, using assertive items built in concise and clear language, and counterbalancing the order of questions. Respondents remained anonymous, and data collected was analyzed for research purposes solely at an aggregate level, and applied technical remedies were also followed as suggested by MacKenzie and Podsakoff (2012) and Fuller et al. (2016).

To assess the multicollinearity between three first-order attributes, the variance inflation factor (VIF) was calculated to determine whether first-order dimensions had a significant relationship with the BDA-enabled dynamic capabilities variable. This test indicates that the value is below the threshold of five, suggesting no concern with multicollinearity (Hair et al., 2017).

4.2. Validation

Convenience sampling was used to collect data from U.S. businesses. The respondents were approached by the authors in various ways, such as social networks (LinkedIn, Facebook, Instagram, WhatsApp), personal contacts in the industry, professional associations, forums, alumni networks, and mailing lists.

The major respondents were C-Suite executives from different business and IT functions who were familiar with the BDA-enabled dynamic capability attributes. The instrument instructions advised respondents who lacked in-depth information and knowledge of certain subjects to seek advice from other peer executives; hence, the data collection process took around ninety days. The respondents' profiles are presented in Table 5. The respondents are from six sectors and cover almost every industry. More than 50% of the respondents were mid-to high-level executives and managers Almost 70% of respondents had more than five years of working experience in the industry and had a good understanding of both technology and management. Therefore, this is a good sample to test the scale across industries and sectors. There were 191 responses collected in total. Table 5 shows the characteristics of the sample.

The consolidated sample size was 191, which included the first 50 responses and 141 later responses. This is considered a good sample size using confirmatory factor analysis in SEM (Hair et al., 2017). By

Table 4
Outcome of the content validity ratio.

Attributes	Measurements	Essential	Important	Not Appropriate	Indices of CVR ($N = 11$, CVR) thresh. = 0.59)	Status
Sensing	SENS1	11.00			1.00	Accepted
CVIs=0.82	SENS2	9.00	2.00		0.64	Accepted
	SENS3	7.00	4.00		0.27	Rejected
	SENS4	9.00	2.00		0.64	Accepted
	SENS5	8.00	2.00	1.00	0.45	Rejected
	SENS6	11.00			1.00	Accepted
Seizing	SEIZ1	5.00	5.00	1.00	- 0.91	Rejected
CVIs=0.73	SEIZ2	10.00	1.00		0.81	Accepted
	SEIZ3	9.00	2.00		0.64	Accepted
	SEIZ4	5.00	2.00	4.00	- 0.91	Rejected
	SEIZ5	10.00	1.00		0.81	Accepted
	SEIZ6	9.00	2.00		0.64	Accepted
Transforming	TRA1	9.00	2.00		0.64	Accepted
CVIs=0.68	TRA2	7.00	3.00	1.00	0.27	Rejected
	TRA3	9.00	2.00		0.64	Accepted
	TRA4	9.00	3.00		0.45	Rejected
	TRA5	10.00	1.00		0.81	Accepted
	TRA6	9.00	2.00		0.64	Accepted

Table 5
Demographic characteristics.

Characteristics		Number	%
Respondent's position	Middle/first line manager	101	53%
	Senior/executive manager	90	47%
Age firms	Young firms (1 to 5)	5	2%
(years of operation)	Mid-aged firms (6 to 20)	93	49%
	Mature firms (more than 21)	93	49%
	Small-size (1 to 99)	78	41%
Firm size	Medium-size (100 to 499)	99	52%
(number of employees)	Large-size (above 500)	14	7%
	Agribusiness	10	5%
	Commerce	30	16%
	Financial	30	16%
Industry sectors	Manufacturing	52	27%
	Service	55	29%
	Public service	14	7%

G*Power v.3.1.9.2 software (Faul, Erdfelder, Lang & Buchner, 2007), it is determined the minimum sample size is seventy-seven instances with a median effect size (f^2) of 0.15 and statistical power of at least 0.80.

Fig. 2 shows the results of a bootstrap analysis using 5000 samples to determine the significance of the estimates (t-statistics). The next stage was to re-test the final sample's VIF, convergent validity, internal consistency of reliability, and discriminant validity (Hair et al., 2017).

The tests reveal that all VIFs across path weights are far below the threshold of three, demonstrating that multicollinearity is not an issue, as recommended by Bido and Silva (2019) in Table 6.

