Big data analytical capabilities and tech-business model innovation: a moderated mediation model

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Big data analytical capabilities and tech-business model innovation: A moderated mediation model

Abstract

Purpose - This study examines the role of big data analytical capabilities (BDAC) in fostering tech-business model innovation (TBMI), focusing on the mediating effect of digital transformation (DT) and the moderating role of digital business ecosystems (DBE).
Design/methodology/approach - Data were collected via an online survey of 313 middle and senior managers in five-star hotels in Antalya, Türkiye. A moderated mediation model examined relationships among BDAC, DT, DBE, and TBMI, with hypotheses tested using structural equation modeling.
Findings - The results reveal that BDAC significantly and positively impacts TBMI. DT mediates the relationship between BDAC and TBMI. Furthermore, the findings demonstrate that DBE strengthens DT's impact on TBMI, highlighting the importance of digital ecosystems in fostering innovation.
Originality/value - This study contributes to the literature by validating a moderated mediation model, showing that DT mediates and DBE moderates the effect of BDAC on TBMI, thereby extending prior research that considered BDAC–innovation relationships as direct.

Keywords: *Big data analytical capabilities, tech-business model innovation, digital transformation, digital business ecosystem, hotels*

Commented [KT1]: Data were collected through an online survey involving 313 middle and senior managers working in five-star hotels located in Antalya, Türkiye. A moderated mediation model was used to analyze the relationships among the variables in the study, and structural equation modeling was employed to test the hypotheses.

Commented [KT2]: The findings show that digital transformation enhances the link between big data analytics capability and technology-based market intelligence, while a dynamic business environment strengthens this effect, highlighting the importance of digital ecosystems in driving innovation.

Commented [KT3]: This study validates a moderated mediation model, showing how digital transformation and dynamic business environment influence the impact of big data analytics capability on technology-based market intelligence. It extends prior research by offering new insights into the complex relationships driving innovation.

1. Introduction

The accelerating pace of digitalization and technological advancement has fundamentally reshaped competitive environments, compelling firms to reconsider their business models (Ritter & Pedersen, 2020; Shah et al., 2025; Vaska *et al.,* 2021). Within this context, business model innovation (BMI) has emerged as a vital mechanism for responding to dynamic market demands, technological disruption, and evolving consumer expectations (Dikhanbayeva, 2025; Tajeddini et al., 2024; Troisi et al., 2023). Yet, the convergence of advanced digital technologies—such as big data analytics, cloud computing, artificial intelligence, and the Internet of Things—has given rise to a more integrated form of transformation: tech-business model innovation (TBMI).

While conventional BMI primarily emphasizes changes in value creation, delivery, and capture mechanisms (Demir *et al.,* 2023; Paiola & Gebauer, 2020), TBMI extends this by embedding digital technologies into the core logic of business models, positioning technology as a central driver of strategic renewal (Ancillai et al., 2023; Demir & Demir, 2015) (see Figure 1). TBMI typically requires specialized dynamic capabilities—such as sensing technological opportunities, reconfiguring digital resources, and adapting to rapid tech-driven change—whereas traditional BMI emphasizes strategic positioning, market sensing, and organizational redesign (Fan et al., 2023; Gretzel *et al.,* 2023; Rachinger *et al.,* 2019). This distinction refines conventional BMI notion by introducing technology intensity as a critical dimension, extending dynamic capabilities view (DCV) and resource-based view (RBV) to incorporate digital resources, and clarifying the conditions under which technology-driven versus market-driven innovations yield competitive advantage.

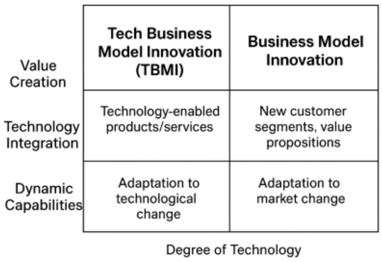

Figure 1: TBMI *vs.* BMI

Despite extensive research linking big data analytical capabilities (BDAC), digital transformation (DT), and innovation outcomes (Mikalef *et al.,* 2020; Ciampi *et al.,* 2021; Cui *et al.,* 2022), few studies conceptualize TBMI as a distinct construct. Prior work often focuses on operational improvements, process innovation, or general performance metrics without isolating how digital capabilities catalyze TBMI reconfiguration (Hanelt *et al.,* 2021; Merkel et al., 2019; Su *et al.,* 2021). Moreover, BDAC and DT have frequently been treated as parallel predictors, overlooking the mediated and conditional pathways through which digital capabilities generate value in complex organizational settings.

