Journal of Innovation & Knowledge 9 (2024) 100589

Journal of Innovation & Knowledge

https://www.journals.elsevier.com/journal-of-innovation-and-knowledge

A dynamic information technology capability model for fostering innovation in digital transformation

Adilson Carlos Yoshikuni[a], Rajeev Dwivedi[b,*], Muhammad Mustafa Kamal[c], Duanning Zhou[d], Pradeep Dwivedi[e], Sérgio Apolinário[a]

[a] Center of Applied Social Science, Program of Postgraduate in Controllership and Corporate Finance, Mackenzie Presbyterian University (UPM), Brazil
[b] Visiting Associate Professor, Department of Information Systems and Business Analytics, School of Business, Eastern Washington University, WA, USA
[c] Associate Professor in Sustainable Operations and Analytics, Head of Sub-Department - Operations & Analytics, Department of Management, University of Exeter Business School Faculty of Environment, Science & Economy Building One, Streatham Ct, Rennes Drive, Exeter, EX4 4PU, UK
[d] Professor, Department of Information Systems and Business Analytics, School of Business, Eastern Washington University, WA, USA
[e] Researcher and Doctoral Candidate of Information Systems Area, Sage University, Indore, MP, India

A R T I C L E I N F O

Article History:
Received 25 July 2024
Accepted 28 September 2024
Available online 6 November 2024

Keywords:
Digital era
Dynamic information technology capability,
Improvisational capabilities
Explorative innovation
Ambidexterity

JEL classification:
000
014
030
031
035
036

A B S T R A C T

The advent of the digital era has transformed the way businesses create, compete, and maintain their existence, particularly in the aftermath of the COVID-19 pandemic. To maintain resilience in the ever-changing business landscapes of today, especially in emerging economies, businesses utilize dynamic information technology capabilities (DITC) to cultivate organizational capacities that foster innovation. This article argues that Dynamic Information Technological Capabilities (DITC) allows companies to develop flexible and adaptive skills to foster innovation. The results from 684 Brazilian businesses showed that implementing DITC improved their ability to come up with both new ideas and ways to use existing ones. This was possible because DITC improved the firms' dynamic and improvisational skills. The post hoc analysis of FIMIX PLS and PLS-POS reveals that DITC plays a greater role in fostering innovation through dynamic capabilities (DCs) rather than improvisational capabilities. The research on unobserved heterogeneity showed that a high level of DITC hasBig and strong effects on developing dynamic and improvisational skills for coming up with new ambidexterity ideas. The results indicated that companies should integrate the potential of digital technology and information to establish organizational capacities that can effectively compete within developing economies.

Introduction

Innovation has consistently been a critical driver of organizational growth, sustainability, and the enhancement of competitive advantage (Mehralian et al., 2024). Recent studies show that enterprises must pursue explorative and exploitative innovations to thrive in the digital era (Al Dhaheri et al., 2024; Wei et al., 2024), even more so in developing economies (Yoshikuni, 2024; Yoshikuni et al., 2024). Explorative innovations are considered radical, targeting emerging markets with new designs and channels, often requiring new knowledge (Aboelmaged et al., 2023). In contrast, exploitative innovations are incremental, enhancing existing products and processes to serve current markets better, building on established knowledge and skills (Jansen and Tempelaar et al., 2009).

Emerging economies face significant challenges in driving innovation in the digital era after the COVID-19 crisis (Aftab et al., 2022), as they often struggle with limited access to advanced technologies, underdeveloped digital infrastructure, and more significant regulatory uncertainty, making it difficult for companies to compete with the innovation capabilities of developed markets (CIA, 2024). However, enterprises in this context must recognize and act upon the uncertain environment's opportunities and mitigate threats, building organizational capabilities and competing through innovation (Dutta et al., 2022; World Economic Forum, 2016).

Organizational capabilities refer to an enterprise's ability to use resources and competencies to achieve business goals effectively (Grant, 1991; Porter, 1998; Wolf & Floyd, 2017). According to Winter (2003) and Daniel et al. (2014) zero-order ordinary and first-order

* Corresponding author
E-mail addresses: adilson.yoshikuni@mackenzie.br (A.C. Yoshikuni), rdwivedi@ewu.edu (R. Dwivedi), m.m.kamal@exeter.ac.uk (M.M. Kamal), dzhou@ewu.edu (D. Zhou), softwarepra@gmail.com (P. Dwivedi), sergio_apol@hotmail.com (S. Apolinário).

https://doi.org/10.1016/j.jik.2024.100589

capabilities can be not sufficient to compete in this environment, and second-order capabilities should be developed by enterprises. Organizational capabilities include ordinary capabilities for routine operations (Kohli & Grover, 2008; Melville et al., 2004), DCs for adapting to market changes (Helfat et al., 2023; Teece, 2018), and improvisational capabilities for quickly reconfiguring resources in response to unexpected situations (Pavlou & El Sawy, 2010). Hence, firms that substantially invest in IT to enhance organizational capabilities through (DCs (Steininger et al., 2022) and improvisational capabilities (ICs) (Yoshikuni & Dwivedi, 2023) can exploit opportunities, mitigate risks, and reconfigure their resource base, enabling them to better navigate and innovate within this dynamic context.

New research studies say that businesses need to adopt digital technologies and build dynamic IT capabilities and flexible IT skills (Li & Chan, 2019; Steininger et al., 2022; Yoshikuni et al., 2024) to stay competitive in today's fast-paced business world, where customer tastes change quickly, boundaries shift, and there is competition from around the world. Therefore, dynamic IT capability (DITC) is a first-order dynamic capability combining IT infrastructure (ITI) and IT knowledge management (ITKM). ITI involves the integration of digital technologies—such as data, computing, communication, and connectivity—to enhance customer understanding and optimize processes (Bharadwaj et al., 2013b; Li & Chan, 2019; Vial, 2019). ITKM focuses on strategic investments in developing digital skills, fostering cross-functional collaboration, and cultivating a digital culture while establishing governance and empowering employees to effectively utilize digital technologies (Li & Chan, 2019; Warner & Wäger, 2019; Yoshikuni et al., 2024). Hence, in the digital era, enterprises face increasing pressure to develop second-order capabilities that leverage digital technologies to support and enhance a wide range of business activities (Li & Chan, 2019) and foster innovation, particularly in developing economies (Dutta et al., 2022).

Furthermore, recent research on innovation highlights the need for future studies to clarify how enterprise characteristics are necessary to compete in uncertain markets in developing economies through innovation (Aboelmaged et al., 2023; Leal-Rodríguez et al., 2023). Innovation studies indicate that investigating the pathways through which digital adoption and knowledge management influence innovation is essential to fully understand the role of these mechanisms in driving innovation (Chen & Pan et al., 2024). Moreover, a recent systematic review on process innovation emphasizes the overlooked role of digital investments in empirical research, including technology infrastructure and digital knowledge, in adapting resources for innovation projects, leading to faster time-to-market, improved product quality, and enhanced customer satisfaction, and suggests that future research should address this gap (Goni & Van Looy, 2022). Additionally, recent studies call for further empirical research to explore different configurations of DITC components to validate the construct and enhance the understanding of it (Li & Chan, 2019). Finally, future research in information systems should investigate how IT helps organizations by using DCs (Mikalef et al., 2020) and improvisational capabilities (ICs) (Yoshikuni, 2022). The research should focus on how to make IT business value through digital technologies (Steininger et al., 2022).

The overall purpose of the paper is to investigate the relationship between DITC, and organizational capabilities to create Innovation, to fill knowledge gaps mentioned by recent studies (Aboelmaged et al., 2023; L. Chen et al., 2024; Goni & Van Looy, 2022; Leal-Rodríguez et al., 2023; Li & Chan, 2019;Luftman et al., 2015; Mikalef, Pateli, et al., 2020; Steininger et al., 2022; Yoshikuni, 2022) and propose the following research question:

(RQ) In developing economies, how can dynamic IT capabilities serve as a precursor to building dynamic and improvisational capabilities that drive explorative and exploitative innovation?

This study makes significant contributions to the existing literature by addressing key gaps. Firstly, it addresses a gap in DITC research by operationalizing, validating, and deepening the understanding of this novel construct as a measure. First-order DITC enhances the IT-business value literature. Second, it advances the literature on organizational capabilities, particularly dynamic and improvisational capabilities, by demonstrating their critical role in driving innovation through DITC in the Digital Era. Lastly, it contributes to innovation literature by showing that explorative and exploitative innovations are viable strategies for competing in developing economies.

The structure of the paper is as follows: The next section reviews the literature and outlines the research hypotheses and proposed model. Following is a detailed description of the research methodology, including variable measurement and statistical techniques. The subsequent section presents the empirical findings. Post hoc analysis examines the interrelationships between latent variables and explores potential unobserved heterogeneity within the proposed model. The final section discusses the findings, highlights contributions to the literature and practical implications, addresses limitations, and offers recommendations for future research. Fig. 1 presents the detailed research design.

Theoretical background and hypotheses

According to Teece et al. (2016), the resource-based view (RBV) underscores that organizations possess distinct resources and capabilities to leverage to secure a competitive edge. This view forms the foundation for understanding organizational capabilities as essential for achieving enterprise success (Amit & Schoemaker, 1993). The RBV suggests that firm capabilities lead to a competitive advantage when organizational assets can be valuable, scarce, difficult to replicate, and irreplaceable in their unique combinations (Taher, 2012).

Previous research has significantly advanced the understanding and definitions of different types of organizational capabilities, particularly by distinguishing between operational (or ordinary) capabilities and DCs (Helfat & Winter, 2011; Winter, 2003). Operational capabilities, such as zero-order capabilities, allow an enterprise to sustain its current operations (Winter, 2003). They enable ongoing activities using consistent methods and scale to support existing products and services for the same customer base, thereby maintaining the status quo (Amit & Schoemaker, 1993; Dwivedi et al., 2023).

On the other hand, a dynamic capability allows an enterprise to change its existing operations, enabling it to adapt or enhance its functions, whether by modifying operational capabilities, the organization's resource base, or aspects of the external environment or ecosystem (Helfat et al., 2023; Teece et al., 1997). According to meta-analyses (Helfat et al., 2023) and theoretical studies (Teece, 2018) on organizational capabilities, the DCs view (DCV) is a better way to explain why companies do better in the market than the rigidity-based view (RBV). This is because DCs make a company more flexible over time and less rigid.

This study uses Teece et al., 1997 definition of dynamic capabilities, which means that an organization can combine, develop, and change its internal and external skills to adapt to a world that is changing quickly and effectively.