The measurement (items) loading was above 0.70, the indicator's reliability was above 0.50, and the average variance extracted (AVE) was greater than 0.50 to confirm convergent validity. Cronbach Alphas (CA) were above 0.75 and Composite Reliability (CR) values were above 0.85, confirming internal consistency reliability. The results favored discriminant validity, revealing that the square roots of AVE's cross-correlations with each latent construct were larger than its maximum relationship (r) with any other construct (Fornell-Larcker criterion), and the [Heterotrait-Monotrait Ratio of Correlations font size change] confidence interval was less than 1.

The construct of BDA was defined as type II reflexive-formative higher-order attributes from the underlying first-order sense, seize, and transformation capabilities. Based on the guidelines of Bido and Silva (2019), Hair, Sarstedt, Ringle and Gudergan (2018), BDA-enabled dynamic capabilities were operationalized through a combination of repetitive items and first-order measurements. The indicators were used to obtain the first-order measurements and served as manifest variables in the measurement model of the higher-order measurement. Thus, reflexive first-order measurements are theoretically distinct (Helfat & Raubitschek, 2018; Teece et al., 2016) and contribute to the measurement of formative second-order measurements. See Table 7.

Table 6
Outcomes of variance inflation factor and path coefficient.

Dimension	Weight	VIF
Sensing	0.377***	2.775
Seizing	0.363***	2.901
Transforming	0.353***	2.862

The PLS-SEM method was used to validate the attributes and measurements (Hair et al., 2017), which is consistent with recent empirical investigations in the IS and strategic management fields (Ciampi et al., 2021; Mikalef & Pateli, 2017; Wamba et al., 2020). The findings revealed that the collection of forceful objects confirms their specific attributes by distinct measurements and dimension levels. Fig. 2 depicts the path coefficient of the first-order measurement and the second-order measurements and the assortative item loading.

5. Discussion

While the true business value of BDA in many organizations is still unexplored and only a few percent of organizations are capable of getting real business value from BDA (Günther et al., 2017; Li & Chan, 2019; Marr, 2016; Mikalef et al., 2020; Woerner & Wixom, 2015), big data analytics is continuously growing, and the mechanisms to capture the dynamic capabilities to create BDA business value need to be explored in empirical research (Daniel et al., 2014; Helfat & Winter, 2011).

Thus, as stated in the literature review part, ordinary capabilities could be insufficient, and BDA embeds firms' dynamic capabilities, as first-order capabilities are required to enable firms to acclimate to novel situations. To address this gap, this empirical study develops a novel scale of big data analytics-enabled dynamic capabilities in innovation through the capability to sense, seize, and transform via big data analytics. The findings provide theoretical and practical implications

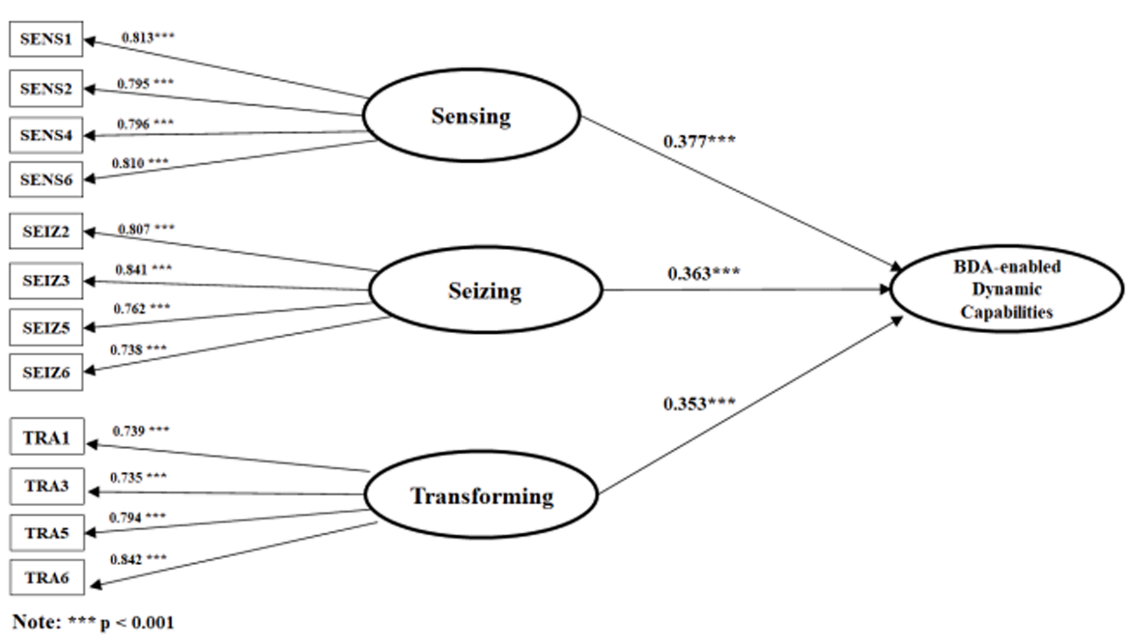

Fig. 2. Model of Measurement.

