Smart insights, stronger performance: Leveraging business intelligence and dynamic capabilities in tourism and hospitality.

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Smart insights, stronger performance: Leveraging business intelligence and dynamic capabilities in tourism and hospitality

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ABSTRACT

The rapid advancement of artificial intelligence (AI) and business intelligence (BI) compels tourism and hospitality firms to redefine their capabilities. This need stems from the growing imperative to fully leverage these technologies for performance enhancement—an area still underexplored in the tourism and hospitality literature. Drawing on the dynamic capabilities view, this paper investigates the interrelationships among resource orchestration capabilities (ROCs), digital marketing capabilities (DMCs), AI capabilities, and firm performance, with a specific focus on the mediating role of BI adoption and the moderating effect of technology orientation (TO). Using data from 297 tourism and hospitality firms across four major Japanese cities, the findings reveal that BI adoption mediates the relationships among ROCs, DMCs, AI capabilities, and firm performance. As anticipated, TO does not moderate the DMC–BI adoption link, potentially due to firm-specific factors warranting further exploration in different contexts. The study contributes to theory by proposing an integrative framework that conceptualizes ROCs, DMCs, and AI capabilities as distinct yet interrelated dynamic capabilities driving performance in tourism and hospitality firms. Practically, the findings encourage tourism and hospitality managers to refine their strategies to better leverage these capabilities, particularly in pursuing digital transformation.

1. Introduction

The emergence of rapid technological progressions, such as AI and BI-related technologies, has prompted a paradigm shift in tourism and hospitality firms (Knani et al., 2022; Jiménez-Partearroyo et al., 2024). Although AI and BI-related technologies have yet to achieve parity with the depth and complexity of human intelligence, their current contributions to enhancing the business performance of firms in the tourism and hospitality industry are nonetheless significant (Dogru et al., 2025; Law et al., 2024). Subsequently, most tourism and hospitality firms embrace AI and BI-related technologies to stay competitive and augment organizational performance (Hsu et al., 2024; Gursoy and Cai, 2025).

Although the digitalization of tourism and hospitality firms has gained momentum in recent years, most tourism and hospitality firms are still lagging in leveraging the inherent potential of digital technologies to enhance their value-delivery processes (Gursoy and Cai, 2025; Solakis et al., 2024). The findings from prior literature highlight that the main challenges in realizing the full spectrum of value potential from emerging technologies are no longer related to technology development but primarily to issues related to a lack of relevant organizational resources and capabilities (Hsu et al., 2024; Saxena and Sarkar, 2023). Further, practical examples of tourism and hospitality firms that effectively harness value from AI and BI-related technologies remain scarce. Central to these untapped potentials lies the swift advancement of

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emerging technologies surpassing the adaptability of most tourism and hospitality firms, and therefore, unlocking their full potential necessitates developing sustainable and novel resources and capabilities (Gursoy and Cai, 2025). However, the scholarly discourse on integrating AI and BI-related technologies with resources and capabilities of tourism and hospitality firms to bolster performance is still embryonic (Ghesh et al., 2024; Kannan, 2024), and numerous knowledge gaps require attention.

First, although a normative bias persists in tourism and hospitality literature suggesting the potential of digitalizing tourism and hospitality firms to enhance firm performance (Gursoy and Cai, 2025; Knani et al., 2022), most conceptual and empirical studies have frequently been denounced for being vague and unclear in elucidating the underlying mechanisms (Ghesh et al., 2024; Kannan, 2024). A likely elucidation for these vague findings may lie in the inadequacy of assuming a simplistic, linear relationship between digitalization and business performance in tourism and hospitality firms. Digital transformation in tourism and hospitality, mainly through the adoption of AI and BI-related technologies, is inherently complex and context-dependent, and its impact on performance is likely mediated or moderated by a range of organizational-level constructs (Gutierriz et al., 2025). Rather than assuming a direct causality, a more nuanced, multivariate analytical approach is required—one that examines how integrating AI and BI technologies with complementary organizational capabilities, such as dynamic capabilities and technological orientation, will reinforce performance (Ghesh et al., 2024; Law et al., 2024). This perspective aligns with the dynamic capabilities view (DCV), which posits that performance gains arise from a firm's ability to effectively leverage advanced technologies within its strategic and operational context, not merely posing them. Consequently, this void has sparked a wave of scholarly calls urging further investigation into the need for more in-depth empirical investigations into how tourism and hospitality firms can strategically deploy AI and BI technologies to enhance performance (Gursoy and Cai, 2025; Solakis et al., 2024).

Second, there exists a dearth of literature grounded in well-established management theories in investigating how organizational-level constructs such as firm resources and capabilities intervene in the link between the digitalization of tourism and hospitality firms and enhancing corporate performance (Hsu et al., 2024; Gursoy and Cai, 2025). To address this gap, this paper adopts the DCV as its principal theoretical framework. The DCV offers a robust lens through which to analyze how tourism and hospitality firms develop, deploy, and reconfigure their capabilities to effectively leverage digitalization and, in turn, achieve sustainable performance outcomes. Further, it postulates that business firms can maximize business performance not merely by possessing firm capabilities and tangible and intangible resources but by purposefully structuring, bundling, and leveraging those resources and capabilities to adapt to the changing market dynamics (Badrinarayanan et al., 2019; Tajeddini et al., 2024). Accordingly, drawing on the DCV, we propose ROCs, DMCs, and AI capabilities as dynamic capabilities in developing the conceptual model of this study. These capabilities were selected because they embody the fundamental dimensions of dynamic capabilities—*sensing, seizing, and reconfiguring*—and are commonly exhibited by firms within the tourism and hospitality sector that engage in digital transformation to varying degrees (Kannan, 2024; Solakis et al., 2024).

Despite growing scholarly interest in dynamic capabilities, the tourism and hospitality literature remains is ambiguous about explicating how the integration of multiple dynamic capabilities may produce synergistic effects in facilitating digitalization and improving firm performance within a unified theoretical model (Ghesh et al., 2024; Kannan, 2024). Acknowledging the potential of dynamic capabilities in harnessing digitalization to unlock its full potential benefits (Eisenhardt and Martin, 2000), numerous scholarly calls have been made to research how tourism and hospitality firms can strategically integrate digital technologies with dynamic capabilities to enhance performance (Bekele and Raj, 2024; Law et al., 2024). This study responds to these calls by developing a conceptual framework based on the DCV that explicitly incorporates dynamic capabilities as key enablers in the digitalization–performance nexus in tourism and hospitality firms.

Third, although a growing research stream on exploring the intersection of dynamic capabilities and digitalization within the tourism and hospitality literature has emerged, there remains a significant gap in understanding how firms mobilize their abilities to rapidly build, integrate, and reconfigure firm resources and capabilities in response to increasingly dynamic market conditions—particularly about the marketing function and its digital transformation (Bekele and Raj, 2024; Kannan, 2024). While digitalization is frequently examined from an operational or technological viewpoint, its strategic role in marketing—mainly mediated by dynamic capabilities—remains underexplored. Integrating marketing with digitalization and dynamic capabilities is increasingly vital for tourism and hospitality firms operating in the contemporary business environment marked by rapid technological innovation and shifting customer preferences (Kannan, 2024; Knani et al., 2022). From the DCV perspective, when effectively integrated with digital technologies, marketing function generates rich market intelligence and facilitates customer-driven innovation, which is critical for achieving sustained competitive advantage (Jiménez-Partearroyo et al., 2024; Knani et al., 2022). In this context, DMCs have emerged as a specialized subset of dynamic capabilities that enable firms to align digital tools with strategic marketing functions. However, the tourism and hospitality literature has yet to sufficiently study DMCs despite their growing relevance in enhancing digital responsiveness and customer engagement (Kannan, 2024; Knani et al., 2022). Furthermore, while it is widely recognized that firms with high levels of TO are better positioned to leverage insights derived from DMCs to facilitate the adoption and integration of advanced technologies (Ismail, 2023), the moderating role of TO in strengthening the relationship between DMCs and digital technology adoption remains unexplored mainly within the tourism and hospitality domain (Ghesh et al., 2024; Kannan, 2024). This theoretical and empirical void underscores the need for further research to elucidate how the interplay between DMCs and TO influences the effective deployment of BI tools and systems, ultimately contributing to superior firm performance.

Motivated by these voids in prior literature, this paper seeks to respond to scholarly calls by addressing the following research questions, offering a fresh perspective and novel insights.

RQ1. Do ROCs, DMCs, and AI capabilities impact BI adoption in tourism and hospitality firms?

RQ2. Does BI adoption mediate the links between ROCs, DMCs, AI capabilities, and performance of tourism and hospitality firms?

RQ3. Does TO moderate the possible relationship between DMCs and BI adoption in tourism and hospitality firms?

This study contributes to the tourism and hospitality literature in three significant ways. First, grounded in the DCV, it proposes a comprehensive theoretical framework that explicates how integrating AI and BI technologies with firm-specific resources and capabilities enhances organizational performance. In contrast to most prior research that often treats digital technologies as standalone drivers of performance (Ratna et al., 2024), this study emphasizes the importance of dynamic capabilities in enabling tourism and hospitality firms to effectively leverage digital tools within their strategic and operational contexts. Specifically, the study conceptualizes ROCs, DMCs, and AI Capabilities as three distinct yet interrelated forms of dynamic capabilities. These capabilities collectively represent the firm's ability to sense, seize, and transform digital opportunities through BI adoption into enhanced performance improvements.