Dynamic IT capabilities (DITC)

When these IT capabilities exhibit characteristics such as rarity, appropriability, non-replicability, and non-substitutability, they can create a competitive advantage, as outlined by the RBV (Taher, 2012; Wade & Hulland, 2004).. However, when IT-enabled operational capabilities are grounded in the RBV framework, they can be insufficient for adapting operational routines to address external challenges (Bharadwaj, 2000). Thus, first-order dynamic IT capabilities by the DCV become essential to empower organizational capabilities to integrate, build, and reconfigure internal and external IT competencies to

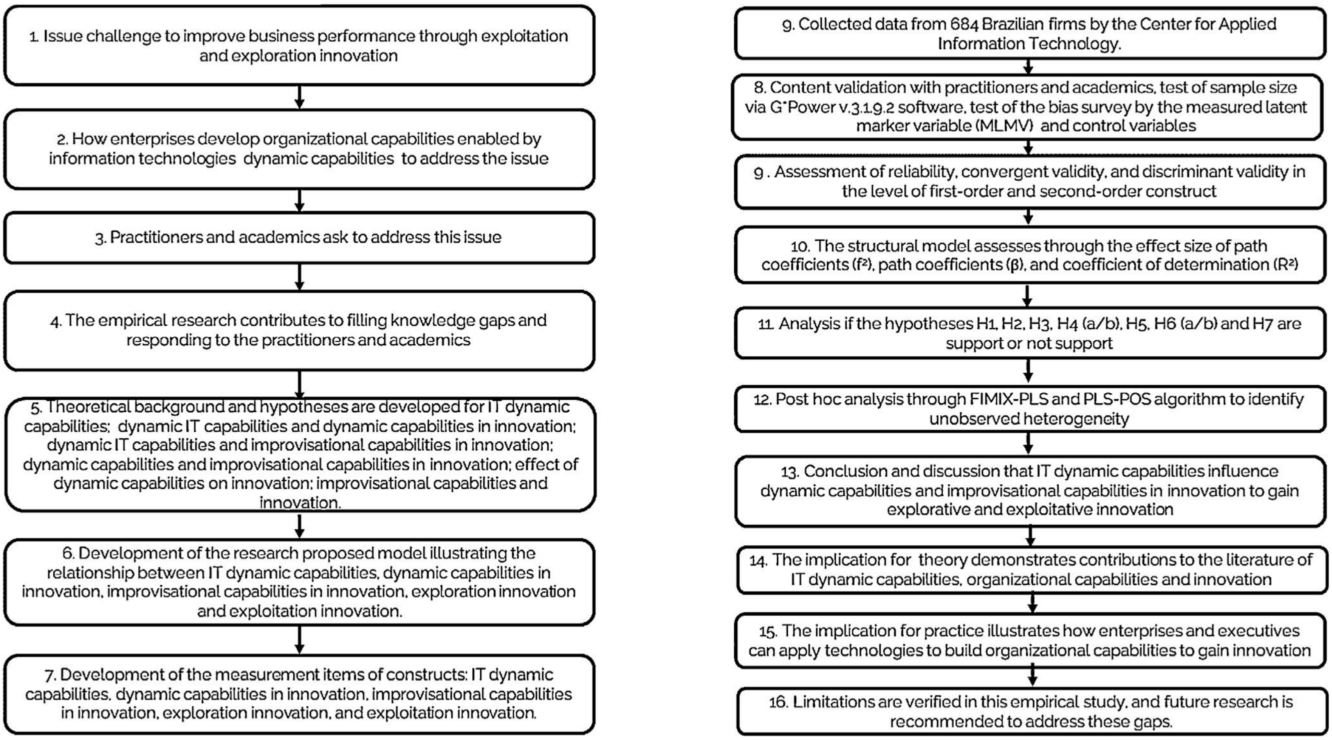

Fig. 1. Research design process

address rapidly changing environments (Li & Chan, 2019; Steininger et al., 2022). The company possesses strong organizational capabilities, with IT playing a crucial role in enhancing them, leading to significant improvements in operational excellence and competitive responsiveness (Mikalef & Pateli, 2017; Yoshikuni et al., 2024). Therefore, DCs are characterized by IT-embedded DCs, incorporating IT resources within their structure (Li & Chan, 2019). These IT-embedded DCs include general DCs and more specific forms, such as IT-enabled agility, flexibility, exploitative innovation, explorative innovation, ambidexterity, business process performance, and other routines (Steininger et al., 2022). Hence, IT-enabled DCs emphasize capacities directly supported by specific technical assets, including IoT data, enterprise resources planning, business data analytics, business intelligence, strategic enterprise management, big data, etc.

IT capabilities include the use of IT resources, including physical and human assets, as well as complementary organizational resources, to optimize business processes and improve immediate and long-term outcomes (Melville et al., 2004). When these IT capabilities exhibit characteristics such as rarity, appropriability, non-replicability, and non-substitutability, they can create a competitive advantage, as outlined by the RBV (Taher, 2012; Wade & Hulland, 2004). However, the RBV framework-based IT-enabled operational capabilities may not be sufficient for adapting operational routines to external challenges (Bharadwaj, 2000). Thus, the DCV's first-order dynamic IT capabilities become essential to empower organizational capabilities to integrate, build, and reconfigure internal and external IT competencies to address rapidly changing environments (Li & Chan, 2019; Steininger et al., 2022). The company possesses strong organizational capabilities, with IT playing a crucial role in enhancing them, leading to significant improvements in operational excellence and competitive responsiveness (Mikalef & Pateli, 2017; Yoshikuni et al., 2024). Therefore, DCs are characterized by IT-embedded DCs, which incorporate IT resources into their structure (Li & Chan, 2019). These DCs with-IT built-in have both broad and specific DCs, such as IT-enabled agility, flexibility, exploitative and explorative innovation, ambidexterity, business process performance, and other routines (Steininger et al., 2022). Hence, IT-enabled DCs emphasize capacities directly supported by specific technical assets, including IoT data, enterprise resources planning, business data analytics, business intelligence, strategic enterprise management, big data, etc.

This research is based on the definition of dynamic IT capability [DITC, (Li & Chan, 2019)], operationalized as the first-order IT dynamic capability created by IT units to remain responsive to evolving technology and market conditions in today's business environment. Broadly, DITC is described as the ability of an IT unit to obtain, utilize, integrate, restructure, and modify the organization's IT resources to enable organizational capabilities and achieve business goals (Bharadwaj, 2000; Bharadwaj et al., 2013a).

In this study, DITC represents a first-order DCs composed of two interconnected and interdependent DCs linked to the ordinary capabilities of IT infrastructure (ITI) and IT knowledge management (ITKM), as proposed by Li and Chan (2019) in their conceptual study on DITC. The ITI refers to how an enterprise integrates IT infrastructure through digital technologies, including data, computing, communication, and connectivity (Bharadwaj et al., 2013a; Vial, 2019), to enable organizational capabilities to understand customers better, connect customer-facing and operational processes, market and sell products and services, deliver customer service, and provide a comprehensive view of critical operational and customer information (Li & Chan, 2019). The ITKM refers to how an enterprise makes a strategic investment in developing an innovative mindset (Li & Chan, 2019) through cross-functional collaboration between business and IT teams, cultivating a digital culture by enhancing digital skills and mindset, advancing digital initiatives and collaborative learning across local and corporate units (Warner & Wäger, 2019), establishing clear roles and responsibilities for governing digital efforts, and empowering all members to engage in discussions around the advantages of utilizing digital technologies (Vial, 2019).

Organizational capabilities enabled by DITC

Organizational capabilities refer to an enterprise's ability to effectively utilize its resources and competencies to achieve specific business objectives (Grant, 1991). These capabilities are categorized into

(1) ordinary (or operational) capabilities, which involve routine activities that support the ongoing production, sales, and service of products or services (Winter, 2003); (2) DCs, which focus on the strategic adaptation and transformation of the firm's ordinary capabilities and resources in response to changing market conditions and opportunities (Helfat & Winter, 2011; Helfat et al., 2023); and (3) improvisational capabilities, which reflect the firm's ability to spontaneously reconfigure existing resources to develop new operational capabilities that address urgent, unpredictable, and novel environmental situations (Pavlou & El Sawy, 2010; Yoshikuni, 2022; Zhang et al., 2023). Together, these capabilities enable an organization to maintain competitiveness and drive long-term success.

DITC is defined as first-order DCs that enable organizational capabilities as a second-order into DCs (Daniel et al., 2014) and improvisational capabilities (Pavlou & El Sawy, 2010). Past research on DCs is grouped into three main organizational capacities: (1) sensing, involving the recognition and evaluation of potential opportunities and risks; (2) seizing, allocating resources to respond to these opportunities or risks and deriving benefits; and (3) transforming, focused on ongoing adaptation and renewal (Teece, 2007, 2018; Teece et al., 2016). Thus, DITC helps firms to capture, harness, and understand customer data (Aydiner et al., 2019; Knabke and Olbrich, 2018; Pappas et al., 2018; Mikalef et al., 2019) through digital technologies, such as social, and mobile, analytics and cloud [ITI, (Frishammar et al., 2018)]. According to Warner and Wäger, (2019), digital innovation comprises new capabilities in digital scenario planning, digital scouting, and digital mindset crafting to pinpoint new technological, customer, and competitor-based trends to create innovation. This study proposes the following hypothesis to address the knowledge gap in IS literature (Li & Chan, 2019; Steininger et al., 2022) on how firms develop organizational DCs through digital and knowledge capabilities to enable second-order DCs.

H1a. *DITC drives the building of dynamic capabilities.*

Improvisation capability (IC) is the capacity to act spontaneously in trying to respond to problems or opportunities in a novel way (Vera et al., 2016; Yoshikuni, 2022). IC utilizes existing resources in real time to build new operational capabilities that better match novel environmental situations (Hadida & Tarvainen, 2015; Tseng et al., 2015; Zhang J. et al., 2023). Digital innovation fosters identification and the rapid embrace of changes, allowing organizations to gain the best performance through faster innovation (Levallet & Chan, 2018; Nambisan et al., 2017). The authors (Levallet & Chan, 2018; Yoshikuni, 2022) defined digital culture as the improvisational ability to act promptly in an unplanned manner (i.e., spontaneously) and/or creatively in the face of uncertainty. DITC enabled by analytics and big data may play a central role in decision-making in the face of highly unstructured tasks being carried out in high uncertainty (Aydiner et al., 2019; Knabke & Olbrich, 2018; Mikalef, Krogstie, et al., 2020; Steininger et al., 2022). Hence, IT infrastructure associated with IT knowledge management leveraging improvisation capabilities among managers brings about more success in decision-making as they move forward. Therefore, DITC's leverage on IC promotes effective improvisation when carrying out our activities, dealing with unanticipated events on the spot, and responding quickly to unexpected problems (Levallet & Chan, 2018).. This study hypothesizes that:

H1b. *DITC drives the building of improvisational capabilities.*

Organizational capabilities for innovation

Most research findings provide different perspectives on the variations of innovation (Benner & Tushman, 2015; Mehralian et al., 2024; Gholamhossein Mehralian et al., 2024). However, most of the studies claim that innovation is anything original or an improved idea, recombination of old ideas, approaches, or methods, or anything that is perceived as new or improved (Alves et al., 2017; Goni & Van Looy, 2022; Jha & Bose, 2016). The exploration-exploitation framework of organizational learning gained prominence within organizational, strategic innovation (Benner & Tushman, 2015; Konlechner et al., 2018) and IS literature (Yoshikuni & Galvão, 2023; Yoshikuni et al., 2024). According to Jansen et al. (2009), exploratory and exploitative innovation are classified into two domains: proximity to existing technologies, products, and services and proximity to existing customers or market segments. However, enterprises that create together explorative and exploitative innovation are considered ambidexterity (Yoshikuni, 2024).