To address these gaps, the current study introduces and empirically tests a moderated mediation model. DT is positioned as a mediator linking BDAC to TBMI, while digital business ecosystems (DBE) are examined as a moderator of the DT–TBMI relationship. TBMI is conceptualized as a technologically embedded innovation process in which value creation is data-driven, enabled by transformation, and accelerated through ecosystem participation. Unlike business models that treat digital technologies as external enablers, TBMI situates them at the core of business model architecture, rendering innovation a digitally configured and continuously adaptive process (Loebbecke & Picot, 2015; Nambisan *et al.,* 2017).

This study contributes in three key ways. First, it advances theoretical clarity by defining TBMI as distinct from traditional BMI, grounded in the integration of BDAC and DT. Second, it responds to calls for examining when digital capabilities drive innovation by validating a moderated mediation model, where DT mediates and DBE moderates the BDAC–TBMI link, extending prior research that viewed this relationship as direct (Adner & Kapoor, 2010; Kohtamäki *et al.,* 2019). Third, by focusing on the hospitality industry—a sector experiencing rapid digitalization yet underrepresented in innovation research—it provides contextual insights into how firms reconfigure business models in data-rich environments (Demir & Demir, 2025; Gretzel *et al.,* 2023). Accordingly, the study addresses the following research questions:

1. How does BDAC influence TBMI in the hospitality sector?
2. What is the mediating role of DT in the BDAC–TBMI relationship?
3. To what extent does DBE moderate the DT–TBMI link?
4. How can the interplay of BDAC, DT, and DBE generate strategic advantages for digitally-oriented firms?

Commented [KT4]: How does big data analytics capability (BDAC) influence technology-based market intelligence (TBMI) in the hospitality sector, and what is the mediating role of digital transformation (DT) in this relationship? Furthermore, to what extent does a dynamic business environment (DBE) moderate the link between DT and TBMI, and how can the interplay of BDAC, DT, and DBE generate strategic advantages for digitally-oriented firms?

By addressing these questions, this study deepens understanding of the DT–innovation nexus and provides a roadmap for firms aiming to leverage technology not merely to enhance operations but to fundamentally redefine their business models.

2. Theoretical background

A business model embodies a firm's ability to respond to complex, uncertain, and dynamic environments by effectively leveraging both its valuable resources and its dynamic capabilities (Ancillai *et al*., 2023; Mostaghel *et al*., 2022; Yaşar, 2022). In this regard, organizational success hinges on the strategic integration of economic and human resources with adaptive capabilities that drive innovation and transformation (Cui *et al*., 2022; Warner & Wäger, 2019). The effective deployment and alignment of such resources are crucial for cultivating firm-specific capabilities and achieving a sustainable competitive advantage (Ciampi *et al*., 2021; Makadok, 2001). Therefore, while the RBV provides a foundational lens by focusing on firm performance through the possession of valuable, rare, inimitable, and non-substitutable resources (Barney, 1991), it does not fully address how firms sustain competitiveness in highly volatile markets.

DCV extends RBV by explaining how firms can create, integrate, and reconfigure internal and external resources to respond to environmental changes (Teece, 2018). This integration reveals that dynamic capabilities serve as a critical mechanism for operationalizing RBV, especially in turbulent contexts where static resource advantages quickly erode (Caputo *et al*., 2021; Ritter & Pedersen, 2020). Accordingly, this study employs a combined RBV–DCV lens to offer a robust theoretical foundation. Through RBV, firms identify and accumulate key resources, such as big data infrastructure or analytical talent. At the same time, DCV explains how these resources can be transformed into innovation outcomes, including TBMI. Specifically, BDAC exemplifies a dynamic capability that enables firms to convert big data—a resource framed within RBV—into adaptive strategic action and competitive renewal, thereby bridging both theoretical perspectives (Ciampi *et al*., 2021; Teece, 2018).