Second, while the literature on dynamic capabilities has grown substantially in recent years, the majority of contributions remain predominantly conceptual or address dynamic capabilities in a broad, generalized manner (Chirumalla et al., 2023; Gheitarani et al., 2023). Empirical studies that systematically examine how specific configurations of dynamic capabilities interact to create synergistic effects on firm performance remain limited—particularly within the tourism and hospitality context (Kannan, 2024; Law et al., 2024). This represents a critical limitation, as the DCV posits that firms achieve superior outcomes not through isolated capabilities but by strategically bundling and deploying complementary capabilities in response to environmental dynamism. Addressing this gap, the present study introduces and empirically examines three interrelated dynamic capabilities—ROCs, DMCs, and AI Capabilities—central to marketing and digital technology integration. To our knowledge, these capabilities have not been investigated collectively within a single study in the tourism and hospitality literature.

Third, this study advances the tourism and hospitality literature by offering novel insights into how emerging technologies—specifically AI and BI—enhance firm capabilities and performance. While prior research has often emphasized the direct effects of technological adoption, this study takes a more nuanced approach by identifying and empirically examining potential mediating and moderating variables that shape the relationship between dynamic capabilities and firm performance. In particular, the study conceptualizes BI adoption as a possible mediator through which firms' dynamic capabilities (i.e., DMCs, ROCs, and AI capabilities) translate into enhanced firm performance. Moreover, the study identifies TO as a moderating variable reflecting the notion that firms with a higher proclivity toward adopting and leveraging technological innovations are better positioned to realize the full potential of their digital marketing capabilities. Collectively, these findings underscore that the successful deployment of AI and BI technologies is contingent upon their alignment with existing organizational capabilities and orientations. These findings imply that tourism and hospitality firms can fully unlock the potential and value of AI and BI-related technologies with their existing resources when deployed with the identified dynamic capabilities.

The rest of this paper is constituted as follows: The following section discusses the theoretical underpinning of the study, followed by an in-depth discourse on the research model and hypotheses development. Next, we explain the research method and discuss the findings in detail. Then, we offer theoretical and managerial implications stemming from the findings.

2. Theoretical background

2.1. Role of BI in tourism and hospitality firms

Over the course of time, Howard Dresner in 1989 (see Llave, 2017) coined the term BI to represent concepts, techniques, and processes for enhancing business decision-making through the use of factual information (Phillips-Wren et al., 2021; Sangari and Razmi, 2015; Younus et al., 2022). Later, several scholars define BI as the means by which firms monitor and adapt to turbulent environments by absorbing information to identify threats and reduce ambiguity (Chaudhuri et al., 2020). From a different perspective, some other scholars perceive BI as a platform for integrating knowledge management, utilizing data collection, storage, and analysis to provide complex analysis through various analytical tools, enabling decision-makers to access viable information (Khaddam et al., 2023; Negash and Gray, 2008). BI is also described as an assortment of technologies and technical applications that can be used within an organization to integrate, structure, and streamline the analysis of extensive datasets (Cheng et al., 2020; Singh and Sai Vijay, 2024).

The tourism and hospitality industry is transforming quickly, driven by evolving consumer expectations and rapid technological progressions (Kannan, 2024; Li, 2025). Today, customers demand personalized experiences, seamless omnichannel interactions, and access to a range of service portfolios from tourism and hospitality firms at competitive prices (Jiménez-Partearroyo et al., 2024). Consequently, tourism and hospitality firms are forced to satisfy these competing demands by offering tailor-made market offerings, and this is where BI plays a vital role (Gursoy and Cai, 2025). By harnessing BI paired with advanced data analytics and integration, tourism and hospitality firms can forge better customer relationships by delivering personalized shopping experiences (Hsu et al., 2024; Gursoy and Cai, 2025).

This empirical study conceptualizes BI as a multifaceted construct characterized by analytical capabilities and data integration (Khaddam et al., 2023). Data integration provides a cohesive perspective on diverse data sources (Boina et al., 2023; Lenzerini, 2002), whereas analytical capabilities refer to the proficient use of techniques to transform firm data into meaningful information that illuminates the logic involved in the decision-making purposes (Patrucco et al., 2023).

2.2. Dynamic capabilities view

One of the pivotal tenets in strategic management literature is how business firms achieve sustained competitive advantage. This question has been addressed in strategic management literature from multiple theoretical perspectives, out of which the resource-based view (RBV) emerges as a prominent theory (Kraaijenbrink et al., 2010; Teece, 2021, 2022). The RBV theory suggests that companies secure a competitive advantage by acquiring tangible (i.e., technological, physical, organizational, and financial) resources and intangible (i.e., skilled workforce, data and information, reputation, and innovation) resources that are *"valuable (organized to capture value), rare, inimitable (costly to imitate), and without strategic substitutes (non-substitutable) (VRIN)"* (Barney, 1986, 1991, 1997).

Although the significance of VRIN resources for enhancing business performance has dominated the strategic management literature for some time, lately, scholars argue that the RBV theory inadequately elucidates the performance differences among firms (Ghosh et al., 2022; Manikasa et al., 2019). These differences primarily stem from a business's ability to transform its resources into capabilities, but the RBV theory does not comprehensively encapsulate these nuances (Kero and Bogale, 2023). Building on the RBV theory, the DCV is introduced to overcome this limitation by illuminating how business firms adapt to changing marketing dynamics in modern markets (Baía and Ferreira, 2024).

Dynamic capabilities pertain to a business firm's ability to continuously mobilize and deploy its deliberate and strategic resources and capabilities to reinforce its core competencies to create and sustain superior performance (Eisenhardt and Martin, 2000; Suder et al., 2026). Core characteristics of dynamic capabilities comprise three interrelated processes: sensing, seizing, and transforming (or reconfiguring) (Teece, 2021, 2022). Sensing refers to a firm's ability to systematically scan, interpret, and assess opportunities and threats in the external environment, including shifts in technology, customer preferences, and competitive dynamics (Teece, 2021, 2022). This is critical for recognizing emerging trends and potential disruptions affecting strategic positioning. Seizing involves effectively mobilizing resources to exploit identified opportunities or mitigate threats (Teece, 2021, 2022). This often necessitates strategic investments in new technologies, products, services, or business models and the realignment of internal processes and structures to create and capture value. Transforming (or reconfiguring) reflects a firm's capacity to continuously renew, recombine, and reconfigure its existing resources and organizational structures (Teece, 2021, 2022). This dimension ensures long-term adaptability and resilience in environmental volatility by enabling a business firm to align strategically with evolving market conditions. By exploiting dynamic capabilities, business firms can respond to altering market underlying forces, maintaining their competitive advantage through reconfiguring, extending, and adjusting the existing resources and capabilities (Baía and Ferreira, 2024; Kero and Bogale, 2023).

In the study context, the fundamental assumptions of VRIN resources and the RBV theory pose conceptual limitations when applied to AI and BI. This is primarily due to the nature of data—the core input underpinning AI and BI systems—which is typically abundant, widely accessible, and increasingly commoditized (Kristoffersen et al., 2021). As such, data does not fulfil the scarcity condition required by the RBV for sustained competitive advantage. Consequently, the DCV offers a more appropriate and nuanced theoretical lens for this study. Unlike the static assumptions of the RBV, the DCV focuses on a firm's ability to dynamically integrate, reconfigure, and renew its resources and capabilities in response to environmental volatility and technological disruption (Kraaijenbrink et al., 2010; Teece, 2021, 2022). Consequently, leveraging the DCV allows for a more contextually relevant and theoretically grounded exploration of how tourism and hospitality firms develop, orchestrate, and deploy AI- and BI-related capabilities to enhance organizational performance. This framework thus shifts the analytical focus from resource possession to resource mobilization and capability-building processes, particularly critical in the fast-evolving, data-driven competitive environments in which tourism and hospitality firms operate today.

3. Hypotheses development

3.1. BI adoption in tourism and hospitality firms

In recent years, BI has emerged as a dominant area of global investment in information technology, particularly within data-intensive industries like tourism and hospitality (Khaddam et al., 2023). BI systems, grounded in advanced information technologies and analytics techniques, are increasingly recognized not merely as technological tools but as enablers of strategic decision-making (Bharadiya, 2022). These systems possess sophisticated capabilities to collect, analyze, and convert historical and real-time data into actionable managerial insights, thereby supporting intelligent responses to both internal and external challenges (Niu et al., 2021).

From the perspective of the DCV, BI adoption can be conceptualized as a higher-order capability that underpins a firm's ability to sense, seize, and transform in response to environmental volatility (Kraaijenbrink et al., 2010; Teece, 2021, 2022). First, sensing involves identifying market shifts, consumer trends, and emerging threats or opportunities (Teece, 2021, 2022). BI systems enable hospitality firms to continuously monitor data streams and derive insights that sharpen environmental awareness (Alzghoul et al., 2024; Khaddam et al., 2023). Second, seizing refers to mobilizing resources to exploit these insights (Teece, 2021, 2022). Through BI-enabled analytics, managers are empowered to make informed strategic choices, allocate resources effectively, and coordinate actions across business units (Khaddam et al., 2023). Third, transforming entails reconfiguring operational and organizational routines to sustain competitive advantage (Teece, 2021, 2022). BI adoption facilitates the ongoing refinement of processes, systems, and decision-making structures, reinforcing strategic agility and enhancing the firm's capacity to adapt to dynamic market conditions (Khaddam et al., 2023).

Thus, BI adoption in hospitality firms extends beyond mere technological implementation. It represents meta-capability—a critical enabler of organizational learning and continuous renewal—allowing firms to reconfigure their assets and capabilities in alignment with evolving business landscapes (Alzghoul et al., 2024). This is particularly salient in the tourism and hospitality sector, where real-time responsiveness, agility, and the capacity to derive actionable insights from vast volumes of data are essential for maintaining competitive advantage and improving firm performance (Gursoy and Cai, 2025; Sarkar et al., 2023). Accordingly, we propose the following hypothesis:

H1. *BI adoption potentially influences the performance of tourism and hospitality firms positively.*

3.2. ROCs and BI adoption

ROC refers to a firm's strategic ability to structure, bundle, and leverage resources in a way that creates, develops, and deploys innovative organizational capabilities to achieve competitive advantage (Sirmon et al., 2007, 2011). Unlike traditional resource-based approaches that emphasize ownership, ROC highlights the dynamic role of managerial action in actively managing and coordinating resources to adapt to environmental changes, foster innovation, and drive improved performance (Sirmon et al., 2011). As such, ROC is conceptually aligned with the core tenets of the DCV, as it enables firms to sense market changes, seize strategic opportunities, and transform organizational processes and capabilities in response to dynamic conditions (Sirmon et al., 2007, 2011).