Exploratory innovations help meet new demands for products and services, embrace challenges to serve new markets, and develop new distribution channels, units, and production lines (Jansen, et al., 2009). Previous studies of innovation (Tsai, 2015; Yoshikuni et al., 2024) defined exploration innovation as a radical innovation that creates innovation value in a novelty dimension that renders the new product radically differentiated from the conventional product specifications. Exploitative innovation is defined as the improvement of existing products and services with minor and frequent adjustments to the value proposition to maintain and/or expand their current customer and market share (Behnam & Cagliano, 2019; Goni & Van Looy, 2022; Jansen, Vera, et al., 2009).

DCs reflect an organization's ability to respond timely, rapidly and flexibly to product innovation to achieve new and innovative forms of competitive advantage given path dependencies and market positions (Lau & Lo, 2019; Lu & Ramamurthy, 2011; Warner & Wäger, 2019; Zhang et al., 2023). The dynamic capability framework recognizes the importance of evolutionary innovation (bottom-up) (Konlechner et al., 2018) as the creation of new knowledge to develop breakthrough products, i.e., exploration innovation (Helfat et al., 2023; Teece, 2018). Previous studies demonstrated that DC was positively and highly significant to exploration innovation (effectiveness to create new products) and exploitation innovation (adaptive efficiency to renew existing products) (Pavlou & El Sawy, 2006, 2010; Protogerou et al., 2012; Wilhelm et al., 2015). To expand the knowledge and contribute to innovation management research, it is recommended that further studies investigate new constructs associated, with exploration and exploitation innovation (Benner & Tushman, 2015; Jansen, Vera, et al., 2009) leveraged by digital technologies (Nambisan et al., 2017) and specific context factors, such as developing economies (Konlechner et al., 2018; Warner & Wäger, 2019). This study declares the following hypotheses:

H2a. *Dynamic capabilities positively influence explorative innovation.*

H2b. *Dynamic capabilities positively influence exploitative innovation.*

ICs are spontaneous and creative abilities (Vera et al., 2016) to reconfigure existing resources, build new operational capabilities, and address urgent, unpredictable, and novel environmental situations (Pavlou & El Sawy, 2006; J. Zhang et al., 2023). Exploratory innovation entails the search for new knowledge to create products and services for emerging markets and customers. On the other hand, exploitative innovation builds on existing knowledge resources and improves existing products and services for current markets (Jansen, Vera, et al., 2009). Previous studies on IC demonstrated that they have positive effects on innovation and are relevant to knowledge-based processes (Vera et al., 2016), information systems development (Du et al., 2019), decision support systems (Mendonça, 2007; Mishra et al., 2023), IT-enabled organizational virtues (Chatterjee et al., 2015) by digital innovation (Levallet & Chan, 2018; Pavlou & El Sawy, 2006, 2010). A growing number of studies are investigating the effects of IC on innovation, but few studies focus on identifying the relationship between improvisational capabilities and exploration/

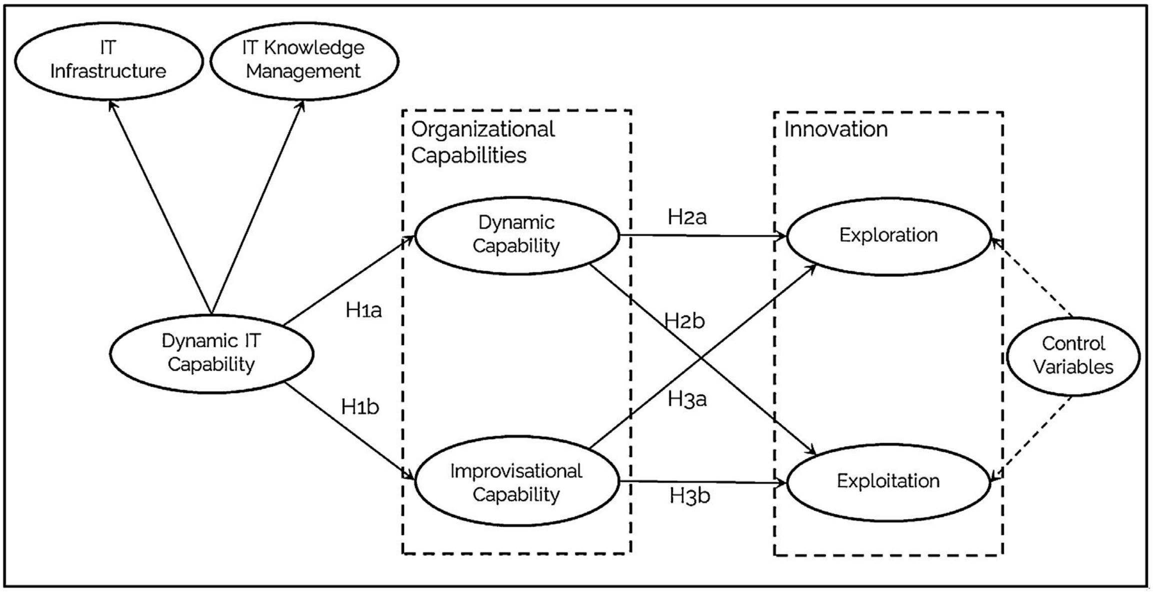

Fig. 2. Proposed model

exploitation innovation. Hence, the study proposed the following hypotheses:

H3a. *Improvisational capabilities positively influence explorative innovation.*

H3b. *Improvisational capabilities positively influence exploitative innovation.*

The proposed research model presented (Fig. 2) illustrates our hypotheses.

Research methodology

Sample size

Based on a comprehensive review of the relevant literature, a survey instrument was developed, and a pre-test survey was conducted to check the clarity of the items' contents, response time, and related observations (Yayla and Hu, 2012). The pre-test respondents were four IT/IS researchers and three senior executives who commented on improving the clarity of the measurement items. See Appendix A, which summarizes the measures and sources of the variables used in the analyses.

Convenience sampling was utilized to gather data from Brazilian organizations. Following established practices in management and IS research, respondents were contacted through diverse channels, such as social media, industry association lists, personal networks, and academic directories curated by the authors. Additionally, the questionnaire instructions encouraged respondents to seek input from other knowledgeable members within their organization if they required additional expertise on the survey constructs. The targeted respondents were chosen based on their position, experience, and professional knowledge of IS and management. To motivate and encourage executive respondents to participate in the IT capabilities survey, they were provided with feedback on how their company performed in the assessed aspects of the proposed model, along with general recommendations on addressing any potential issues identified. The study used an online data collection approach that did not permit missing data entry, as participants had to respond to a particular question before proceeding to the next question. The research instrument was prepared before the onset of COVID-19. However, due to the pandemic, respondent participation was initially low, and most responses were collected after the pandemic began. The final response was received in mid-2023. Additionally, the study examined suspicious response patterns as recommended by Hair et al. (2022). A visual inspection of the data was analyzed and verified to see if respondents marked the same response for all questions or alternated between extreme pole responses, and none of the cases were removed. The total sample size of respondents in the online platform was 684 firms.

The minimum study sample size was tested using the G*Power v.3.1.9.2 software (Faul et al., 2007) with a median effect size [f^2] of 0.15 and statistical power of not less than 0.80. The minimum sample size was 92 cases, which indicated the sample size validation. Outliers were analyzed by the Mahalanobis square distance (DM^2) (Cousineau & Chartier, 2017), and five cases presented high DM^2 values (range of statistical residual of the DM variable = 17,878 until 22,799 and, with a probability value of $p > 0.001$) indicating multivariate outliers. The outcomes were obtained from the database and the final sample was 684 cases. The sample size exceeded the requirements.

Data distribution was verified, and the variables' normality was evaluated using coefficients of skewness (Sk) and kurtosis (Ku). Univariate and multivariate variables showed no severe violation of the normal distribution assumption ($|Sk| < 3$ and $|Ku| < 10$) (Hair et al., 2022). Finally, statistical techniques were applied to detect and (where possible) control the common method bias. Consistent with Chin et al. (2013), the measured latent marker variable (MLMV) technique was used for the model as the dependent variable.

Measurement of the variables

DITC was a second-order (reflective construct) measured through two constructs (Li & Chan, 2019): IT knowledge management (ITKM) was measured as a first-order construct (reflective) based on the conceptual studies from Li and Chan (2019), Warner and Wäger (2019), and Chanias et al., (2019); while IT infrastructure (ITI) was a first-order construct (reflective) based on the conceptual studies from Bharadwaj et al., (2013a); Li and Chan (2019); Vial, (2019). Organizational capabilities through DCs were based on Pavlou and El Sawy (2010) as a first-order construct, and improvisational capabilities as a first order-construct from Chatterjee and colleagues (Chatterjee et al. 2015), Innovation of exploration and exploitation adopted by Jansen and colleagues (Jansen, Vera, et al., 2009). Measured latent marker variable (MLMV- formative) (Almeida et al., 2022; Yoshikuni, 2024) were also determined, see Appendix A. The scale content was

Table 1
Summary of constructs, measures and sources

Constructs	Measures	Sources
Dynamic IT capabilities	IT Infrastructure	Li and Chan (2019), Chanais et al. (2019)
	IT knowledge manage	Bharadwaj et al. (2013a), Li and Chan (2019), Vial (2019).
Organizational capabilitiies	Dynamic capability	Pavlou and El Sawy (2010)
	Improvisational capability	Chatterjee et al. (2015)
Innovation	Exploration	Jansen et al. (2009), Yoshikuni et al. (2024)
	Exploitation	Jansen et al. (2009), Yoshikuni et al. (2024)
Control variables	Firm-sized	Melville et al. (2004)
	Industry sector	Melville et al. (2004)
Measured latent marker variable	MLMV	Yoshikuni et al. (2024)

validated by an IS field specialist with more than 10 years of experience (researchers and professors), and validity and reliability were assessed by statistical tests (see Table 3), as indicated by Morgado et al. (2018). The primary constructs were measured through seven-point Likert-type scales ranging from 1 = "strongly disagree" to 7 = "strongly agree.". Table 1 measures and data sources for the constructs used in the proposed model.

Control variables

According to Melville et al. (2004) and Kohli and Grover (2008), an enterprise's characteristics, including size, age, industry sector, and other factors, can influence how IT generates business value. Previous information systems (IS) studies have highlighted these aspects (Mikalef & Pateli, 2017; Yayla & Hu, 2012; Yoshikuni, 2022). Firm size (SIZE) was measured by the number of employees. It was measured as an ordinal variable with the following values: micro (1–9 employees), small (10–49 employees), medium (50–249 employees), and large (above 250 employees). To control the effect of the industry sector (SECTOR), four categories were created: agribusiness, manufacturing, service, and government. Responses were collected from agribusiness (3 %), manufacturing (30 %), services (63 %) and government (4 %). The survey was predominantly completed by 31 % C-level executives (e.g. chief executive officers), 33 % management and coordination personnel, and 36 % supervisors with decision-making powers. The firm size (number of employees) was grouped into large (65 % > 500 employees), medium (17 % - 50-249 employees), small (12 % - 10-49 employees), and micro (5 % - 0-9 employees) classes.

Statistical Techniques Hypotheses

Hypotheses were tested using partial least squares structural path modeling (PLS-PM) by the SmartPLS software package (Ringle et al., 2015). PLS-PM was particularly appropriate for this study because the structural model was complex (many constructs and many indicators). Formative measured constructs are part of the structural model, which helps comprehend the FIMIX-PLS and PLS-POS approaches for identifying and treating unobserved heterogeneity.