Table 1. Current studies mapped to the dimensions of the conceptual model

Source	Key Focus	Theoretical Contributions	Managerial Implications
Almheiri *et al*. (2025)	BDAC, competitive performance, and environmental uncertainty.	Emphasizing the role of managerial support and data-driven culture.	Cultivating a data-driven culture to enhance competitiveness.
Demir (2025) and Demir and Demir (2025)	Technology investments, innovation strategies, and hospitality competitiveness.	Testing a mixed-methods model of technology and performance.	Aligning tech investments with innovation strategies in hospitality firms.
Liu and Qu (2024); Mikalef *et al*. (2020) and Teece (2018)	BDAC, competitive performance, dynamic and operational capabilities.	Confirming the role of dynamic and operational capabilities in achieving competitive advantage.	Developing dynamic capabilities alongside big data analytics to sustain competitiveness.
Naz *et al*. (2024) and Orero-Blat *et al*. (2024)	BDAC, innovation, and organizational performance.	Extending the RBV with big data and innovation linkages.	Investing in big data capabilities for innovation.
Kissi (2024) and Yaşar *et al*. (2024)	Big data analytics and intrapreneurship / collaborative culture and innovation.	Exploring mediation and moderation effects in innovation.	Encouraging intrapreneurship / collaborative culture alongside big data use.
Ladeira *et al*. (2024)	Big data, AI, and industry performance.	Confirming AI and big data's impact on services through meta-analysis.	Adopting AI and big data analytics in service firms.
Khatami *et al*. (2024)	Digital entrepreneurial ecosystems, tourism and social sustainability.	Linking digital ecosystems to tourism sustainability.	Supporting digital entrepreneurship in tourism policymaking.
Fernández-Portillo *et al*. (2024)	DEB, stakeholder satisfaction, and performance.	Examining the impact of digital ecosystems on business performance.	Engaging stakeholders in digital ecosystems.
Prakasa and Jumani (2024)	DT, digital capability, and small business performance.	Confirming DT as a critical mediator in RBV theory.	Prioritizing DT in small businesses to enhance performance.
Zhang *et al*. (2023) and Verhoef and Bijmolt (2019)	DT, business model innovation, and corporate performance.	Validating the dual mediating-moderation framework for DT.	Aligning DT with innovation capabilities in manufacturing for optimal results.
Chen and Kim (2023)	DT, innovation factors, and innovation performance.	Highlighting innovation factors as underlying mechanisms in DT.	Fostering an innovation culture to maximize DT benefits.
Gretzel *et al*. (2023)	Smart tourism.	Advancing smart tourism as a transformative force.	Adopting smart tourism technologies among tourism stakeholders.
Ancillai *et al*. (2023) and Vaska *et al*. (2021)	DT and business model innovation.	Providing a comprehensive research agenda linking digital	Prioritizing digital adoption to enable continuous business model reinvention.

Source	Key Focus	Theoretical Contributions	Managerial Implications
		technologies and business model innovation.	
Wirtz (2022)	DT, AI, big data, cloud computing, and IoT.	Integrating digital technologies into governance and business models.	Adopting emerging technologies for efficiency in governments and businesses.
Cui *et al*. (2022) and Ciampi *et al*. (2021)	BDAC and business model innovation.	Extending the RBV by integrating entrepreneurial orientation as a mediator.	Fostering entrepreneurial mindsets to leverage big data for business model innovation.
Su *et al*. (2021)	BDAC, organizational performance and dual innovation.	Highlighting dual innovation as a key mediator between big data and performance.	Balancing product and process innovation when deploying big data analytics.
Hanelt *et al*. (2021)	DT and strategy.	Identifying gaps in organizational change theories.	Aligning DT with cultural change and leadership buy-in.

2.1 Big data analytical capabilities and tech-business model innovation

BDAC enable firms to process and interpret large, diverse datasets from multiple channels, extracting strategic insights that enhance competitive differentiation (Demir *et al.,* 2023; Dubey *et al.,* 2019; Mikalef *et al.,* 2020). While traditional BMI focuses on reconfiguring value creation and delivery mechanisms in response to technological and market changes (Ancillai *et al.,* 2023), TBMI emphasizes the integration of digital technologies into core business models to generate value (Demir & Demir, 2015). Effective TBMI implementation requires digital competence across stakeholders, as firms lacking BDAC often struggle to achieve meaningful innovation outcomes (Ritter & Pedersen, 2020; Cui *et al.,* 2022).

Empirical evidence (Table 1) indicates that BDAC positively influences TBMI by enabling firms to identify new market opportunities, enhance performance, and drive innovation (Mostaghel *et al.,* 2022). Data-driven technologies support precise analytics, real-time reporting, personalized customer experiences, and cost efficiencies, transforming innovation into a strategic capability (Merín-Rodrigáñez *et al.,* 2024; Zhang *et al.,* 2023).

However, BDAC alone does not guarantee innovation. Firms may adopt big data for symbolic legitimacy rather than substantive transformation, and cultural resistance, weak leadership, or misaligned structures can impede TBMI (Hanelt *et al.,* 2021; Loebbecke & Picot, 2015; Agrawal *et al.,* 2019; Dubey *et al.,* 2019). Successful TBMI thus requires alignment between technical capabilities, strategic processes, and organizational culture (Su et al., 2021; Warner & Wäger, 2019).