In line with this perspective, prior research has established that the effective implementation of technological innovations—such as BI systems—is not purely a technical challenge. Rather, it depends fundamentally on a firm's ability to strategically manage and coordinate its technological, human, and organizational resources (Gutierriz et al., 2025; Kristoffersen et al., 2021). In the tourism and hospitality industry, this dependency is especially pronounced due to the sector's dynamic environment, marked by rapid digital transformation, shifting customer expectations, and heightened competitive pressures.

From a DCV standpoint, the technological and analytical capabilities of employees, including competencies in data extraction, cleansing, visualization, and interpretation, are vital for successful BI adoption (Majhi et al., 2023). These individual-level capabilities form the micro-foundations of dynamic capabilities, enabling firms to sense changes in market trends and operational inefficiencies, seize opportunities by converting data into actionable insights, and transform existing processes to support strategic agility (Teece, 2021, 2022). In highly data-driven environments, such as tourism and hospitality, employee proficiency in BI tools facilitates proactive, evidence-based decision-making, embedding BI use into both operational routines and strategic decision-making layers (Bekele and Raj, 2024; Li, 2025).

In parallel, technological infrastructure and system interoperability represent essential technological resources that support BI implementation by enabling the seamless integration of information across departments and organizational boundaries (Gursoy and Cai, 2025). Furthermore, organizational-level capabilities—such as strategic alignment with firm objectives, top management support, and a culture of innovation—significantly influence the structured, strategic, and sustainable deployment of BI technologies (Bose et al., 2024; Mudau et al., 2024).

Given the turbulent and technology-intensive nature of the tourism and hospitality sector, ROC plays a critical role in aligning emerging digital technologies like BI with human capital, operational systems, and strategic goals. By effectively orchestrating cross-functional resources, ROC enhances a firm's ability to adopt and integrate BI systems in a coherent and strategically aligned manner. Accordingly, we propose the following hypothesis:

H$_2$. *ROCs positively influence BI adoption in tourism and hospitality firms.*

3.3. AI capabilities and BI adoption

AI is widely regarded as one of the most advanced forms of digitalization, distinguished by its capacity to replicate human cognitive functions, learn autonomously, and continuously improve through self-correction (Sjödin et al., 2023; Enholm et al., 2022). AI technologies have broad applications—including automating repetitive tasks, enhancing data analytics, powering virtual assistants, conducting risk assessments, and detecting fraud—which collectively enable firms to improve operational efficiency, enhance accuracy, and reduce costs (Polisetty et al., 2024; Enholm et al., 2022).

Despite these transformative potentials, many tourism and hospitality firms struggle to fully capitalize on AI technologies (Dogru et al., 2025; Li, 2025). This underperformance is not typically due to limitations of AI itself but rather the absence of sufficient AI capabilities—defined as a firm's ability to select, orchestrate, and leverage AI-specific resources (Mikalef and Gupta, 2021). In this context, AI capabilities reflect a strategic orientation that extends beyond operational improvements, enabling fundamentally novel ways to manage, scale, and innovate within organizational systems (Kar and Kushwaha, 2023).

Framed within the DCV, AI capabilities can be conceptualized as dynamic capabilities that empower firms to sense, seize, and transform in response to environmental dynamism (Mikalef et al., 2021; Siaw and Ali, 2024). First, by processing vast amounts of real-time and historical data, AI enhances firms' ability to sense emerging market trends, customer preferences, and potential threats with greater speed and accuracy (Siaw and Ali, 2024). Second, AI enables firms to seize these insights by supporting rapid, data-driven decision-making that can be integrated into strategic planning and resource allocation (Mikalef et al., 2021). Third, AI capabilities allow firms to transform their existing structures and processes, embedding intelligent automation and adaptive learning mechanisms that foster innovation and strategic agility (Mikalef et al., 2021; Siaw and Ali, 2024).

In the tourism and hospitality industry—where responsiveness, customer personalization, and real-time intelligence are essential—AI capabilities are especially critical for facilitating BI adoption (Samara et al., 2020). These capabilities enhance the analytical depth of BI systems, improve the precision of forecasting and reporting, and nurture an organizational culture oriented toward digital transformation. Moreover, AI enables firms to align BI efforts with broader strategic goals, ensuring that data-driven insights are not only generated but also acted upon in meaningful ways (Mikalef et al., 2021).

Despite this potential, there remains a significant gap in the literature concerning how tourism and hospitality firms can strategically develop and leverage AI capabilities as a new form of dynamic capability to drive BI adoption (Siaw and Ali, 2024). Exploring this relationship is essential for understanding how AI can modernize managerial decision-making, reconfigure operational models, and create pathways for sustained value creation and competitive advantage. Therefore, we propose the following hypothesis:

H_3. *AI capabilities positively influence BI adoption in tourism and hospitality firms.*

3.4. DMCs and BI adoption

Marketing capabilities are widely recognized as complex bundles of firm-specific knowledge, skills, and tools that are deeply embedded in organizational routines (Hunt and Madhavaram, 2020). These capabilities enable firms to execute effective marketing strategies and adapt to evolving market dynamics. However, with the increasing digitization of the business landscape, firms are now compelled to develop more specialized competencies known as DMCs to remain competitive (Herhausen et al., 2020). DMCs are defined as *"a specific set of qualifications of business capacity supported by technological skills and processes designed to access and utilize current and prospective customer data both online and offline, allowing more effectiveness in identifying, interacting, and engaging with customers"* (Apasrawirote et al., 2022, p. 480).

Framed within the DCV, DMCs can be conceptualized as dynamic capabilities that enable firms to sense, seize, and transform in response to digital disruption and shifting consumer expectations (Pfajfar et al., 2024). First, DMCs enhance a firm's sensing capabilities by enabling real-time monitoring of customer preferences, digital engagement patterns, and competitive dynamics (Apasrawirote et al., 2022). Through intensive interaction with customers across various digital platforms—such as social media, websites, mobile apps, and email campaigns—hospitality firms with advanced DMCs generate a vast amount of structured and unstructured data. This creates a compelling need for BI adoption, as BI systems can transform this data into actionable insights, enabling firms to detect trends and identify new market opportunities (Bose et al., 2024).

Second, DMCs facilitate seizing opportunities by supporting the personalization of services and precise customer targeting (Pfajfar et al., 2024). When complemented by BI systems, these capabilities enhance decision-making through predictive analytics and segmentation strategies, allowing firms to respond to customer needs with greater precision and speed. Third, DMCs contribute to transforming organizational processes by integrating technologies such as CRM systems, digital analytics platforms, and marketing automation tools, which collectively build the technological infrastructure and organizational readiness necessary for effective BI integration (Apasrawirote et al., 2022).

Thus, DMCs do not merely function at an operational level but act as strategic enablers of BI adoption, supporting the continuous reconfiguration of marketing processes, data assets, and digital infrastructure. In this sense, DMCs contribute to the firm's broader dynamic capabilities by enabling data-driven responsiveness, fostering organizational learning, and reinforcing strategic agility in the face of market uncertainty and digital complexity.

Despite their strategic relevance, the role of DMCs in driving BI adoption within the tourism and hospitality context has received limited scholarly attention (Ghesh et al., 2024; Kannan, 2024; Li, 2025). Addressing this gap is essential for understanding how DMCs help firms unlock the full potential of BI systems to enhance performance, competitiveness, and innovation. Accordingly, we propose the following hypothesis:

H_4. *DMCs positively influence BI adoption in tourism and hospitality firms.*

3.5. TO and BI adoption

With rapid technological development and the swift obsolescence of tangible and intangible products, tourism and hospitality firms have been compelled to improve technological expertise to be competitive (Ghesh et al., 2024; Knani et al., 2022). TO is defined as *"one where firms have an R&D focus and emphasize on acquiring and incorporating new technologies in product development"* (Deshpandé et al., 2013, p. 232). TO, in terms of technological skills, research and development resources, and technological infrastructure, is central to fostering successful technology adoption in tourism and hospitality firms (Kannan, 2024).

Prior literature indicates that tourism and hospitality firms with a high level of TO characteristically possess advanced technological infrastructure, strong IT capabilities, and a deep understanding of emerging technologies (Bhatiasevi and Naglis, 2020). These firms are more proactive in monitoring technological developments and also strategically positioned to adopt and integrate emerging technologies—such as BI systems—more rapidly than their less technologically oriented counterparts (Opazo-Basáez et al., 2022). Their technological readiness serves as a critical enabler for successfully deploying BI tools, necessitating seamless integration with internal databases, cloud computing environments, and ERP systems.