Common Method Bias in the Survey

There is potential for common method bias (CMB) in this study. The bias is controlled during the research design phase by using priori approaches (Schwarz et al., 2017), such as choosing respondents who are able to answer the questionnaire, items constructed in clear and concise language, counterbalancing the order of questions and anonymity of the respondent, and applied technical remedies as suggested by MacKenzie and Podsakoff (2012) and Fuller et al. (2016).

Finally, the statistical technique was applied to detect where possible to control CMB in line with Chin et al., (2013). The MLMV technique was used for the model of exploitation and exploration innovation constructs. According to Chin et al., (2013), four items designed to have the lowest possible correlation with the other constructs under investigation were used. The MLMV was adapted through formative indicators used for MLMV analysis by Yoshikuni et al. (2024). The model with MLMV variables revealed a more fitting sight than the original one (difference less than 1 % in all variance explanation – R^2), see Table 4 Thus, this suggests that CMB is not a severe concern in this study.

Measurement of the first-order model

The reflective latent variables were subjected to the tests of reliability, convergent validity, and discriminant validity. (Akter et al., 2017; Hair et al., 2022), and all latent variables were connected for these analyses as recommended by Bido and Silva (2019). Table 3 shows that the indicators have higher factor loadings on their assigned constructs, above 0.70, and indicate the discriminant validity (Akter et al., 2017; Hair et al., 2022). Items with lower loadings were omitted from the measurement model, as indicated by Bido and Silva (2019) and Hair et al. (2022).

Convergent validity was assessed by examining whether AVE > 0.50 and each construct's AVE square root was greater than its highest correlation with any other construct (Fornell-Larcker criterion). Composite reliabilities, Cronbach's alpha, and Dijkstra-Henseler's indicator (Rho_A) are > 0.68 (Bido & Silva, 2019; Hair et al., 2017) of all constructs (Table 2) and all values of HTMT confidence interval were lower than 0.85 which supported the HTMT criterion (Henseler et al., 2015). The second-order DITC variable yielded an AVE value of 0.535 and a CR estimate of 0.919. A comparison of the Fornell–Larcker criterion with the square root of DITC (0.731) AVE values showed the criterion to be satisfied.

Empirical results

Structural model

Fig. 3 and Table 4 summarize the structural model from the PLS analysis: the effect size of path coefficients (f^2), path coefficients (β), and coefficient of determination (R^2). The significance of estimates (t-statistics) is obtained by performing a bootstrap analysis with 5000 resamples.

From the observation of Table 4, the result of the direct effects was presented (value $p < 0.05$) to the relationship between DITC → DC, DITC → IC, DC→ER, DCI → EP, IC → ER, and IC → EP, thus, hypotheses H1a, H1b, H2a, H2b, H3a, and H3b were supported. The structural model accounts for 44,8 % of the variance in dynamic capability (R^2 = 0.448), 19.4 % of the variance in improvisational capability (R^2 = 0.194), 35.3 % of the variance in the innovation of exploration (R^2 = 0.353), and 45.8 % of the variance the innovation of exploitation (R^2 = 0.458).

For the control variables, only Sector was found to significantly influence EP and ER (p-value < 0.05), demonstrated in Table 4.

Table 2
Assessment of convergent and discriminant validity of reflective constructs.

Constructs	1	2	3	4	5	6
1. IT Infrastructure	0.784					
2. IT Knowledge Management	0.697	0.806				
3. Dynamic Capabilities	0.656	0.567	0.811			
4. Improvisational Capabilities	0.408	0.334	0.576	0.798		
5. Exploitative Innovation	0.599	0.619	0.650	0.446	0.765	
6. Explorative Innovation	0.525	0.550	0.573	0.411	0.741	0.817
Cronbach's Alpha	0.842	0.865	0.895	0.732	0.857	0.834
Rho_A	0.855	0.870	0.897	0.774	0.863	0.841
Composite Reliability	0.888	0.902	0.920	0.840	0.894	0.889
Average Variance Extracted (AVE)	0.615	0.649	0.657	0.636	0.585	0.668

Table 3
Factor loadings (bolded) and cross-loadings of reflective constructs.

First Latent Variable	Items	DCI	ICI	ITI	IKM	EPIA	ERIA
Dynamic Capabilities in Innovation (DCI)	DC1	**0.809**	0.423	0.530	0.487	0.579	0.520
	DC2	**0.804**	0.412	0.539	0.488	0.551	0.458
	DC3	**0.837**	0.431	0.570	0.487	0.515	0.436
	DC4	**0.776**	0.495	0.522	0.414	0.450	0.390
	DC5	**0.816**	0.559	0.515	0.419	0.503	0.459
	DC6	**0.820**	0.492	0.513	0.454	0.551	0.510
Improvisational Capabilities in Innovation (ICI)	IC1	0.600	**0.821**	0.467	0.361	0.457	0.414
	IC5	0.325	**0.765**	0.177	0.175	0.239	0.223
	IC6	0.370	**0.805**	0.243	0.206	0.309	0.293
IT Knowledge Management (ITKM)	ITKM1	0.534	0.368	**0.816**	0.544	0.517	0.487
	ITKM2	0.569	0.325	**0.861**	0.627	0.554	0.498
	ITKM3	0.549	0.318	**0.819**	0.671	0.520	0.423
	ITKM4	0.454	0.278	**0.744**	0.452	0.368	0.316
	ITKM5	0.453	0.315	**0.664**	0.395	0.356	0.303
IT Infrastructure (ITI)	ITI1	0.484	0.270	0.636	**0.866**	0.518	0.453
	ITI2	0.372	0.235	0.453	**0.773**	0.444	0.409
	ITI3	0.359	0.244	0.476	**0.796**	0.430	0.412
	ITI4	0.510	0.312	0.545	**0.773**	0.540	0.477
	ITI5	0.539	0.283	0.670	**0.815**	0.550	0.462
Innovation of Exploitation (EPI)	EP2	0.348	0.241	0.343	0.305	**0.660**	0.562
	EP3	0.558	0.447	0.506	0.491	**0.758**	0.557
	EP4	0.588	0.393	0.507	0.488	**0.809**	0.599
	EP5	0.519	0.344	0.438	0.440	**0.787**	0.545
	EP6	0.473	0.335	0.436	0.517	**0.808**	0.647
Innovation of Exploration (ERI)	ER2	0.564	0.462	0.459	0.460	0.594	**0.785**
	ER3	0.475	0.312	0.478	0.497	0.647	**0.881**
	ER4	0.383	0.307	0.361	0.416	0.525	**0.772**
	ER5	0.429	0.249	0.401	0.416	0.646	**0.826**

Post-hoc analysis

Several post hoc analyses were conducted to clarify (1) the interrelationships between DITC, DC, IC, EP, and ER further and explore (2) potential unobserved heterogeneity within the proposed model. The first post hoc analysis assessed statistical differences between parameter estimates in Partial Least Squares Path Modeling (PLS-PM) by comparing the effects of two-parameter estimates with two separate tests (Rodríguez-Entrena et al., 2018). Table 5 highlights the differences in the relationships between DITC and DC, and DITC and IC, as well as the differences in the effects of DC on EP and ER, and finally, the differences in the relationships between IC and EP, and IC and ER. The (1) difference of 0.208 between the path coefficients of DITC → DC and DITC → IC was statistically significant (p-value < 0.05). Similarly, the (2) difference of 0.059 between the path coefficients of DC → ER and DC → EP was also statistically significant (p-value < 0.05). However, the (3) difference of 0.002 between the path coefficients of IC → EP and IC → ER was not statistically significant (p-value > 0.05). All tests were conducted following the methodological framework recommended by Rodríguez-Entrena et al. (2018).

Second, post hoc analysis allowed us to identify and interpret possible "unobserved heterogeneity" in the relationship within the proposed model, verifying the existence of factors not included in the original analysis, which may explain the differences between various groups. For these companies, the final blending technique (FIMIX-PLS) was used as recommended by Hair et al. (2016) and Matthews et al. (2016) On the PLS-PM analyses.

To identify the number of unobservable segments the FIMIX-PLS algorithm [SmartPLS v3 software (Ringle et al., 2015)] was used and executed 10 times for g = 2-5 segments using the Akaike Information Criteria (AIC), Factor 3 Modified AIC (AIC3), Bayesian Information Criteria (BIC), Consistent AIC (CAIC), Hannan-Quinn Criteria (HQ) and Standard Entropy Statistics (EN) that presented satisfactory criteria for segment selection. Indicators that presented lower values in specific information criteria portrayed the best segment solution and showed EN values above 0.50 (Hair et al., 2019). According to the authors (Hair et al., 2022), the first criterion verified that the AIC3 and CAIC values were smaller per segment tentatively considering the lower values together between AIC3 and BIC, plus the segment number as indicated by AIC4 and BIC (lowest values). Generally, the study chooses the smallest segment indicated by AIC and more segments than indicated by MDL5 in cases where the segment size meets the minimum sample size (92 cases). Table 6 shows the fit indices for a one- to five-segment solution.

According to the segmentation's criteria, the three segments were adequate and thus preceded the prediction-oriented segmentation

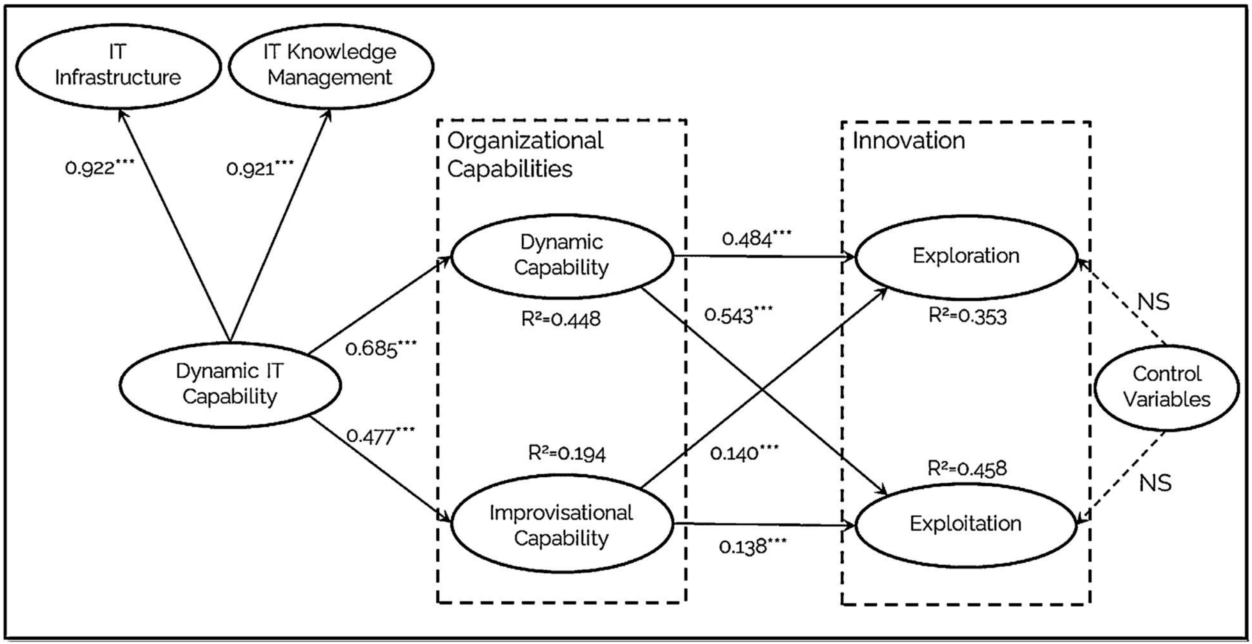

Fig. 3. Final model. **Note:** *p*-value < 0.5 *; *p*-value < 0.01 **; *p*-value < 0.001 ***; no significant NS.