Table 7
Outcomes of the reflective measurements.

Dimensions	Indicators	Loadings	Indicator Reliability	VIF	AVE	Composite Reliability	Cronbach's Alpha	Discriminant Validity	
		>0.70	>0.50	< 5	>0.50	0.60–0.90	0.60–0.90	HTMT does not include 1	Square Root of the AVE Fornell–Larcker criterion
Sensing	SENS1	0.813	0.660	2.775	0.646	0.879	0,817	Yes	Yes
	SENS2	0.795	0.632						
	SENS4	0.796	0.633						
	SENS6	0.810	0.656						
Seizing	SEIZ2	0.807	0.651	2.901	0.621	0.867	0.795	Yes	Yes
	SEIZ3	0.841	0.707						
	SEIZ5	0.762	0.580						
	SEIZ6	0.738	0.544						
Transforming	TRA1	0.739	0.546	2.862	0.606	0.860	0.782	Yes	Yes
	TRA3	0.735	0.540						
	TRA5	0.794	0.630						
	TRA6	0.842	0.708						

discussed below. The limitations of the study are also presented.

5.1. Theoretical implications

This study has several theoretical implications for BDA-enabled DC research, contributing to the existing literature in the following ways.

Firstly, through a rigorous methodology, this is the first study that developed the scale of big data analytics-enabled dynamic capabilities of sensing, seizing, and transforming to create innovation. Although there is a rich body of literature on BDA (Collis, 1994; Dubey et al., 2018; Shuradze et al., 2018; Wamba et al., 2017) and DC (Helfat & Winter, 2011; Teece et al., 2016), research on integrating the two constructs as a second-order construct is scant. The role of BDA-enabled DC emerges to answer questions from the previous literature (Günther et al., 2017; Marr, 2016; Woerner & Wixom, 2015). Therefore, this empirical study developed a higher-order construct to measure BDA-enabled DC using data gathered from USA firms. Therefore, this study also combined dynamic capabilities in sensing, seizing, and transforming as reflexive first-order constructs to measure BDA-enabled DC as a reflexive-formative second-order construct, see Fig. 2.

The role of such novel BDA measures can lead scholars and practitioners to adopt BDA tools to incorporate a new and existing innovation process to achieve innovation and competitive advantage.

To date, few studies have investigated the BDA embedded in the dynamic capabilities dimensions of sensing, seizing, and transforming, and, through three first-order dynamic capabilities in the aggregate, as a second-order dynamic capability, such as BDA-enabled DC in innovation. This approach was adopted in a recent BDA study of DC (Wamba et al., 2020) and supports mitigating the tautological issue associated with DC theory.

The different and complementary first-order capabilities for achieving high levels of dynamic capabilities in innovation are sufficient to measure the BDA-enabled DC and contributing to extend the literature knowledge of dynamic capabilities (Daniel et al., 2014; Helfat & Raubitschek, 2018; Teece et al., 2016) and BDA (Grover et al., 2018; Mikalef et al., 2020; Wamba et al., 2020).

Moreover, the results address the gaps which are presented in existing studies on the dynamic capabilities view and big data and business analytics to develop future literature to understand how firms build sensing, seizing, and transforming capabilities using the dynamic capabilities view (Teece et al., 2016) and big data and business analytics applications (Conboy, Mikalef, Dennehy & Krogstie, 2020). Finally, an instrument with fewer items to measure one latent variable can contribute to reducing the respondent bias of answering all constructs composited in a complex research model, as mentioned by Sekaran (2016).