In the tourism and hospitality context, TO supports the presence of critical technological enablers such as real-time connectivity, integration of POS systems, booking engines, and CRM systems—all of which are essential for implementing and utilizing BI systems (Kannan, 2024). Moreover, technology-oriented tourism and hospitality firms demonstrate a strategic capacity to transform raw customer data into actionable insights, enabling a more profound understanding of consumer behaviour, emerging market trends, and opportunities for enhanced operational efficiencies (Knani et al., 2022; Jiménez-Partearroyo et al., 2024). Accordingly, it is reasonable to posit that technology-oriented tourism and hospitality firms are better positioned to leverage BI tools to drive data-informed decision-making and gain competitive advantage. Thus, we hypothesize:

H_5. *TO positively affects BI adoption in tourism and hospitality firms.*

3.6. Moderating effect of TO

While DMCs enable tourism and hospitality firms to capture valuable customer and market insights through digital channels, effectively translating these capabilities into BI adoption fundamentally depends on the firm's underlying technological orientation (Knani et al., 2022; Tajeddini et al., 2023). TO, which reflects a firm's inclination to embrace and strategically integrate new technologies, is a critical moderating role in this relationship. Firms with high TO are more likely to have the necessary infrastructure, technical expertise, and cultural alignment to integrate digital marketing outputs with BI tools, thereby enhancing data-driven decision-making (Jiménez-Partearroyo et al., 2024; Kannan, 2024). Conversely, firms with low TO may encounter structural or technical barriers that hinder the effective utilization of BI systems, even when DMCs are well-developed (Jiménez-Partearroyo et al., 2024; Kannan, 2024). Therefore, TO strengthens the positive association between DMCs and BI adoption by facilitating technological integration and organizational readiness. Based on this reasoning, we propose the following hypothesis:

H_6. *TO positively moderates the relationship between DMCs and BI adoption in tourism and hospitality firms, such that the relationship is stronger when TO is high.*

3.7. Mediating effects of BI adoption

While ROCs, DMCs, and AI capabilities represent critical dynamic capabilities within tourism and hospitality firms, their influence on performance is not necessarily direct or immediate (Herhausen et al., 2020; Sjödin et al., 2023). Instead, these capabilities enhance the firm's ability to gather, process, and act on data, which can be actualized through adopting and strategically using BI systems. Thus, BI adoption functions as a mediator, translating these dynamic capabilities to enhanced performance.

On the one hand, in tourism and hospitality, where agility and rapid decision-making are vital, ROCs enable firms to effectively mobilize and align human, technological, and informational resources toward adopting BI systems. Once implemented, BI systems enhance data-driven decision-making, optimize resource allocation, and generate actionable insights, translating orchestration capabilities into improved performance. On the other hand, while DMCs create a gamut of structured and unstructured data through customer interactions across various digital platforms, these data often remain underexploited without BI systems (Kannan, 2024; Solakis et al., 2024). BI adoption empowers tourism and hospitality firms to analyze and extract insights from digital marketing data, facilitating real-time campaign optimization and better customer targeting, thus improving performance.

Further, AI capabilities support predictive analysis, machine learning, and real-time decision-making. However, for tourism and hospitality firms to translate these capabilities into performance gains, robust BI systems are essential to integrate AI-generated insights into core business processes (Gursoy and Cai, 2025; Jiménez-Partearroyo et al., 2024; Solakis et al., 2024). BI tools provide the infrastructure to contextualize AI outputs within broader performance metrics, bridging the gap between algorithmic potential and business value realization (Gursoy and Cai, 2025; Solakis et al., 2024). In this way, when operationalized through BI adoption, AI capabilities lead to enhanced performance. Thus, drawing from the preceding discussion, the following hypotheses emerged:

H_7. *BI adoption mediates the link between (a) ROCs, (b) DMCs (b), (c) AI capabilities, and performance of tourism and hospitality firms.*

This study suggests the hypothesized research theoretical framework depicted in Fig. 1, leveraging insights from the DVC.

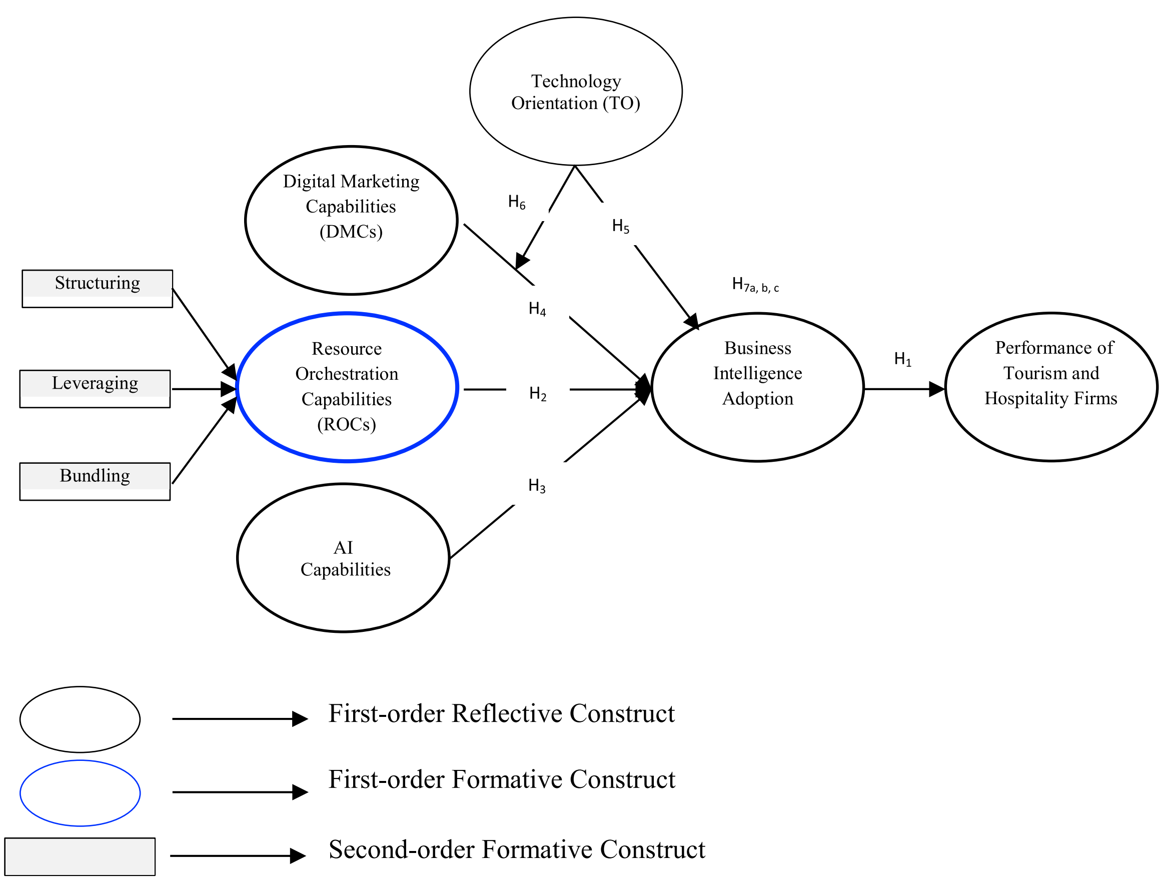

Fig. 1. Hypothesized framework.

4. Method

4.1. Description of the sample

To test the hypotheses, we employed primary data gathered through surveys administered to owners and top and middle managers (e.g., marketing and operation managers) across various levels within the tourism and hospitality sector in Japan. This included independent and chain hotels, resorts, travel agencies catering to both inbound and domestic tourists, restaurants, and bars. While the tourism and hospitality industry encompass a wide range of establishments, the scope of our research objective necessitated the exclusion of certain types, such as ryokans (traditional inns), minshukus (guesthouses), love hotels, temple lodgings (shukubo), budget-friendly business hotels, restaurants, and bars. Instead, our study focused on luxury, resort, boutique hotels, travel agencies, tour operators, transportation services, eco-tourism firms, event and conference organizers, theme parks and attractions, and online travel platforms. This targeted approach ensured that our research remained closely aligned with its specific aims and objectives. The data collection spanned from December 2023 to June 2024. Prior studies on multiple resource orchestration, digital and AI capabilities and BI adoption have predominantly focused on specific industries, such as manufacturing (e.g., Wu et al., 2025) and service sectors like healthcare (e.g., Sullivan and Wamba, 2024), higher education (e.g., Frisk and Bannister, 2017), information technology (e.g., Tajeddini, 2009, Turing, 2009), and various service SMEs, particularly in high-technology firms (cf. Murire, 2024). However, there is a need for further studies to enhance our understanding of the key factors influencing BI in diverse service industries, including tourism and hospitality firms (e.g., Stylos and Zwiegelaar, 2019).

While some scholars (e.g., Tajeddini et al., 2024; Zehrer et al., 2015) suggest that the relatively low entry barriers and employee qualification levels in the tourism and hospitality industry may hinder its competitiveness, the sector has consistently demonstrated resilience in the face of international competition. It is widely recognized as a vital contributor to economic growth in modern economies (e.g., Alzubi et al., 2025). Moreover, the tourism and hospitality industry captures a significant portion of tourists' total spending on accommodation, underscoring its economic significance and fostering innovations in areas such as business intelligence, resource orchestration capabilities, and AI adoption. These advancements enable the industry to effectively respond to evolving customer preferences and escalating competitive pressures (Kallmuenzer et al., 2022). The research setting for this paper was chosen to be Japan for various reasons. First, Japan has a long history of close ties between the government and business sectors. The government has substantially assisted the country's economic recovery and industrial achievements after World War II, with organizations like the Ministry of Economy, Trade, and Industry (METI) playing a crucial role (Ikeya and Ishikawa, 2001). This historical background offers a comprehensive setting for examining the development and influence of BI in Japan. Second, according to Soebandrija and Meilani (2022), implementing advanced AI technology in disaster management showcases Japan's innovative adoption of BI tools to enhance organizational resilience and response. Third, the intricate nature of the Japanese market and the demanding expectations of customers need the implementation of sophisticated resource management techniques in tourism and hospitality firms (Gursoy and Cai, 2025). This makes it an excellent environment for studying how integrating unique resources and skills may improve customer service performance. Fourth, Japan focuses on digital transformation in tourism and hospitality firms, highlighting the need to create new DMCs to stay competitive (Tajeddini et al., 2024). Collectively, these factors make Japan an exemplary case for examining how resource orchestration, digital marketing, and AI capabilities influence the adoption of BI in Japanese tourism and hospitality firms.