Table 4
Relationships between all latent variables.

Variables Relationship	f^2 effect Size	Path Coefficient	Standard Error	*t* value	*p*-value	R^2	R^2 with MLMV
DITC → DC	0.724	0.685	0.026	26.353	0.000	0.448	0.463
DITC → IC	0.241	0.477	0.037	12.858	0.000	0.194	0.194
DC → ER	0.223	0.484	0.039	12.308	0.000		
IC → ER	0.020	0.140	0.040	3.515	0.000	0.353	0.356
SIZE → ER	0.001	-0.030	0.046	0.644	0.520		
SECTOR → ER	0.009	0.078	0.035	2.207	0.028		
DC → EP	0.336	0.543	0.040	13.742	0.000		
IC → EP	0.023	0.138	0.038	3.662	0.000	0.458	0.464
SIZE → EP	0.023	-0.114	0.083	1.375	0.169		
SECTOR → EP	0.015	0.090	0.036	2.483	0.013		

Note: DITC: Dynamic IT capabilities; DC: Dynamic Capability; IC: Improvisational Capability; ER: Explorative Innovation; EP: Exploitative Innovation; SECTOR: Firm Sector; SIZE: Firm Size.

Table 5
Results of parameter differences based on different confidence intervals (CI).

Type of Confidence Interval (a=5 %)	Differences of path coefficients					
	(1) β1a ≠ B1b		(2) β2a ≠ β2b		(3) β3a ≠ β3b	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Standard	0.202	0.206	0.316	0.332	- 0.008	- 0.003
Percentile	0.149	0.273	0.215	0.471	- 0.075	0.065
Basic	0.148	0.272	0.221	0.477	- 0.077	0.063

Note: β1a: DITC → DC; BH1b: DITC → IC; β2a:DC → ER; β2b:DC → EP; β3a:IC → ER; β3b:IC → EP

(PLS-POS). The PLS-POS algorithm [SmarPLS v3 software, (Ringle et al., 2015)] was run to evaluate the differences in the segments and workarounds. The sample sizes defined by PLS_POS were 1-segment, 253 (38 %), 2-segment, 264 (40 %), and 3-segment, 157 (24 %). The PLS-POS R^2 values of the variables were compared. Table 8 shows the coefficient of determination (R^2) for Original, 1-segment, 2-segment, 3-segment, and PLS-POS Average. It demonstrates high differences between the original sample R^2 and segments 1, 2, and 3 and the PLS-R^2 Average, see Table 7.

The values were compared, and evidence showed clear differences between the path coefficient estimates of three segments in the structural models' effects, see Table 8. All segmentation (1, 2, and 3)

Table 6
Fit indices for a one- to five-segment solution.

S	AIC	AIC3	AIC4	BIC	CAIC	HQ	MDL5	EN	Relative Segment Sizes				
									g = 1	g = 2	g = 3	g = 4	g = 5
s = 2	7,418.57	7,463.57	7,508.57	7,622.33	7,667.33	7,497.42	8,797.36	0.66	0.604	0.396			
s = 3	7,221.90	7,289.90	7,357.90	7,529.80	7,597.80	7,341.05	9,305.41	0.65	0.479	0.312	0.209		
s = 4	7,010.35	7,101.35	7,192.35	7,422.39	7,513.39	7,169.80	9,798.57	0.72	0.339	0.33	0.211	0.120	
s = 5	6,834.31	6,948.31	7,062.31	7,350.50	7,464.50	7,034.06	10,327.25	0.75	0.317	0.203	0.177	0.159	0.144

Legend: AIC - Akaike's Information Criterion, AIC3 - Modified AIC with Factor 3, AIC4 - Modified AIC with Factor 4, BIC - Bayesian Information Criteria, CAIC - Consistent AIC, HQ - Hannan Quinn Criterion, MDL5 - Minimum Description Length with Factor 5, and EN - Entropy Statistic (Normed)

Table 7
PLS-POS segment solution.

	R Squares Values				PLS-POS
Constructs	Full Data Set	PLS-POS Segment 1	PLS-POS Segment 2	PLS-POS Segment 3	Weighted Average R-Squares
DC	0.448	0.175	0.753	0.698	0.691
IC	0.194	0.094	0.579	0.517	0.461
EP	0.353	0.365	0.710	0.782	0.737
ER	0.458	0.263	0.642	0.804	0.722

Note: DITC: Dynamic IT capabilities; DC: Dynamic Capability; IC: Improvisational Capability; ER: Explorative Innovation; EP: Exploitative Innovation; SECTOR: Firm Sector; SIZE: Firm Size.

Table 8
Final segmentation results.

Variables	Original		1-segment		2-segment		3-segment	
Relationship	684 cases	p	253 cases	p	264 cases	p	157 cases	p
	β	value	β	value	β	value	β	value
DITC → DC	0.685	0.000	0.286	0.000	0.885	0.000	0.775	0.000
DITC → IC	0.477	0.000	-0.277	0.000	0.788	0.000	0.504	0.000
DC → ER	0.484	0.000	0.015	0.000	0.477	0.000	0.886	0.000
IC → ER	0.140	0.000	-0.230	0.000	0.388	0.000	0.097	0.040
SIZE → ER	-0.030	0.520	0.181	0.355	-0.018	0.714	0.056	0.433
SECTOR → ER	0.078	0.028	0.360	0.004	0.049	0.363	-0.186	0.000
DC → EP	0.543	0.000	0.358	0.000	0.305	0.000	0.898	0.000
IC → EP	0.138	0.000	-0.341	0.817	0.556	0.000	0.051	0.263
SIZE → EP	-0.114	0.169	0.181	0.846	-0.115	0.009	0.087	0.319
SECTOR → EP	0.090	0.013	0.168	0.045	0.111	0.131	-0.065	0.090

Note: DITC: Dynamic IT capabilities; DC: Dynamic Capability; IC: Improvisational Capability; ER: Explorative Innovation; EP: Exploitative Innovation; SECTOR: Firm Sector; SIZE: Firm Size.

in the relationship between DITC and DC showed positive effects and statistical significance (p-value < 0.001). IC was positive and statistically significant (p-value < 0.001) and was influenced by DITC in the 2-segment, 3, but in the 1-segment. The influence of DC on explorative and DC on exploitative innovation presented a positive relationship and statistical significance (p-value < 0.001) in all segmentations. The relationship between IC and ER demonstrated a positive association and was statistically significant (p-value < 0.001) in the 2-segment and 3-segment. On the other hand, 1-segment showed a negative correlation and statistical significance (p-value < 0.001) in this relationship. In the direct relationship between IC and EP, there was positive and significant (p-value < 0.001) in the 2-segment and the 1-segment and 3-segment; these relationships were not statistically significant (p-value > 0.05).

The control variables sector is present in the 1 and 2 segmentations on ER (p-value < 0.05). EP was influenced through the sector in the 1 segment (p-value < 0.05) and size in the 2 segment (p-value < 0.01).

Table 8 used observable variables in the data set to compare the PLS-POS partition and explain the latent segment structure in terms of observable and practically meaningful variables.

Table 9 shows the cross tab of the PLS-POS partition and level of DITC (low and high intensity of ITI and ITKM), sector, and firm size. Comparing the cell counts, the 1-segment showed a major percentage of cases in the low level of DITC, manufacturing sector, and small and medium-sized firms (1-249 employees). At the same time, the 2-segment demonstrated a major percentual case in the high level of DITC, agribusiness, and government sectors, as well as large firms (+250 employees). Additionally, the 3-segment showed major percentual cases in the high level of DITC, the agribusiness and services sector, and large firms.

Discussion

This study looked at how the modularity of the IT function, which is defined by the interaction between IT infrastructure and IT

Table 9
Cross tab of PLS-POS partition and observable variables.

Observed Variables		PLS-POS Segments				Sample Percentage by PLS-POS Segment			
		1	2	3	Sum	1	2	3	Sum
Level of DITC	Low	140	105	68	313	45 %	34 %	22 %	46 %
	High	113	159	99	371	30 %	43 %	27 %	54 %
Sector	Agribusiness	5	9	7	21	24 %	43 %	33 %	3 %
	Manufacturing	90	70	46	206	44 %	34 %	22 %	30 %
	Services	151	169	108	428	35 %	39 %	25 %	63 %
	Government	7	16	6	29	24 %	55 %	21 %	4 %
Firm Size *(number of employees)*	until 9	18	10	8	36	50 %	28 %	22 %	5 %
	10 until 49	39	32	14	85	46 %	38 %	16 %	12 %
	50 until 99	22	19	11	52	42 %	37 %	21 %	8 %
	99 until 249	27	25	14	66	41 %	38 %	21 %	10 %
	250 until 499	14	22	13	49	29 %	45 %	27 %	7 %
	above 500	133	156	107	396	34 %	39 %	27 %	58 %

knowledge management in the first-order dynamic IT capabilities, improves the growth of dynamic and improvisational skills, leading to the creation of innovative ideas that explore and use new technologies in the digital age. Drawing from a sample of 684 Brazilian enterprises and utilizing PLS-SEM analyses, this study underscores significant theoretical and practical implications.

Theoretical implications

First, the study conceptualizes, operationalizes, and measures dynamic IT capabilities as a first-order construct through the routines described in the DCs view. In contrast to previous studies that primarily rely on the resource-based view (RBV) for IT capabilities, these dynamic IT capabilities constructs more effectively illustrate how digital technologies embedded in IT infrastructure and IT knowledge management influence proximate and distal outcomes, contributing to filling knowledge gaps in IT capabilities (Li and Chan, 2019).

The study provides empirical evidence that developing dynamic IT capabilities (DITC) enhances organizational capabilities. This finding supports hypotheses H1a and H1b by showing that firms can create IT-drivenDCs by using IT infrastructure and knowledge management. This is because DITC builds dynamic and improvisational capabilities. For example, expanding big data and business analytics underscores the increasing reliance on IT systems for detecting external changes, such as evolving customer behaviors, identifying trends, and gauging public opinions (Yoshikuni et al., 2023). As a result, the IT infrastructure that underpins these solutions is vital for enabling the deployment of digital tools that support key business functions while enhancing IT knowledge management, fostering digital skills, and cultivating a digital culture across the organization (Steininger et al., 2022). Thus, hypothesis H1a confirmed that dynamic IT capabilities empower firms to develop DCs, enabling them to sense, seize, and transform in response to opportunities and risks. These capabilities also enable digital technologies to capture customer data, driving digital innovation. Hence, this finding addresses the questions that Steininger and colleagues posed (Steininger et al., 2022) regarding IT-enabled DCs in the digital era, contributing to the broader IT-business value literature. The results of Hypothesis H1b showed that DITC's improvement of improvisational skills makes it easier for organizations to improvise effectively, which lets them quickly adapt to unplanned events and deal with unplanned challenges, ultimately meeting customer and market needs. As a result, this finding helps to address the knowledge gaps identified in the dynamic and improvisational literature, as mentioned by Zhang et al. (2023), who emphasized the need for further empirical studies to explore how DCs contribute to improvisational capabilities, particularly when enhanced by dynamic IT capabilities.