5.2. Practical implications

The findings from the empirical study provide guidelines that support managers contemplating investments in BDA-enabled DC. First, before BDA investment, organizations must assess (a) their inherent capabilities to discern dynamic shifts within both internal and external environments, which can potentially mold opportunities and attenuate risks, i.e., BDA-DC helps organizations scan the business trends in the external environment and make strategic decisions for achieving advantage over competitors by identifying the changes in customers and targeted markets and identifying new business practices and customer experience. (b) If their organizations can seize the opportunities, i.e., BDA-DC organization to create exploration and exploitation innovation (unique and incremental solutions) to meet market and customer requirements. (c) The organization's capacity to reconfigure its intangible and tangible resources to foster innovation. Managers can use BDA-DC to optimize and adjust routines and prioritize and develop new and innovative business processes to achieve innovation and organizational goals and objectives. Managers can also leverage existing organizational knowledge in new business areas and integrate new know-how with the company's business processes.

Moreover, recent studies reflected that investments in big data analytics create innovation to meet external business, market, and competition requirements. This could be addressed by adopting technology, collecting a variety of and vast volume of data, and developing competence with analytics tools. An essential element of leveraging strategic business value from big data investments to build organizational capabilities in innovation is how business and technical executives incorporate big data analytics applications in the routines to sensing, seizing, and transforming, i.e., big data analytics are embedded in the decision-making at all organizational levels (Luftman et al., 2015).

It is essential to build these dynamic capabilities in innovation enabled by BDA. It is necessary to build effective orchestration (tangible, human skill, and organizational intangible resources) to put in action and combine the routines of innovations. Recent studies have demonstrated the role of top executive commitment and a structured plan (IT resources, human competencies, and complementary organizational resources) for enterprise use of big data analytics ability to gain maturity of BDA capabilities (Blank & Naveh, 2019; Ciampi et al., 2021; Kristoffersen et al., 2021).

Finally, big data analytics can provide insights to a firm to adapt, reconfigure, change, and transform its business processes to create innovations. Hence, big data analytics increase the quality, agility, and efficiency of decision-making.

5.3. Limitations and scope for future research

Despite the several contributions, this study has limitations that can open the avenues for future research.

First, the instrument uses a single respondent, which may suggest research bias. Therefore, future research should indicate the need to consult other executives in the firm with expertise and knowledge to better respond to the questions.

This empirical study proposes a novel construct to measure big data analytics-enabled dynamic capabilities in innovation as a second-order latent variable. Further research can investigate antecedent variables that influence BDA-DC related to the literature on accounting information systems, strategic management accounting, strategic enterprise management, knowledge strategy, knowledge management process, organizational memory, and digital business strategy.

In another way, consequent variables that BDA-DC will influence can be investigated in relation to the literature on innovation, organizational agility, supply chain management, decision-making, strategic flexibility, ambidexterity, business process performance, business model innovation, innovation and competitive advantage, and corporate performance (Yoshikuni, Dwivedi, Dultra-de-Lima, Parisi & Oyadomari, 2023).

Finally, future research could investigate the moderation effects of organizational contingencies (e.g., age, size, centralization, complexity, developmental stage (growth rate), capital intensity, organizational culture, sector, orientation strategy, etc.) and environmental contingencies (e.g., turbulence, uncertainty, dynamism, complexity, ambiguity, region, institutional, industry context, cross-country, etc.).

6. Conclusion

BDA helps organizations build dynamic capabilities that help them sense, seize, and transform for a competitive advantage. The BDA-enabled dynamic capabilities scale has been developed and validated in the study using three constructs: sensing, seizing, and transforming for innovation and competitive advantage.

There are six items in each construct based on the literature. However, four essential items in each construct were confirmed. BDA dynamic capabilities in sensing did not confirm two items: (1) identifying changes in people's behavior and attitudes (values and lifestyles) and (2) new business practices to create unique customer experiences. Similarly, the scale of BDA-enabled dynamic capabilities in seizing did not confirm two items: (1) developing potential business solutions to meet changes in the micro-operating environment to deal with opportunities and threats detected and (2) developing potential business solutions to actively influence the direction of the sector in which it belongs. The BDA dynamic capabilities in transforming also did not confirm two items: (1) reconfiguring business processes to generate new productive assets (resources) and (2) optimizing the use of existing knowledge in new areas for new purposes.

This empirical research extended the discussion of scholars and practitioners to create BDA business value. Many articles have discussed how specific aspects or resources can build BDA capabilities, but there is limited research about how BDA enables organizational capabilities through dynamic capabilities in sensing, seizing, and transforming to create BDA business value and to produce innovation. Through the RBV and dynamic capabilities view, and recent literature on big data analytics, this study fills the gaps by having developed and confirmed the BDA-enabled innovations and dynamic capabilities scale.

Ethical approval

The research is based on the anonymous survey.

Declaration of Competing Interest

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.

Data availability

The data can be available upon request.

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