Grounded in the DCV, which emphasizes continuous resource renewal and reconfiguration under dynamic conditions (Ciampi *et al.,* 2021; Mikalef *et al.,* 2020; Teece, 2018), this study proposes the following hypothesis:

H$_1$. *BDAC has a positive impact on TBMI.*

2.2 Big data analytical capabilities and digital transformation

DT involves reconfiguring core business processes through the use of digital technologies and reallocating organizational resources and competencies to address evolving market conditions (Demir *et al*., 2023; Hanelt *et al*., 2021). Successfully achieving DT via BDAC requires strategic alignment across internal management structures, organizational culture, and implementation processes (Loebbecke & Picot, 2015). BDAC serves as a solution to DT's structural and operational barriers, supporting data-driven decision-making (Dremel *et al*., 2017). Several studies (e.g., Dremel *et al*., 2017; Mikalef *et al*., 2020) emphasize the value of BDAC-enabled tools, systems, and applications in generating actionable insights that drive DT initiatives.

BDAC enhances DT outcomes by facilitating the collection, storage, processing, and interpretation of complex data (Su *et al*., 2021). It improves organizational competitiveness, agility, and innovation capacity (Dubey *et al*., 2019). By applying BDAC, firms can assess prior performance, increase technological maturity, and develop adaptive transformation strategies. These capabilities also optimize production processes, allowing for greater customization and faster market responses (Tsai & Zdravkovic, 2020).

Beyond technical functions, BDAC contributes to shaping an innovation-oriented culture, fostering inclusion, and delivering tailored responses to emerging challenges (Agrawal *et al*., 2019; Warner & Wäger, 2019). BDAC also enhances digital agility through advanced technologies, including AI, IoT, AR/VR, MR, and cloud computing, thereby improving overall organizational performance (Buhalis & Leung, 2018; Vial, 2019). From an RBV lens, BDAC is a valuable, rare, inimitable, and non-substitutable resource that enhances digital readiness (Barney, 1991). In contrast, the DCV highlights its role in enabling firms to sense and capitalize on transformational opportunities (Dubey *et al*., 2019; Warner & Wäger, 2019). The second hypothesis is proposed as follows:

H$_2$. *BDA has a positive impact on DT.*

2.3 Digital transformation and tech-business model innovation

Extant research highlights the strong relationship between DT and TBMI, showing that DT plays a crucial role in enabling and shaping TBMI (Demir *et al*., 2023). Organizations that prioritize digital technologies for data acquisition, processing, and implementation tend to achieve greater competitiveness (Dikhanbayeva, 2025). Unlike traditional business model approaches, these organizations leverage DT to enhance data flow and decision-making, thereby accelerating TBMI outcomes (Pigni *et al*., 2016; Wang *et al*., 2022; Zott *et al*., 2011). DT is increasingly viewed as a key strategic driver in developing innovative business models (Demir *et al*., 2023; Vaska *et al*., 2021), as it supports creative, technology-driven changes in business operations and stakeholder engagement.

Prior findings affirm that DT significantly contributes to BMI, particularly through its influence on technology-based innovation structures (Chen *et al*., 2015; Cui *et al*., 2022). In an increasingly globalized and digital economy, the integration of DT enables firms to differentiate themselves and generate new forms of stakeholder value (Demir & Demir, 2015). However, the successful realization of TBMI depends on a firm's readiness to embrace DT, which requires both digital infrastructure and strategic change initiatives (Nambisan *et al*., 2017). TBMI allows firms to innovate through digitally enabled systems, generating economic, social, and environmental value (Demir & Demir, 2015). Literature suggests DT advances TBMI in three key ways: optimizing current models (e.g., reducing costs), transforming structures (e.g., process redesign), and redeveloping models (e.g., targeting new markets) (Loebbecke & Picot, 2015; Rachinger *et al*., 2019). Within the DCV, DT represents a firm's ability to realign internal and external competencies in response to digital change, enabling technology-driven innovation (Rachinger et al., 2019; Teece, 2018; Vaska *et al*., 2021). Accordingly, the following hypothesis is proposed:

H$_3$. *DT has a positive impact on TBMI.*

2.4 The mediating role of digital transformation

The widespread accessibility of big data through digital technologies has positioned DT as a central driver of contemporary business operations (Correani et al., 2020). While BDAC are critical for enabling TBMI, their impact is maximized when supported by DT tools, platforms, and competencies (Tsai & Zdravkovic, 2020). Firms operating within digitally mature environments leverage BDAC more effectively, translating data volume, velocity, and variety into innovative outcomes (Cui et al., 2022; Dremel et al., 2017). Empirical studies indicate that organizations actively engaged in DT achieve more radical innovations, as DT amplifies the strategic use of big data (Demir et al., 2023; Su et al., 2021; Tsai & Zdravkovic, 2020).