Despite extensive theoretical discussion and empirical evidence regarding the regenerative impact of IT capabilities on organizational capabilities, limited large-scale empirical studies substantiate the role of dynamic IT capabilities. What remains less explored is the mediating role that dynamic and improvisational capabilities play in the relationship between a firm's DITC and innovation (Steininger et al., 2022). As a result, this study extends the literature on organizational capabilities (Zhang et al., 2023) by positioning dynamic and improvisational capabilities as second-order constructs that influence explorative and exploitative innovation as distal outcomes.

Post hoc analysis shows that DITC is more relevant in the development of DCs in terms of planning and anticipating changes to innovation than improvisation capabilities. DITC is pertinent in prior planning for situation-specific events through structured actions that are geared at sensing opportunities and spurring innovation. Therefore, this study bridges the knowledge gap in organizational capabilities literature by demonstrating how IT infrastructure and IT knowledge management could influence competition in innovation by harnessing an organization's improvisational capabilities, in line with recent studies (Levallet & Chan, 2018; Steininger et al., 2022; Zhang et al., 2023). Moreover, enterprises have more benefits from creating explorative and exploitative innovation through DCs than improvisational capabilities. The findings demonstrate that companies obtain greater benefits from dynamic IT capabilities for innovation through the organization's ability to timely responsiveness and rapid and flexible product innovation in achieving new and incremental innovative forms than improvisational activities, and following advances in the organizational capabilities literature (Helfat et al., 2023; Zhang et al., 2023).

The post hoc analysis of unobserved heterogeneity revealed that firms with a low level of DITC could influence DCs and create more exploitation than the exploration of innovation. However, the IT infrastructure and IT knowledge management combined have negative effects on improvisational capabilities, and in the same way, improvisational capabilities harm exploration and exploitation innovation. These findings contribute to innovation management literature by identifying antecedent variables to create innovation through digital technologies (Aboelmaged et al., 2023; Goni & Van Looy, 2022; Leal-Rodríguez et al., 2023). The 2-segment has more substantial effects in all endogenous variables (DC, IC, ER, and EP). Organizations with a high DITC level enhance a firm's capacity to innovate, adapt to change, and implement customer-friendly changes, thereby fostering ambidexterity in innovation. The result showed that a high level of DITC contributes to building more IC than DC. Therefore, these firms possess the spontaneous and creative ability to reconfigure existing resources, develop new operational capabilities, and respond to urgent, unpredictable, and novel environmental situations, thereby promoting exploitation rather than exploration through digital innovation. The 3-segment showed significant and robust impacts from DITC, empowering DC to foster both exploitation and exploration, a concept known as ambidexterity. In this 3-segment, the influence of IC on exploration innovation was found to be minimal.

Implications for practice

In practice, the results of this study provide managers with a clear understanding of DITC and how the combination of IT infrastructure and IT knowledge management is necessary to enable the firm's improvisational and DCs to adapt, change, and create change that impacts customers. The study also shows that in some areas, low investment in DITC makes it impossible to improvise and hurts both exploratory and exploitative innovation.

These insights benefit enterprises by providing a practical justification for enhancing corporate capabilities through dynamic and improvisational innovation, as well as strategies for leveraging investments in dynamic information technology capabilities. This study also gives businesses that are trying to build dynamic and adaptable skills in the digital age good reasons to manage both exploratory and exploitative innovation in a balanced way. This is called ambidexterity innovation. Consequently, it assists organizations in recognizing the significance of IT infrastructure and IT knowledge management, which enable dynamic IT capabilities and foster innovation in exploration and exploitation within developing economies. This study explains a complete way to handle information by focusing on the balance between dynamic and improvisational skills, meeting the needs of the market and customers to maintain a competitive edge.

Focusing on DCs is essential for identifying opportunities, capturing business value, and transforming routines, thereby enhancing the performance returns of IT investments. Similarly, this study depicts improvisational capabilities as spontaneous and creative abilities to reconfigure existing resources and develop new operational capabilities. These skills are critical for addressing urgent, unpredictable, and novel customer needs through explorative and exploitative innovation. The resource-based view aligns with prior strategic management theories, suggesting that merely acquiring and possessing valuable resources does not necessarily lead to enhanced business value or performance outcomes (Kohli and Grover 2008; Wade and Hulland 2004). Instead, enterprises, through the lens of the dynamic capability view theory, should cultivate internal dynamic IT capabilities to meet market challenges and customer needs, thereby gaining an edge through dynamic and improvisational abilities. As a result, this study can serve as a valuable guide for practitioners, assisting them in achieving both incremental and radical innovation by more effectively managing their IT infrastructure and knowledge management investments, and fostering spontaneous and dynamic business processes in the digital era.

Limitations and future research

Despite the study's contributions, several limitations remain. First, this study examined only a limited number of dimensions of DITC, organizational capabilities, and innovation. Other dimensions of emerging technologies as first-order can be examined through the DCs perspective to identify the influence on proximate and distal outcomes. Similarly, future research could explore additional dimensions within the second order of organizational capabilities and their impacts on innovation and firm performance. For instance, further research could investigate more approaches, factors, contexts, and other aspects through which firms build organizational capabilities in dynamics and improvisational capabilities to enable radical and incremental innovation. Thus, future research should also focus on the moderating effects of uncertain environments, such as market dynamism, competition, and new technologies, on the relationship between DITC and organizational capabilities.

Second, we should employ a longitudinal approach to identify the differences before and after the development of DITC, highlighting the impact of DITC over time and identifying how innovation influences performance outcomes. Third, future research could incorporate new observed variables, such as firm age, origin/ethnicity, and capital type—distinguishing between digital and pre-digital-era firms and providing options to test the impact of control variables in different contexts. While the study in Brazil provided relevant insights into DITC in an emerging economy recovering from the COVID-19 crisis, it is important to note that these findings may not be fully applicable to developed economies. Therefore, we recommend that future studies explore DITC outcomes in firms from both developed and emerging countries. This will enable cross-context comparisons and a broader understanding of how performance differences manifest in varying environments. A global study could assess whether the impact of DITC differs across countries and continents or remains consistent regardless of the geographical context, thereby promoting a more comprehensive understanding of the topic.

Conclusions

This study provides empirical support for the research question by demonstrating the crucial role of dynamic IT capabilities in fostering dynamic and improvisational capabilities. These capabilities drive explorative and exploitative innovation, including ambidexterity innovation, and support enterprises in competing in uncertain markets in developing economies. The analysis of 684 Brazilian enterprises underscores the importance of IT infrastructure and IT knowledge management in fostering dynamic and improvisational capabilities. The study contributes to theory and practice, emphasizing that DITC as a first-order dynamic capability enhances second-order organizational capabilities to create innovation, especially post-COVID-19, by enabling firms to adapt, compete, and thrive in dynamic environments.

Funding

The authors did not receive any funding support from any organization for the submitted work.

Ethical approval

Not Applicable (The research is based on an anonymous survey).

Declaration of competing interest

The author(s) declared no potential conflicts of interest concerning the research, authorship, and/or publication of this article.

CRediT authorship contribution statement

Adilson Carlos Yoshikuni: Writing – review & editing, Writing – original draft, Validation, Software, Resources, Methodology, Formal analysis, Conceptualization. **Rajeev Dwivedi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Data curation, Conceptualization. **Muhammad Mustafa Kamal:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Duanning Zhou:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Pradeep Dwivedi:** Writing – review & editing, Writing – original draft, Resources, Methodology, Data curation. **Sérgio Apolinário:** Writing – review & editing, Visualization, Validation, Formal analysis, Data curation.

Appendix A. – Measurement Items for Constructs

Dynamic IT Capabilities—DITC was measured second-order based on a concept study by T. Li and Chan (2019) combining ITI and ITKM.

IT infrastructure – ITI was a first-order construct based on the conceptual studies from Bharadwaj et al. (2013a), Vial (2019), and Li and Chan (2019). Instructions: "Please rate how well your organization is in building IT infrastructure." Our organization uses a combination of digital technologies (information, computing, communication, and connectivity technologies).

- [ITI1] to understand their customer better.
- [ITI2] to to link customer-facing and operational processes in new ways.
- [ITI3] to market and sell their products and services.
- [ITI4] to provide customer service.
- [ITI5] to integrated view of key operational and customer information.

IT knowledge management – ITKM was measured as a first-order based on the conceptual studies from Li and Chan (2019), Warner and Wäger (2019), and Chanias et al. (2019). Instructions: "Please rate how well your organization is in building IT knowledge management capabilities". Our organizational investing in build IT knowledge management by:

- [ITKM1] promoting innovation mindset through a cross-functional collaboration (business and IT teams).
- [ITKM2] developing digital culture by digital skills and digital mindset.
- [ITKM3] developing digital iniciatives and collaborative learning across local and and corporative unit.
- [ITKM4] defining clear roles and responsibilities for governing digital initiatives.

- [ITKM5] enabling the possibility to everyone take part in the conversation around benefits to use digital technologies.

Dynamic Capabilities in Innovation – DCI was based on Pavlou and El Sawy (2006).

Instructions: “Please rate the effectiveness by which your organization reconfigures its operational capabilities in innovation activities to address rapidly changing environments relative to your major competitors.”

- [DC1] We frequently scan the environment to identify business opportunities.
- [DC2] We periodically review the likely effect of changes in our business environment on customers.
- [DC3] We have effective routines to identify, value, and import new information and knowledge.
- [DC4] We have adequate routines to assimilate new information and knowledge.
- [DC5] We are effective in transforming existing information into new knowledge.
- [DC6] We are effective in utilizing knowledge into current and new products.

Improvisational capabilities in innovation – ICI was based on Chatterjee at al. (2015).

Instructions: “Please rate the effectiveness by which your organization spontaneously reconfigures its operational capabilities in innovation activities in novel environmental situations relative to your major competitors.”

- [IC1] We are successful in deciding on our actions as we go along.
- [IC2] We effectively improvise when carrying out our activities.
- [IC3] We often improvise during our activities.
- [IC4] We deal with unanticipated events on the spot.
- [IC5] We respond quickly to unexpected problems.
- [IC6] We think quickly when carrying out actions.

Explorative innovation – ER was based on Jansen et al., (2009). Instructions: “Please rate the effectiveness by which your organization creates exploration innovation.”

- [ER1] We quickly invent new products and services.
- [ER2] We quickly experiment with new products and services in our local market.
- [ER3] We quickly commercialize products and services that are completely new to our unit.
- [ER4] We frequently utilize new opportunities in new markets.
- [ER5] Our unit regularly uses new distribution channels.
- [ER6] We frequently search for and approach new clients in new markets.

Exploitative innovation – EP was based on Jansen et al. (2009). Instructions: “Please rate the effectiveness by which your organization creates exploitation innovation.”