Initially, a survey questionnaire was developed in English and adapted from established measurement scales in prior research. Two highly proficient translators implemented a meticulous back-translation procedure to ensure linguistic accuracy and alignment with the original version. This involved translating the questionnaire into Japanese and then back into English to identify and resolve any inconsistencies. To further enhance the clarity and comprehensibility of the questions, a pre-test was conducted by interviewing five Japanese experts specializing in marketing within the tourism and hospitality sector. Their insights confirmed the relevance, significance, and comprehensiveness of the questionnaire.

From December 2023 to June 2024, a random sampling strategy was devised via a comprehensive list of managers at different levels from various tourism and hospitality firms in Kyoto, Saitama, Tokyo, and Yokohama. This list was obtained from multiple sources, such as Tokyo Shoko Research Company, JETRO, and corporate websites. A total of one thousand survey questionnaires and consent forms were distributed to the selected managers.

To ensure our sample accurately reflects the research objective, we requested participation from several managers at each identified firm. We took care to receive at least two responses from each participating business, and in many cases, we had to gather data from several branches of the same corporation. The key respondents were the branch managers or senior managers of each business. Several surveys were delivered and collected throughout working hours, with a three-business-day interval between drop-off and pick-up. After three rounds of data collection from December 2023 to June 2024, with two additional reminders, we received 331 survey questionnaires. However, prior to data analysis, 34 questionnaires with significant missing values and outliers were excluded. Hence, the final sample consisted of 297 usable questionnaires, leading to an effective response rate of 29.7 %. This response rate did not significantly influence the expected confidence levels or estimated error. Many exhibit a wide variety of sensible responses, validating the survey questionnaire's face and construct validity. Cohen's (1992) power analysis method sets a foundational guideline, recommending a minimum sample size of 85 to achieve 80 % power with an effect size of 0.15, a standard widely accepted in social sciences. However, more recent advice from Kock (2018) suggests a higher minimum sample size of 146 for Partial Least Square-Structural Equation Modeling (PLS-SEM) to better handle the complexity and variability in effect sizes, thus ensuring more reliable and replicable outcomes. Indeed, the sample size in this research far surpassed the required benchmark, guaranteeing an exceptionally high statistical power of 99.99 %. Furthermore, this study employed PLS-SEM instead of Covariance-based Structural Equation Modeling (CB-SEM) because the structural model employed in this study comprises both reflective and formative measurement constructs. Unlike CB-SEM, which primarily assumes reflective measurement and imposes strict identification and model fit requirements, PLS-SEM offers greater flexibility in modeling formative constructs (Hair et al., 2019; Hair et al., 2017). In formative measurement, indicators define the construct and are not expected to covary, making CB-SEM unsuitable without significant model modifications. Conversely, PLS-SEM does not require assumptions about indicator intercorrelation and is thus considered more appropriate for complex models involving both types of constructs (Hair et al., 2019; Sarstedt et al., 2014). This methodological flexibility makes PLS-SEM particularly suitable for this study.

Furthermore, we employed two post-hoc tests to assess potential differences: first, between early and late respondents across various managerial levels, and second, between tourism and hospitality family and non-family hotels for the assessed variables. The outcomes of the post-hoc analyses showed no statistically significant alterations in responses between early and late respondents across various managerial levels. Furthermore, the analyses indicated no significant distinctions concerning the assessed variables between among various types of tourism and hospitality family and non-family hotels. For example, t-tests were conducted between early and late respondents across various managerial levels to evaluate the non-response error. Certain demographic variables, including firm type, size, and age, were integrated to compute t-values. The results of t-values were between.53 and.223, indicating no significant distinctions between the two groups. In addition, the t-values for the main concepts in tourism and hospitality family and non-family hotels were as follows: BI adoption ($t = .22$, $p = .34$), TO ($t = .46$, $p = .25$), ROCs ($t = .55$, $p = .18$), DMCs ($t = .23$, $p = .35$), AI capabilities ($t = 1.21$, $p = .77$). As the t-values demonstrate, there were no considerable distinctions between these two categories, which reduces the likelihood of non-response errors, rendering them less significant and ineffective.

Furthermore, to mitigate potential non-causal relationships between DMCs, ROCs, and service performance, several control variables were incorporated, including firm size, firm age, firm ownership, firm category, and respondent experience. These variables were included to address potential endogeneity issues and are consistent with prior theoretical frameworks (Alzubi et al., 2025; Fan et al., 2023; Gamage et al., 2025; Tajeddini et al., 2024; Wu et al., 2025). Firm size was measured as the logarithm of the number of employees, while firm age was calculated as the logarithm of the number of years since the firm's establishment or incorporation. Firm ownership was coded as a binary variable, with a value of 1 assigned to family-owned businesses and 0 otherwise. Similarly, firm category was coded as 1 for traditional and budget-oriented businesses and 0 for high-end and specialized tourism services. Respondent experience was measured as the logarithm of the number of years the respondent had been working with the firm. The results indicated that the control variables had no significant influence on business performance ($\beta_{\text{Firm size}} = -0.003$; $\beta_{\text{Firm age}} = 0.001$; $\beta_{\text{Firm ownership}} = -0.027$; $\beta_{\text{Firm Category}} = 0.074$; $\beta_{\text{Experience}} = -0.038$; $p > 0.05$). This suggests that these factors did not play a significant role in shaping the observed outcomes.

Finally, given that the sample size and the firms range from traditional and budget-oriented businesses (e.g., ryokans, minshukus, and budget-friendly hotels) to high-end and specialized tourism services (e.g., luxury hotels, eco-tourism firms, and event organizers) (Table 1), it is crucial to ensure that the variation in sample composition does not affect the results (Nilsson, 2007; Tajeddini, 2011). To control for differences in respondent demographics between the two groups, samples from traditional and budget-oriented businesses (Group A) were randomly selected to align with the high-end and specialized tourism services samples (Group B) in terms of respondents' positions and experience levels. Subsequently, two multiple regression analyses were conducted using the same dependent and independent variables as in previous analyses. The results of these regressions were nearly identical to those obtained from the full sample, indicating that differences in sample size did not significantly impact the findings. Additionally, the study's results suggest that traditional and budget-oriented businesses (Group A) are well-established in their strategic approaches, while high-end and specialized tourism services (Group B) operate in a more volatile and turbulent environment. This implies that Group B may be more motivated to refine and enhance their existing services, potentially leading to improved performance. Furthermore, feedback from open-ended questions revealed that most Group B respondents expressed a strong interest in receiving a detailed report of the research findings. This suggests a desire to gain deeper insights into strategic decision-making and to apply theoretical knowledge in practical settings.

Moreover, we adopted several procedural remedies to reduce the risk of common method bias (CMB). The survey ensured respondent anonymity and confidentiality to minimize social desirability bias. We used previously validated scales and randomized the order of items to prevent pattern bias. Furthermore, Harman's single-factor test was performed, and results indicated that no single factor accounted for most variance, suggesting that CMB is not a significant concern. Furthermore, there is a chance that CMB will take place since data is gathered from just a single respondent. Kock (2015) points towards CMB in the context of structural equation modeling (SEM) via PLS-SEM. Kock (2015) suggests that full collinearity might be utilized to measure CMB when using PLS-SEM.

Table 1
Profile of respondents (demographic variables).

Characteristics	Frequency	Relative Frequency (%)
Gender		
Male	184	61.9
Female	113	38.1
Age (years)		
>30	2	0.67
30–35	18	6.06
36–41	31	10.5
42–47	44	14.8
48–53	95	32.0
54–59	58	19.5
60–65	49	16.47
Median	48–53	
Education		
General Business Administration	65	21.9
Finance/Accounting	31	10.4
Operations/Management	20	6.7
Marketing	73	24.6
Hospitality/Tourism	84	28.3
Others	24	8.1
Median	Hospitality/ Tourism	
Position held		
Top manager (e.g., owners, managing director, director of operations)	145	48.8
Middle managers (e.g., marketing and operation managers)	148	52.2
Family-Oriented and Non-Family Business	Chi-square =0.084	
Family business	146	49.2
Non-family business	151	50.8
Categorization of the Businesses	Chi-square =0.0303	
Group 1: Traditional and Budget-Oriented Businesses	150	50.5
-Accommodation (e.g., Ryokans (traditional inns), Minshukus (guesthouses) Love hotels, Temple lodgings (shukubo), Budget-friendly business hotels), -Food & Beverage (e.g., Restaurants & Bars)		
Group 2: High-End and Specialized Tourism Services	147	49.5
-Accommodation (e.g., Luxury hotels, Resort hotels, Boutique hotels), -Travel & Transportation (e.g., Travel agencies, Tour operators, Online travel platforms, Car rentals), -Specialized Tourism & Events (e.g., Eco-tourism firms, Event and conference organizers, Theme parks and attractions)		

Kock (2015) proposed CMB using variance inflation factors (VIFs) generated by a full collinearity test. VIF values greater than 3.30 suggest that the model is CMB-free. Findings from the study uncovered that all values of VIFs for all constructs were less than 3.3, suggesting no contamination of CMB in this research.

We examined the respondents' years of experience and managerial levels to provide further context on the sample. Regarding managers' years of experience, 77 informants had between one and five years of experience, 122 had between six and ten years, 51 had between eleven and fifteen years, and 47 had more than fifteen years of relevant experience. Regarding the managerial levels represented by the informants, the majority were middle-level managers ($n = 157$, 52.86 %), followed by front-level managers ($n = 128$, 43.10 %) and top-level managers ($n = 12$, 4.04 %).