- [EP1] We are agile to refine the provision of existing products and services.
- [EP2] We quickly implement small adaptations to existing products and services.
- [EP3] We are agile to improve our existing products and services for our local market.
- [EP4] We quickly improve our efficiency in provision of products and services.
- [EP5] We increase economies of scale in existing markets.
- [EP6] Our unit quickly expands services for existing clients.

Measured latent marker variable - MLMV was based on Yoshikuni et al. (2024). Instructions: “Please rate the view about your life"

- [MLMV_01] It is easy for me to reach my goals.
- [MLMV_02] I would never abandon the desire to have my own business.
- [MLMV_03] I have a positive attitude towards others.
- [MLMV_04] I always imagine my house in the future.

References

Aboelmaged, M., Bani-Melhem, S., Al-Hawari, M. A., & Ali, I. (2023). Product innovation research over the past 60 years: a bibliometric analysis of intellectual structure and emergent trends. *Benchmarking*. doi:10.1108/BIJ-09-2022-0595.

Aftab, J., Veneziani, M., Sarwar, H., & Ishaq, M. I. (2022). Organizational ambidexterity, firm performance, and sustainable development: Mediating role of entrepreneurial orientation in Pakistani SMEs. *Journal of Cleaner Production*, *367*,(October 2021) 132956. doi:10.1016/j.jclepro.2022.132956.

Akter, S., Wamba, S. F., & Dewan, S. (2017). Why PLS-SEM is suitable for complex modeling? An empirical illustration in big data analytics quality. *Production Planning and Control*, *28*(11–12), 1011–1021. doi:10.1080/09537287.2016.1267411.

Al Dhaheri, M. H., Ahmad, S. Z., & Papastathopoulos, A (2024). Do environmental turbulence, dynamic capabilities, and artificial intelligence force SMEs to be innovative? *Journal of Innovation and Knowledge*, *9*,(3) 100528. doi:10.1016/j.jik.2024.100528.

Almeida, M. C., Yoshikuni, A. C., Dwivedi, R., & Larieira, C. L. C. (2022). Do Leadership Styles Influence Employee Information Systems Security Intention ? A Study of the Banking Industry. Global Journal of Flexible Systems Management, ahead of p. doi:10.1007/s40171-022-00320-1.

Alves, A. C., Barbieux, D., Reichert, F. M., Tello-Gamarra, J., & Zawislak, P. A. (2017). Innovation and Dynamic Capabilities of the Firm: Defining an Assessment Model. *Journal of Business Management*, *57*(3), 232–244. doi:10.1590/s0034-759020170304.

Amit, R., & Schoemaker, P. J. H. (1993). Strategic Assets and Organizational Rent. *Strategic Management Journal*, *14*(1), 33–46.

Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., & Delen, D. (2019). Business analytics and firm performance: The mediating role of business process performance. *Journal of Business Research*, *96*(October 2018), 228–237. doi:10.1016/j.jbusres.2018.11.028.

Behnam, S., & Cagliano, R. (2019). Are innovation resources and capabilities enough to make businesses sustainable? An empirical study of leading sustainable innovative firms. *International Journal of Technology Management*, *79*(1), 1–20. doi:10.1504/IJBCRM.2018.096510.

Benner, M. J., & Tushman, M. L. (2015). Reflections on the 2013 Decade Award–"Exploitation, Exploration, and Process Management: The Productivity Dilemma Revisited" Ten Years Later. *Academy of Management Review*, *40*(4), 497–514. doi:10.5465/amr.2015.0042.

Bharadwaj, A. (2000). A resource-based perspective on information technology capability and firm performance. *MIS Quarterly*, *24*(1), 169–196.

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013a). Visions and voices on emerging challenges in digital business strategy. *MIS Quarterly*, *37*(2), 633–661.

Bharadwaj, A., El Sawy, O. A., Pavlou, P., & Venkatraman, N. (2013b). Digital business strategy: toward a next generation of insights. *MIS Quarterly*, *37*(2), 471–482.

Bido, D. S., & Silva, D. (2019). SmartPLS 3: specification, estimation, evaluation, and reporting. *RAEP*, *20*(2), 1–31. doi:10.13058/raep.2019.v20n2.1545.

Chanias, S., Myers, M. D., & Hess, T. (2019). Digital transformation strategy making in pre-digital organizations: The case of a financial services provider. *Journal of Strategic Information Systems*, *28*(1), 17–33. doi:10.1016/j.jsis.2018.11.003.

Chatterjee, S., Moody, G., Lowry, P. B., Chakraborty, S., & Hardin, A. (2015). Strategic relevance of organizational virtues enabled by information technology in organizational innovation. *Journal of Management Information Systems*, *32*(3), 158–196. doi:10.1080/07421222.2015.1099180.

Chen, L., Tu, R., Huang, B. X., Zhou, H., & Wu, Y. (2024). Digital transformation's impact on innovation in private enterprises: Evidence from China. *Journal of Innovation and Knowledge*, *9*,(2) 100491. doi:10.1016/j.jik.2024.100491.

Chen, Y., Pan, X., Liu, P., & Vanhaverbeke, W. (2024). How does digital transformation empower knowledge creation? Evidence from Chinese manufacturing enterprises. *Journal of Innovation and Knowledge*, *9*,(2) 100481. doi:10.1016/j.jik.2024.100481.

Chin, W. W., Thatcher, J. B., Wright, R. T., & Steel, D. (2013). Controlling for common method variance in PLS analysis: the measured latent marker variable approach. In AbdiL. , H, ChinW. W. , VinziV. E. , RussolilloG. , Trinchera (Eds.), *New Perspectives in Partial Least Squares and Related Methods* (pp. 231–239). Springer.

CIA. (2024). *The World Factbook - Central Intelligence Agency*. . https://www.cia.gov/library/publications/resources/the-world-factbook/geos/print_br.html.

Cousineau, D., & Chartier, S. (2017). Outliers detection and treatment: a review. *International Journal of Psychological Research*, *3*(1), 58. doi:10.21500/20112084.844.

Daniel, E. M., Ward, J. M., & Franken, A. (2014). A dynamic capabilities perspective of IS project portfolio management. *Journal of Strategic Information Systems*, *23*(2), 95–111. doi:10.1016/j.jsis.2014.03.001.

Du, W., Wu, J., Liu, S., & Hackney, R. A. (2019). Effective organizational improvisation in information systems development: Insights from the Tencent messaging system

development. *Information and Management*, *56*(4), 614–624. doi:10.1016/j.im.2018.10.003.
Dutta, S., Lanvin, B., Leon, L. R., & Vincent, S. W. (2022). *What is the future of innovation-driven growth?* Global Innovation Index 2022.
Dwivedi, P., Dwivedi, R., Yoshikuni, A. C., Xie, B., & Naik, B. K. R. (2023). Role of Digitalization in Business Process to Reduce Manpower : A Case of Human Resource Management Process. *International Journal of Economics and Business Administration*, *XI*(1), 66–76.
Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. doi:10.3758/BF03193146.
Frishammar, J., Cenamor, J., Cavalli-Björkman, H., Hernell, E., & Carlsson, J. (2018). Digital strategies for two-sided markets: A case study of shopping malls. *Decision Support Systems*, *108*, 34–44. doi:10.1016/j.dss.2018.02.003.
Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. *Journal of Business Research*, *69*(8), 3192–3198. doi:10.1016/j.jbusres.2015.12.008.
Goni, J. I. C., & Van Looy, A. (2022). Process innovation capability in less-structured business processes: a systematic literature review. *Business Process Management Journal*, *28*(3), 557–584. doi:10.1108/BPMJ-07-2021-0487.
Grant, R. M. (1991). The Resource-Based Theory of Competitive Advantage: Implications for Strategy Formulation. *California Management Review*, *33*(3), 114–135. doi:10.2307/41166664.
Hadida, A. L., & Tarvainen, W. (2015). Organizational Improvisation: A Consolidating Review and Framework. *International Journal of Management Reviews*, *17*(4), 437–459. doi:10.1111/ijmr.12047.
Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*, *117*(3), 442–458.
Hair, J. F., Hult, M. T., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. (SAGE (ed.); Third). SAGE Publications, Inc.
Hair, J. F., Sarstedt, M., Matthews, L. M., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS : part I – method. *European Business Review*, *28*(1), 63–76. doi:10.1108/EBR-09-2015-0094.
Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. *European Journal of Marketing*, *53*(4), 566–584.
Helfat, C. E., Kaul, A., & Ketchen, D. J. (2023). Renewing the resource-based view New contexts new concepts and new.pdf. Strategic Management Journal, Special Issue Article, 1–34.
Helfat, C. E., & Winter, S. G. (2011). Research prospectives untangling dynamic and operational capabilities: a strategy for (n)ever-changing world. *Strategic Management Journal*, *32*, 1243–1250. doi:10.1002/smj.955.
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. doi:10.1007/s11747-014-0403-8.
Jansen, J. J. P., Tempelaar, M. P., Van den Bosch, F. A. J., & Volberda, H. W. (2009). Structural Differentiation and Ambidexterity: The Mediating Role of Integration Mechanisms. *Organization Science*, *20*(4), 797–811. doi:10.1287/orsc.1080.0415.
Jansen, J. J. P., Vera, D., & Crossan, M. (2009). Strategic leadership for exploration and exploitation: The moderating role of environmental dynamism. *The Leadership Quarterly*, *20*, 5–18. doi:10.1016/j.leaqua.2008.11.008.
Jha, A. K., & Bose, I. (2016). Innovation research in information systems: A commentary on contemporary trends and issues. *Information and Management*, *53*(3), 297–306. doi:10.1016/j.im.2015.10.007.
Knabke, T., & Olbrich, S. (2018). Building novel capabilities to enable business intelligence agility: results from a quantitative study. *Information Systems and E-Business Management*, *16*(3), 493–546. doi:10.1007/s10257-017-0361-z.
Kohli, R., & Grover, V. (2008). Business Value of IT: An Essay on Expanding Research Directions to Keep up with the Times. *Journal of the Association for Information Systems*, *9*(1), 23–39. https://aisel.aisnet.org/jais/vol9/iss1/1/.
Konlechner, S., Müller, B., & Güttel, W. H. (2018). A dynamic capabilities perspective on managing technological change: a review, framework and research agenda. *International Journal of Technology Management*, *76*(3/4), 188. doi:10.1504/ijtm.2018.10012460.
Lau, A. K. W., & Lo, W. (2019). Absorptive capacity, technological innovation capability, and innovation performance: An empirical study in Hong Kong. *International Journal of Technology Management*, *80*(1–2), 107–148. doi:10.1504/IJTM.2019.099750.
Leal-Rodríguez, A. L., Sanchís-Pedregosa, C., Moreno-Moreno, A. M., & Leal-Millán, A. G. (2023). Digitalization beyond technology: Proposing an explanatory and predictive model for digital culture in organizations. *Journal of Innovation and Knowledge*, *8*(3). doi:10.1016/j.jik.2023.100409.
Levallet, N., & Chan, Y. E. (2018). Role of Digital Capabilities in Unleashing the Power of Managerial Improvisation. *MIS Quarterly Executive*, *17*(1), 1–21. https://aisel.aisnet.org/misqe/vol17/iss1/3.
Li, T., & Chan, Y. E. (2019). Dynamic information technology capability: Concept definition and framework development. *Journal of Strategic Information Systems*, *28*,(4) 101575. doi:10.1016/j.jsis.2019.101575.
Lu, Y., & Ramamurthy, K. (2011). Understanding the Link Between Information Technology Capability and Organizational Agility: An Empirical Examination. *MIS Quarterly*, *35*(4), 931–954.
Luftman, J., Derksen, B., Dwivedi, R., Santana, M., Zadeh, H. S., & Rigoni, E. (2015). Influential IT management trends: An international study. *Journal of Information Technology*, *30*(3), 293–305.
MacKenzie, S. B., & Podsakoff, P. M. (2012). Common method bias in marketing: Causes, mechanisms, and procedural remedies. *Journal of Retailing*, *88*(4), 542–555.
Matthews, L. M., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: Part II – A case study. *European Business Review*, *28*(2), 208–224. doi:10.1108/EBR-09-2015-0095.
Mehralian, G., Farzaneh, M., Yousefi, N., & Haloub, R. (2024). Driving new product development performance: Intellectual capital antecedents and the moderating role of innovation culture. *Journal of Innovation and Knowledge*, *9*(3). doi:10.1016/j.jik.2024.100503.
Mehralian, Gholamhossein, Farzaneh, M., Yousefi, N., & Haloub, R. (2024). Driving new product development performance: Intellectual capital antecedents and the moderating role of innovation culture. *Journal of Innovation and Knowledge*, *9*(3). doi:10.1016/j.jik.2024.100503.
Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: Information Technology and Organizational Performance. *MIS Quarterly*, *28*(2), 283–322.
Mendonça, D. (2007). Decision support for improvisation in response to extreme events: Learning from the response to the 2001 World Trade Center attack. *Decision Support Systems*, *43*(3), 952–967. doi:10.1016/j.dss.2005.05.025.
Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research*, *98*, 261–276.
Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information and Management* 103169. doi:10.1016/j.im.2019.05.004 February 2018.
Mikalef, P., & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. *Journal of Business Research*, *70*, 1–16. doi:10.1016/j.jbusres.2016.09.004.
Mikalef, P., Pateli, A., & Van de Wetering, R. (2020). IT architecture flexibility and IT governance decentralization as drivers of IT-enabled dynamic capabilities and competitive performance: The moderating effect of the external environment. *European Journal of Information Systems*, *27*(5), 1–29. doi:10.1080/0960085X.2020.1808541.
Mishra, A. R., Rani, P., Alrasheedi, A. F., & Dwivedi, R. (2023). Evaluating the blockchain-based healthcare supply chain using interval-valued Pythagorean fuzzy entropy-based decision support system. *Engineering Applications of Artificial Intelligence*, *126*, 107112.
Morgado, F. F. R., Meireles, J. F. F., Neves, C. M., Amaral, A. C. S., & Ferreira, M. E. C. (2018). Scale development: ten main limitations and recommendations to improve future research practices. *Psychology: Research and Review*, *30*(1), 1–20. doi:10.1186/s41155-016-0057-1.
Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital Innovation Management: Reinventing Innovation Management Research in a Digital World. *MIS Quarterly*, *14*(1), 223–238.
Pappas, I., Mikalef, P., Giannakos, M., & Krogstie, J. (2018). Big Data and Business Analytics Ecosystems : Paving the way towards digital transformation and sustainable societies. *Information Systems and E-Business Management*, *16*(August), 14. doi:10.1007/s10257-018-0377-z.
Pavlou, P. A., & El Sawy, O. A (2006). From IT Leveraging Competence to Competitive Advantage in Turbulent Environments: The Case of New Product Development. *Information Systems Research*, *17*(3), 198–227. doi:10.1287/isre.1060.0094.
Pavlou, P. A., & El Sawy, O. A (2010). The 'third hand': IT-enabled competitive advantage in turbulence through improvisational capabilities. *Information Systems Research*, *21*(3), 443–471. doi:10.1287/isre.1100.0280.
Porter, M. E. (1998). *Competitive advantage: Creating and sustaining superior performance: with a introduction*. (Free press). Simon and Schuster.
Protogerou, A., Caloghirou, Y., & Lioukas, S. (2012). Dynamic capabilities and their indirect impact on firm performance. *Industrial and Corporate Change*, *21*(3), 615–647. doi:10.1093/icc/dtr049.
Ringle, C. M., Wende, S., & Becker, J. (2015). SmartPLS GmbH, www.smartpls.com *(SmartPLS 3.2.6)*. . http://www.smartpls.com.
Rodríguez-Entrena, M., Schuberth, F., & Gelhard, C. (2018). Assessing statistical differences between parameters estimates in Partial Least Squares path modeling. *Quality and Quantity*, *52*(1), 57–69. doi:10.1007/s11135-016-0400-8.
Schwarz, A., Rizzuto, T., Wolverton, C. C., & Roldán, J. L. (2017). Examining the Impact and Detection of the " Urban Legend " of Common Method Bias. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, *48*(1), 93–119.
Steininger, D. M., Mikalef, P., Pateli, A., & Ortiz-De-guinea, A. (2022). Dynamic Capabilities in Information Systems Research: A Critical Review, Synthesis of Current Knowledge, and Recommendations for Future Research. *Journal of the Association for Information Systems*, *23*(2), 447–490. doi:10.17705/1jais.00736.
Taher, M. (2012). Resource-Based View Theory. In DwivediY. K. , WadeM. R. , SchnebergerS. L. (Eds.), *Information Systems Theory: Explaining and Predictin Our Digital Society. Vol. 1. Integrated Series in Information Systems 28* (pp. 151–163). New York Dordrecht Heidelberg London: Spring. doi:10.1007/978-1-44'9-6108-2.
Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350.
Teece, D. J. (2018). Dynamic capabilities as (workable) management systems theory. *Journal of Management & Organization*1–10. doi:10.1017/jmo.2017.75 May.
Teece, D. J., Peteraf, M., & Leih, S. (2016). Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy. *California Management Review*, *58*(4), 13–35. doi:10.1525/cmr.2016.58.4.13.
Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(March), 509–533. doi:10.1002/(Sici)1097-0266(199708)18:7<509::Aid-Smj882>3.0.Co;2-Z.
Tsai, S. P. (2015). Dynamic marketing capabilities and radical innovation commercialisation. *International Journal of Technology Management*, *67*(2), 174–195. doi:10.1504/IJTM.2015.068223.

Tseng, H. L., Lee, Y. C., & Chu, P. Y. (2015). Improvisational Capabilities in e-Commerce Adoption: A Multiyear Comparison. *Journal of Global Information Technology Management*, *18*(1), 48–66. doi:10.1080/1097198X.2015.1015827.

Vera, D., Nemanich, L., Vélez-Castrillón, S., & Werner, S. (2016). Knowledge-Based and Contextual Factors Associated with R&D Teams' Improvisation Capability. *Journal of Management*, *42*(7), 1874–1903. doi:10.1177/0149206314530168.

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *Journal of Strategic Information Systems*, *28*(2), 118–144. doi:10.1016/j.jsis.2019.01.003.

Wade, M., & Hulland, J. (2004). Review: the Resource-Based View and Information Systems Research: Review, Extension, and Suggestions for Future Research1. *MIS Quarterly*, *28*(1), 107–142. doi:10.2307/25148626.

Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, *52*(3), 326–349. doi:10.1016/j.lrp.2018.12.001.

Wei, J., Zhang, X., & Tamamine, T. (2024). Digital transformation in supply chains: Assessing the spillover effects on midstream firm innovation. *Journal of Innovation and Knowledge*, *9*,(2) 100483. doi:10.1016/j.jik.2024.100483.

Wilhelm, H., Schlömer, M., & Maurer, I. (2015). How dynamic capabilities affect the effectiveness and efficiency of operating routines under high and low levels of environmental dynamism. *British Journal of Management*, *26*(2), 327–345. doi:10.1111/1467-8551.12085.

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal*, *24*(10 SPEC ISS), 991–995. doi:10.1002/smj.318.

Wolf, C., & Floyd, S. W. (2017). Strategic Planning Research: Toward a Theory-Driven Agenda. *Journal of Management*, *43*(6), 1754–1788. doi:10.1177/0149206313478185.

World Economic Forum. (2016). *The Global Information Technology Report 2016 Innovating in the Digital Economy*. In BallerS. , DuttaS. , LanvinB. (Eds.), World Economic Forum.

Yayla, A. A., & Hu, Q. (2012). The impact of IT-business strategic alignment on firm performance in a developing country setting: exploring moderating roles of environmental uncertainty and strategic orientation. *European Journal of Information Systems*, *21*(4), 373–387. doi:10.1057/ejis.2011.52.

Yoshikuni, A. C. (2022). Effects on corporate performance through ISS-enabled strategy-making on dynamic and improvisational capabilities. *International Journal of Productivity and Performance Management*, *71*(6), 2161–2187. doi:10.1108/ijppm-03-2021-0177.

Yoshikuni, A. C. (2024). The innovation ambidexterity enabled through business process performance and information systems strategy: an empirical study by strategy-as-practice perspective. *International Journal of Business Innovation and Research*, *1*(33), 118–136.

Yoshikuni, A. C., & Dwivedi, R. (2023). The role of enterprise information systems strategies enabled strategy-making on organizational innovativeness: a resource orchestration perspective. *Journal of Enterprise Information Management*, *36*(1), 172–196. doi:10.1108/jeim-10-2021-0442.

Yoshikuni, A. C., Dwivedi, R., & Dwivedi, Y. K. (2024). Strategic knowledge, IT capabilities and innovation ambidexterity : role of business process performance. *Industrial Management & Data Systems*, *124*(2), 915–948. doi:10.1108/IMDS-01-2023-0056.

Yoshikuni, A. C., Dwivedi, R., Santos, M. Q. L., Fragoso, R., Souza, A. C., Sousa, F. H., Santos, W. A. P., & Romboli, D. S. (2024). Effects of Knowledge Management Processes by Strategic Management Accounting on Organizational Ambidexterity : Mediation of Operational Processes Under Environmental Dynamism. *Global Journal of Flexible Systems Management*, 1–20. doi:10.1007/s40171-024-00398-9.

Yoshikuni, A. C., Dwivedi, R., Zhou, D., & Fosso, S. (2023). Big data and business analytics enabled innovation and dynamic capabilities in organizations : Developing and validating scale. *International Journal of Information Management Data Insights*, *3*,(2) 100206. doi:10.1016/j.jjimei.2023.100206.

Yoshikuni, A. C., & Galvão, F. R. (2023). The effects of information technology-enabled supply chain ambidexterity and their indirect effect on firm performance: an empirical study conducted under environmental turbulence. *International Journal of Logistics Systems and Management*, *45*(3), 369–396. doi:10.1504/IJLSM.2023.132985.

Zhang, J., Chen, Y., Li, Q., & Li, Y. (2023). A review of dynamic capabilities evolution—based on organisational routines, entrepreneurship and improvisational capabilities perspectives. *Journal of Business Research*, *168*,(August) 114214. doi:10.1016/j.jbusres.2023.114214.

Zhang, K., Liu, H., Li, Y., & Wu, X. (2023). Effects of social media usage on exploratory innovation, exploitative innovation and organizational agility: the moderating role of learning goal orientation. *Internet Research*. doi:10.1108/INTR-07-2021-0503.