4.2. Measurement development

The survey questionnaire was carefully designed to enhance both linguistic accuracy and cultural appropriateness. All variables were derived from established, well-tested measurement scales in prior research (Almheiri et al., 2024). BI adoption was operationalized utilizing a four-reflective item measurement scale derived from Khaddam et al. (2023). TO was evaluated by conducting a four-reflective item scale borrowed from Gatignon and Xuereb (1997). AI capabilities were calculated using a three-item scale from Gursoy et al. (2019). We used a three-item reflective scale that Hat et al. (2024) suggested to assess DMCs. ROCs are theorized as a higher-order construct (HOC) with three formative dimensions: structure, bond, and leverage (Kristoffersen et al., 2021).

5. Research findings

The outcomes of the study were obtained by employing PLS-SEM, a widely recognized data analysis technique in tourism and hospitality literature. It is an effective procedure to rigorously test theoretically-driven hypotheses using empirical data amassed through a survey questionnaire (Hair et al., 2021; Ringle et al., 2015). Furthermore, this research paper follows a two-step approach to PLS-SEM, systematically evaluating both a) the measurement model and b) the structural model (Hameed et al., 2018).

5.1. Measurement model assessment (MMA)

The first stage of PLS-SEM is grounded in MMA, which assesses the reliability and validity of the measurement scales. Reliability and validity assessment is addressed in the context of reflective and formative indicators, as the study framework comprises both HOC and lower-order constructs (LOC). For instance, the ROCs are conceptualized as a higher-order formative construct. In contrast, other study constructs, such as AI capabilities, DMCs, TO, BI adoption, and performance of tourism and hospitality firms, are conceptualized as reflective constructs. Therefore, the MMA is discussed in two sections: reflective and formative MMA.

5.1.1. Reflective MMA

Table 2 reports the outcomes of the reflective MMA. Factor loadings were computed to gauge the reliability of the individual items. The construct reliability was considered using Cronbach alpha and composite reliability (CR). Furthermore, convergent validity and discriminant validity were measured using factor loadings and average variance extracted (AVE).

Table 2
Convergent validity.

Constructs	Items	Loading	Alpha	CR	AVE
AI Capabilities	AI1	0.776	0.768	0.867	0.687
	AI2	0.775			
	AI3	0.926			
BI Adoption	BI1	0.742	0.796	0.867	0.62
	BI2	0.801			
	BI3	0.822			
	BI4	0.783			
DMCs	DMC1	0.975	0.956	0.971	0.819
	DMC2	0.974			
	DMC3	0.927			
PTHF	PTHF1	0.762	0.749	0.841	0.57
	PTHF2	0.719			
	PTHF3	0.784			
	PTHF4	0.752			
Bond	RoB1	0.764	0.781	0.875	0.701
	RoB2	0.791			
	RoB3	0.945			
Leverage	RoL1	0.797	0.807	0.888	0.726
	RoL2	0.798			
	RoL3	0.952			
Structure	RoS1	0.705	0.748	0.857	0.67
	RoS2	0.793			
	RoS3	0.941			
TO	TO1	0.727	0.747	0.841	0.569
	TO2	0.744			
	TO3	0.774			
	TO4	0.771			

Note: RoB = Bond; RoS = Structure; RoL = Leverage; AI = AI Capabilities; DMC = DMCs; BI = Business Intelligence; TO = Technology Orientation; PTHF = Performance of Tourism and Hospitality Firms.

The findings reveal that all factor loadings of scale items surpassed the advocated threshold level of 0.5 (Hair, 2010). Besides, for all four reflective constructs, Cronbach alpha and CR values surpassed the proposed value of 0.7 (Hair et al., 2020). Furthermore, it is observed that the AVE value of the structure is 0.67, bond 0.701, leverage 0.726, AI capabilities 0.687, DMCs 0.819, TO 0.569, BI adoption 0.62, and performance of tourism and hospitality firms 0.57. All the AVE values exceed 0.5 (Hameed et al., 2021; Henseler et al., 2014). Factor loadings, Cronbach alpha, CR, and AVE confirmed the convergent validity. Hence, there is a correlation between the scale items of the same variables. In addition, the absence of correlation between the scale items of AI capabilities, DMCs, TO, BI adoption, and performance of tourism and hospitality is confirmed by assessing discriminant validity. Discriminant validity was reviewed by computing the Heterotrait-Monotrait ratio of correlations (HTMT) suggested by Henseler et al. (2015). In assessing discriminant validity through HTMT, Gold et al. (2001) recommended that all values should be below 0.90. Table 3 reported the results of HTMT and confirmed that all calculated values are less than 0.9. Hence, there was no correlation between the scale items of all variables.

5.1.2. Formative MMA

As explained above, ROCs is conceptualized as a higher-order formative construct encompassing three dimensions: structure, bond, and leverage. According to Hair and Alamer (2022), assessing formative construct requires the evaluation of the convergent validity, examining indicator multicollinearity, the significance of the indicator weights, and evaluating the indicator loadings, if needed. Convergent validity was measured using redundancy analysis as shown in Table 4. To establish convergent validity, the path coefficient should exceed 0.7; either the p-value must be less than 0.05 or the t-value greater than 1.96. The redundancy analysis confirmed that these criteria were met. In the case of structure, bond, and leverage, the p-value <0.05 and the t-value >1.96. Furthermore, indicator multicollinearity was assessed for all the dimensions. According to previous studies, multicollinearity should be determined using the variation inflation factor (VIF), which should be less than 5.0 (Hair et al., 2019). It is observed that VIF values are less than 0.5, which confirms that formative constructs are not highly correlated (Hair and Alamer, 2022). Moreover, in this study, the significance of the indicator weights is also considered. Weights are considered statistically significant if $p \leq 0.05$ or the t-value exceeds 1.96, a standard successfully achieved in this study.

5.2. Structural model assessment

PLS bootstrapping was performed to assess the structural model, which analyzes the relationships among ROCs, AI capabilities, DMCs, TO, BI adoption, and performance of tourism and hospitality. Following previous studies, PLS bootstrapping was applied to assess the study hypotheses using path coefficients, t-values, and standard errors (Hair and Alamer, 2022). Further, direct effect, indirect effect, and moderation effect were used to test the hypotheses related to mediating and moderating consequences. While examining the mediation effect, this study followed the recommendations of Zhao et al. (2010), who proposed a revised approach to mediation analysis that moves beyond the traditional Baron and Kenny (1986) framework. Specifically, the study adopted the indirect-only mediation model, which does not require a significant total or direct effect between the independent and dependent variables to establish mediation. The analysis was conducted using the SPSS PROCESS Macro recommended by Hayes (2017), which provides a more robust method for testing moderation and mediation effects.

Results of the direct and moderation effect assessment are reported in Table 5. It is observed that BI adoption positively and significantly influences the performance of tourism and hospitality ($\beta = 0.157$, t-value = 2.599; p = 0.01, LL = 0.322, UL = 0.575), which supported H_1. ROCs significantly and positively influenced BI adoption ($\beta = 0.46$, t-

Table 3
Discriminant validity ($HTMT_{0.9}$).

	AI Capabilities	Bond	BI Adoption	PTHF	DMCs	Leverage	Structure	Technology Orientation
AI Capabilities								
Bond	0.330							
BI Adoption	0.609	0.492						
PTHF	0.569	0.391	0.586					
DMCs	0.487	0.331	0.531	0.453				
Leverage	0.379	0.535	0.532	0.388	0.334			
Structure	0.266	0.391	0.369	0.231	0.27	0.308		
Technology Orientation	0.48	0.745	0.712	0.432	0.431	0.633	0.386	

Table 4
Measurement model (formative indicators).

Higher-order construct (HOC)	Lower-order construct (LOC)	Variance inflation factor (VIF)	Weights	t-value	Outer Loadings
RO Capabilities	Structure	2.702	0.321	2.423	0.725
	Bond	1.508	0.152	2.136	0.801
	Leverage	1.635	0.407	2.697	0.785

value = 7.17; p = 0, LL= 0.062, UL = 0.288), supporting H_2. Similarly, AI capabilities significantly and positively influenced BI adoption (β = 0.213, t-value = 3.868; p = 0, LL = 0.106, UL = 0.318), supporting H3. DMCs significantly and positively influence BI adoption (β = 0.202, t-value = 4.098; p = 0, LL = 0.101, UL = 0.293), supporting H_4. TO significantly and positively affected BI adoption (β = 0.233, t-value = 3.75; p = 0, LL = 0.099, UL = 0.343), supporting H_5. Additionally, the proposed moderation effect of TO on the connection between DMCs and BI adoption is assessed. However, contrary to the expectation, the moderation effect was statistically insignificant (β = −0.001, t-value = 0.025; p = 0.098, LL = −0.112, UL = 0.097); hence, H_6 was not supported.

Nevertheless, the results of r-squared (R^2), effect size (f^2), and predictive relevance (Q^2) are reported in Table 4. This study considered R^2 to ascertain the extent to which the variance in the criterion variable can be attributed to the independent variables. The results of the PLS measurement model highlighted that R^2 is 0.211 for performance of tourism and hospitality, indicating that all variables account for the 21.1 % variance explained in performance of tourism and hospitality. Previous studies in the literature, such as Chin (1998), highlighted that a *"R^2 value of 0.60 is considered substantial, 0.33 is regarded as moderate, and 0.19 is viewed as weak."* In this paper, R^2 is weak. Furthermore, f^2 was utilized to observe the strength of the relationship. Consistent with Cohen (1988), *"0.02 is considered small, 0.15 is considered moderate, and 0.35 is considered strong."* It is observed that BI adoption has a moderate effect on performance of tourism and hospitality; however, in all other cases, f^2 is small. Finally, this study addressed the quality of the study framework by using predictive relevance (Q^2). It serves as a further measure of goodness-of-fit (Geisser, 1975) and must not be less than zero. In this study, Q^2 is 0.116 for service firm performance, higher than zero.

As indicated in Table 6, the indirect effect of BI adoption on the relationship between ROCs and performance of tourism and hospitality was found to be significant (β = 0.072, t-value = 2.625; p = 0.009, LL = 0.103, UL = 0.351), supporting H_{7a}. Similarly, the indirect effect of BI adoption on the link between DMCs and performance of tourism and hospitality was also statistically significant (β = 0.093, t-value = 3.604; p = 0, LL = 0.037, UL = 0.319), supporting H_{7b}. Finally, the indirect effect of BI adoption on the relationship between AI capabilities and performance of tourism and hospitality was identified as significant (β = 0.098, t-value = 3.279; p = 0.001, LL = 0.044, UL = 0.151), supporting H_{7c}.

6. Discussion and implications

The study findings are broadly aligned with extant tourism and hospitality literature across several dimensions. First, the study demonstrates that BI adoption significantly impacts the performance of tourism and hospitality firms. This result reinforces prior empirical evidence suggesting that adopting digital technologies contributes positively to business outcomes in this sector (Gursoy and Cai, 2025; Kannan, 2024; Knani et al., 2022).

Second, the positive influence of ROCs, AI capabilities, and DMCs on BI adoption is consistent with the central tenets of the DCV. According to DCV, merely possessing VRIN resources is insufficient for achieving sustained competitive advantage or superior performance outcomes (Sirmon et al., 2007, 2011). Instead, the firm's ability to dynamically configure, integrate, and deploy these resources through internally

Table 5
Path coefficient.

Hypothesis	Relationship	β	Mean	SD	T Statistics	P Values	LL-2.50 %	UL-97.50 %	R^2	f^2	Q^2	Decision
H1	BI Adoption → SFP	0.46	0.461	0.064	7.17	0	0.322	0.575	0.211	0.267	0.116	Supported
H2	RO Capabilities → BI Adoption	0.157	0.173	0.06	2.599	0.01	0.062	0.288		0.03		Supported
H3	AI Capabilities → BI Adoption	0.213	0.213	0.055	3.868	0	0.106	0.317		0.075		Supported
H4	DMCs → BI Adoption	0.202	0.198	0.049	4.098	0	0.101	0.293		0.054		Supported
H5	TO→ BI Adoption	0.233	0.229	0.062	3.75	0	0.099	0.343		0.087		Supported
H6	Technology Orientation* DMCs → BI Adoption	−0.001	−0.005	0.051	0.025	0.98	−0.112	0.097				Not Supported

Table 6
Path coefficient.

Hypothesis	Relationship	β	Mean	SD	T Statistics	P Values	LL-2.50%	UL-97.50%
H7 *a*	RO Capabilities → BI Adoption → PTHF	0.072	0.079	0.027	2.625	0.009	0.103	0.351
H7b	DMCs →BI Adoption -> PTHF	0.093	0.091	0.026	3.604	0	0.037	0.319
H7c	AI Capabilities → BI Adoption → PTHF	0.098	0.098	0.03	3.279	0.001	0.044	0.151

developed capabilities will determine their strategic value. In this context, our findings underscore the critical role of resource orchestration, whereby tourism and hospitality firms must actively develop and leverage dynamic capabilities to align BI technologies with organizational goals and processes. This reinforces the argument that performance gains from digital technology deployment are contingent upon the firm's ability to orchestrate complementary capabilities in response to the rapidly evolving technological landscape.

Third, the interrelationships among ROCs, DMCs, and AI capabilities—and their collective impact on firm performance—are more intricate and multifaceted than has been acknowledged in the extant tourism and hospitality literature (Ghesh et al., 2024; Li, 2025). While previous studies have studied these capabilities in isolation, few have systematically examined how their interaction shapes performance outcomes through digital technology adoption, particularly within the tourism and hospitality context (Ghesh et al., 2024; Kannan, 2024). Addressing this critical gap, the present study offers a novel contribution by empirically demonstrating BI adoption as a positive mediating mechanism linking ROCs, AI capabilities, and DMCs to the performance of tourism and hospitality firms.

Fourth, consistent with prior literature suggesting that firms with a strong TO are more likely to adopt emerging technologies at a faster pace than their less technologically inclined counterparts (Bhatiasevi and Naglis, 2020; Opazo-Basáez et al., 2022), our findings confirm that TO exerts a significant positive influence on BI adoption. This reinforces the view that TO serves as a strategic posture that enhances a firm's digital readiness and capacity for technological engagement. However, contrary to our expectations and prior empirical findings (e.g., Tlili et al., 2023), TO does not moderate the relationship between DMCs and BI adoption in the context of the sampled tourism and hospitality firms.

A potential theoretical explanation for this unexpected finding lies in Contingency Theory, which suggests that the effectiveness of strategic postures such as TO is contingent on external and internal contextual variables (Müller et al., 2024). In highly resource-constrained environments, particularly among SMEs in the tourism and hospitality sector, structural limitations, such as limited financial capital, skill shortages, and underdeveloped digital infrastructure, may constrain the extent to which TO can be operationalized. Even firms with a strategic inclination toward technology may be unable to leverage that orientation effectively due to these contextual barriers.

Moreover, from a DCV perspective, TO alone may not suffice unless it is complemented by well-integrated operational and organizational routines that can translate digital marketing outputs into BI-driven insights (Teece, 2021, 2022). If firms lack the necessary absorptive capacity or data integration mechanisms, DMCs may not interact meaningfully with TO to enhance BI adoption. Additionally, in some hospitality firms, institutional or managerial inertia, such as resistance to change or low digital literacy among decision-makers, may override the potential benefits of TO, thereby weakening its moderating role. Another plausible rationale is that in certain firms, DMCs may already be sufficiently advanced or independent, such that their influence on BI adoption does not rely heavily on the firm's broader technological posture (Pfajfar et al., 2024). In such cases, DMCs might operate as self-sustaining capabilities that drive BI adoption regardless of the firm's TO level, particularly if marketing teams are empowered with specialized tools, analytics platforms, or external support (Mehta and Tajeddini, 2016).

Taken together, these contextual contingencies suggest that the relationship between TO, DMCs, and BI adoption may be more complex and non-linear than initially hypothesized. As such, this finding highlights a potentially critical boundary condition and points to the need for further research in diverse organizational and geographical contexts to better understand how organizational maturity, resource endowments, and cultural readiness mediate or moderate these dynamics.

6.1. Implications for theory

The findings of this research offer substantial contributions to the tourism and hospitality literature in three fundamental ways. First, grounded in the DCV, the study proposes a comprehensive theoretical framework that explains how integrating AI and BI technologies with firm-specific resources and capabilities can enhance the performance of tourism and hospitality firms. In contrast to prior studies that often conceptualize digital technologies as standalone determinants of performance, this research highlights the pivotal role of dynamic capabilities in enabling tourism and hospitality firms to effectively deploy and exploit digital tools within their strategic and operational contexts. In particular, the study conceptualizes ROCs, DMCs, and AI capabilities as three distinct yet interrelated dimensions of dynamic capabilities. Collectively, these capabilities reflect a tourism and hospitality firm's capacity to sense, seize, and transform digital opportunities.

Second, although the literature on dynamic capabilities has expanded considerably in recent years, much of the existing work remains largely conceptual or examines dynamic capabilities broadly (Chirumalla et al., 2023; Gheitarani et al., 2023). Empirical research that systematically explores how specific configurations of dynamic capabilities interact to produce synergistic effects on firm performance is still limited—particularly within the tourism and hospitality context (Kannan, 2024; Law et al., 2024). This represents a significant gap, given that the DCV asserts that firms achieve sustained competitive advantage not through isolated capabilities but by strategically bundling and orchestrating complementary capabilities in response to environmental volatility and technological change. Addressing this limitation, the present study introduces and empirically investigates three interrelated dynamic capabilities—ROCs, DMCs, and AI capabilities—central to digital technology integration and marketing effectiveness. To the best of our knowledge, this is the first study in the tourism and hospitality literature to examine how these capabilities collectively shape the digital transformation outcomes of tourism and hospitality firms within a unified framework.

Third, while previous research has primarily focused on the direct effects of technological adoption, this study adopts a more nuanced perspective by identifying and empirically testing key mediating and moderating mechanisms that shape the relationship between dynamic capabilities and organizational performance. Specifically, BI adoption is conceptualized as a mediating variable through which dynamic capabilities—DMCs, ROCs, and AI capabilities—are translated into performance outcomes. Furthermore, the study introduces TO as a moderating variable, grounded in the premise that tourism and hospitality firms with a stronger strategic inclination toward adopting and leveraging technological innovations are better positioned to exploit the full potential of their dynamic capabilities. Collectively, these findings underscore that the effective deployment of AI and BI technologies is not solely a matter of access or adoption but of strategic integration with existing capabilities and orientations. In doing so, the study responds directly to recent scholarly calls (e.g., Li, 2025; Kannan, 2024) for more granular investigations into the mechanisms through which tourism and hospitality firms can harness the transformative potential of AI- and BI-related technologies to drive sustained performance improvements.

Fourth, the unexpected finding that TO does not moderate the relationship between DMCs and BI adoption in the context of the sampled tourism and hospitality firms carries important theoretical implications, particularly for research grounded in the DCV. It suggests that TO, although recognized as a critical enabler of technology adoption in prior literature, may not function uniformly as a dynamic capability across all contexts. While TO contributes positively to BI adoption as a strategic posture, its moderating influence may be contingent upon other organizational and environmental factors, such as firm size, digital maturity, resource availability, and managerial competencies. This finding extends the DCV by emphasizing that higher-order capabilities like TO require complementary capabilities and enabling conditions to exert influence on inter-capability relationships, such as the link between DMCs and BI adoption.

6.2. Implications for practice

The findings of this study offer practical relevance for tourism and hospitality firms, BI developers, industry practitioners, and policymakers in several important areas. The study identifies and empirically validates the critical determinants of successful BI adoption, offering a comprehensive understanding of how dynamic capabilities interact to influence firm performance. These insights can inform strategic planning and implementation decisions across the sector.

First, tourism and hospitality firms should systematically assess their internal capabilities before investing in BI systems. Central to this process is developing the three dynamic capabilities identified in this study—ROCs, DMCs, and AI capabilities. These capabilities should not be cultivated in isolation. Instead, they must be strategically integrated to create synergistic effects that enhance the effectiveness of BI adoption and its impact on firm performance. Tourism and hospitality firms should implement targeted training and capacity-building programs to operationalize this integration, equip managers and employees with the skills necessary for data-driven decision-making, and upskill staff using AI and other digital tools. Investment in technological infrastructure and process redesign is also critical to ensure the seamless integration of BI systems into existing resource portfolios and operational workflows. By strengthening and aligning these dynamic capabilities, tourism and hospitality firms will be better positioned to deploy BI in ways that are strategically coherent, responsive to environmental dynamism, and oriented toward sustained performance improvement.

Second, owners and managers of tourism and hospitality firms, particularly SMEs, should recalibrate their strategic planning processes to prioritize the development of internal capabilities that enable effective resource orchestration. Central to this is the formation of cross-functional teams that facilitate the bundling, redeployment, and strategic integration of resources across the organization. These teams should comprise representatives from key functional areas, including marketing, operations, IT, finance, and customer service, ensuring a diversity of perspectives and domain expertise. Such collaboration fosters alignment between technological capabilities and strategic objectives, creating an environment conducive to digital innovation. Cross-functional teams can play a pivotal role in managing digital transformation initiatives, including the implementation of BI systems, the coordination of data-driven projects, and ensuring the interoperability of technological platforms across departments. Their integrative function helps bridge organizational silos, enhancing the coherence and scalability of digital strategies.

In parallel, firms should embrace a bottom-up approach to innovation, which empowers employees at all levels, particularly those with direct customer interaction, to contribute insights and propose improvements to digital processes and service delivery. This approach can be institutionalized through mechanisms such as innovation labs, digital suggestion platforms, or internal hackathons, enabling employees to co-create and experiment with novel digital solutions. To ensure meaningful participation, firms must also invest in digital skills development, including training in data literacy and the use of emerging digital tools, thereby equipping employees to engage confidently in transformation efforts. Collectively, these strategies reinforce a culture of innovation and agility, strengthening the firm's dynamic capabilities and supporting the successful adoption and integration of advanced technologies within the tourism and hospitality sector.

Third, tourism and hospitality firms should systematically embed BI use cases into key business processes, such as customer relationship management, revenue management, and demand forecasting. By doing so, firms can ensure that BI adoption is not merely a technological upgrade but a central element of their strategic and operational framework. This alignment will enable tourism and hospitality firms to leverage digital tools more effectively, enhancing operational efficiency and customer-centric decision-making.

Finally, tourism and hospitality firms engaged in digital marketing and AI integration should go beyond merely enhancing technical skills. They should invest in developing broader digital competencies, such as data literacy, analytical thinking, and strategic use of AI tools. This holistic approach to capability building will facilitate successful BI adoption and strengthen a tourism and hospitality firm's long-term digital resilience for sustained competitive advantage.

7. Conclusion

The rapid advancement of digital technologies—particularly those driven by AI and BI—compels tourism and hospitality firms to reconfigure their resources and capabilities to remain competitive. This imperative arises from the growing necessity to effectively leverage such technologies to enhance firm performance—an area that remains underexplored within the tourism and hospitality literature. Anchored in the DCV, this study investigates the interrelationships among ROCs, DMCs, AI capabilities, and firm performance in the tourism and hospitality sector. Specifically, it examines the mediating role of BI adoption in these relationships and the moderating role of technological orientation (TO). Drawing on data collected through a questionnaire survey of 297 tourism and hospitality firms in Japan, the findings reveal that BI adoption significantly mediates the relationships among ROCs, DMCs, AI capabilities, and firm performance. However, contrary to theoretical expectations, TO does not moderate the relationship between DMCs and BI adoption—potentially due to the contextual characteristics of the sampled firms, which suggests a need for further investigation across different settings. This study contributes to the growing body of literature by presenting an integrative conceptual framework that illustrates how the alignment of AI and BI technologies with firm-level capabilities can enhance organizational performance in the tourism and hospitality industry. These findings offer both theoretical and practical insights and are expected to stimulate further scholarly inquiry in this emerging domain.

7.1. Limitations and future research

The study findings are subject to several imitations that offer exciting avenues for future researchers. First, it exclusively focuses on tourism and hospitality firms in Japan, which may limit the results' applicability to other contexts. Second, as the survey relies on self-reported data for both predictor and outcome variables, it is subject to CMB. Despite efforts to minimize this issue and ensure data quality, fully eliminating such bias remains challenging. Future research could strengthen the validity of the findings by adopting a multi-respondent design and gathering data from various managerial levels within the same tourism and hospitality firms. This would offer a more comprehensive view of organizational dynamics and reduce individual-level response bias. Third, constructs such as BI adoption, firm performance, and ROCs were measured through subjective evaluations of respondents, some in comparative terms. This assumes that respondents have accurate benchmarking knowledge, which may not always be the case. Thus, to strengthen the validity of the proposed interrelationships among the theoretical constructs, future studies could explore the proposed relationships by collecting data from various levels and types of managers within the same tourism and hospitality firms. Fourth, we could not use objective data to gauge the performance of tourism and hospitality firms due to confidentiality reasons, so we relied on self-reported measures. In future studies, conceptualizing the performance of tourism and hospitality firms as a HOC addresses this issue. It provides multiple performance measures, thus enabling future researchers to concentrate on detecting unbiased, multiple objective data sources to assess the performance of tourism and hospitality firms. Fifth, since this study offers a snapshot in time, longitudinal studies could help comprehend how disruptive digital technological advancement requires an integration of different combinations of firm capabilities to foster stage-wise BI adoption within tourism and hospitality firms to enhance performance. Finally, another limitation of this study is the absence of control variables such as hotel size, firm age, or ownership structure, which could influence results. While our sample was relatively homogeneous in terms of industry and operational characteristics, future research should include such variables to address potential omitted variable bias and improve internal validity.

CRediT authorship contribution statement

Kayhan Tajeddini: Validation, Supervision, Software, Project administration, Methodology, Conceptualization. **Omid Tajeddini:** Writing – original draft, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Waseem Ul Hameed:** Validation, Formal analysis, Data curation. **Thilini Chathurika Gamage:** Writing – review & editing, Visualization, Resources, Project administration.

Declaration of Competing Interest

My colleagues (Omid Tajeddini, Thilini Chathurika Gamage, Waseem Ul Hameed) and I (Kayhan tajeddini) as the authors of this paper declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. We hereby declare that the disclosed information is correct and that no other situation of real, potential or apparent conflict of interest is known to us. I undertake to inform you of any change in these circumstances, including if an issue arises during the course of the meeting or work itself.

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Appendix

Constructs	Items	Reference
TO	TO1. We use sophisticated technologies in our new product/service development TO2. Our new products/services always involve state-of-the-art technology TO3. We actively solicit and develop technologically advanced new products/services TO4. Technical innovation, based on research results, is readily accepted at this organization	Gatignon and Xuereb (1997, p. 240)
DMCs	DMC1. Our business creates and manages durable customer relationships through digital media DMC2. Our business use channel-bonding with wholesalers, retailers through digital media DMC3. Our business is able to use digital marketing to retain customers	Hat et al. (2024)
AI CAPABILITIES	AI1. Our firm explores AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology AI2. Our managers are able to work with data scientists, other employees and customers to determine opportunities that AI might bring to our organization AI3. Our managers are able to anticipate future business needs of functional managers, suppliers and customers and proactively design AI solutions to support these needs	Mikalef and Gupta (2021)
ROCs Structure	ROS1. We are effective at purchasing valuable strategic resources/assets from suppliers ROS2. We are effective at developing valuable IT resources/assets internally ROS3. We are effective at decommission less- valuable strategic resources/assets	Kristoffersen et al. (2021)
Bounding	ROB1. We are effective at integrating strategic resources/ assets to build strategic capabilities ROB2. We are effective at enriching, or extending, existing strategic capabilities with new strategic resources/assets ROB3. We are effective at pioneering, or creating, new strategic capabilities	
Leveraging	ROL1. We are effective at mobilizing our strategic capabilities towards a common vision ROL2. We are effective at coordinating, or integrating, our strategic capabilities ROL3. We are effective at deploying our joint strategic capabilities to take advantage of specific market opportunities	
BI Data Integration Analytical Capability	BI1. Compared with competitors, we can integrate diversified available data better BI2. Compared with competitors, our organization is well synchronized with other organizational databases in targeted markets BI3. Compared with competitors, we comprehensively analyze information on an ongoing basis BI4. Compared with competitors, employees from different departments in our firm share knowledge and insights smoothly	Khaddam et al. (2023)
PTHF	PTHF1. Our profitability has been substantially better PTHF2.Our return on investment has been substantially better PTHF3.Our growth in market share has been substantially better PTHF 4.Our sales growth has been substantially better	Chen et al. (2014)

Note: TO = Technology Orientation, DMCs = Digital Marketing Capabilities, AI = Artificial Intelligence, ROCs = Resource Orchestration Capabilities, BI = Business Intelligence, PTHF = Performance of Tourism and Hospitality Firms.

Data availability

The data that has been used is confidential.

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