Although prior research has examined DT's influence on BMI and firm performance (Merín-Rodrigáñez et al., 2024; Zhang et al., 2023), its specific mediating role between BDAC and TBMI remains underexplored. Studies suggest that DT functions as a key intermediary, enabling BDAC to generate innovation by integrating technological, human, and process dimensions (Chen & Kim, 2023; Cui et al., 2022; Mikalef et al., 2020; Su et al., 2021). This perspective aligns with the DCV, which posits that BDAC alone is insufficient without processes that operationalize transformation, and the Resource-Based View, which frames DT as a capability that converts data resources into innovation outcomes (Chen & Kim, 2023; Mikalef et al., 2020).

Drawing on these theoretical foundations, this study proposes that DT mediates the relationship between BDAC and TBMI, highlighting the essential role of DT in translating analytical capabilities into BMI.

H$_4$. *DT mediates the relationship between BDAC and TBMI.*

2.5 The moderator role of the digital business ecosystem

A DBE refers to a functionally integrated network of digital technologies, systems, structures, and diverse stakeholders, including suppliers, customers, commercial partners, applications, and data providers (Demir & Demir, 2015). By aligning these actors and resources, DBE enables firms to replace outdated processes and enhance business value creation through innovation (Graça & Camarinha-Matos, 2017; Kohtamäki, 2019). Through the integration of digital platforms, services, and technologies, DBE facilitates collaboration, co-creation, and the effective implementation of TBMI (Nachira et al., 2007; Teece, 2018).

Innovation within ecosystems relies on open, decentralized collaboration rather than hierarchical control, and the performance of a firm's innovation activities often depends on the contributions and competencies of other actors within the network (Adner & Kapoor, 2010). Cooperation and competitive dynamics among innovation-driven partners within DBEs have become essential to firms' strategic growth (Fernández-Portillo et al., 2024). In this context, DBEs are shown to positively moderate the impact of DT on TBMI, especially in large and complex organizations (Masucci et al., 2020). Within these ecosystems, DT contributes to building robust, technology-enabled infrastructures that enhance TBMI, while actors continuously adapt their skills and roles to foster systemic innovation (Graça & Camarinha-Matos, 2017).

Despite these insights, prior studies summarized in Table 1 often focus on specific industries, overlook the combined role of internal digital capabilities and external ecosystems, or provide limited empirical evidence on the moderating mechanisms of DBEs. The current study addresses these gaps by examining how DBEs influence the relationship between digital transformation and TBMI across diverse organizational contexts, integrating both technological and human resource perspectives. This approach enables a more comprehensive understanding of the ecosystem's moderating effects, capturing the dynamic interactions among stakeholders and their contributions to sustainable innovation outcomes.

For sustained success, businesses leverage DBEs to improve R&D, talent development, operations, and financing. They also promote interoperability, trust, and collaboration across partners (Camarinha-Matos & Afsarmanesh, 2008). Studies confirm the moderating role of DBEs in the relationship between digital capabilities and performance (Fernández-Portillo et al., 2024), the enhancement of tourism sustainability (Khatami et al., 2024), and the innovation-performance link in smart tourism ecosystems (Gretzel et al., 2023). Aligned with the DCV, external ecosystems are critical enablers that amplify internal transformation efforts (Adner & Kapoor, 2010; Teece, 2018). Thus, we propose the following hypothesis:

H$_5$. *DBE moderates the relationship between DT and TBMI, strengthening this link at higher levels of innovation.*

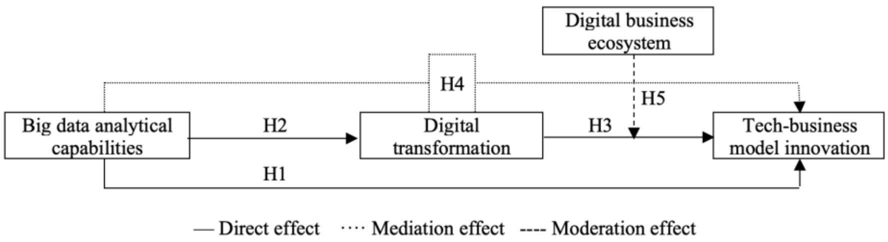

Figure 2. Hypothesized model

3. Methodology

3.1 Data collection and sample

This study's data was collected using online questionnaires from middle and senior managers of five-star hotels in Antalya (Türkiye) between 1st May and 30th November 2023. The data collection process consisted of four stages. In the first stage, hotel managers were interviewed over the phone, and the study's purpose, scope, and method were explained to them. All managers were then asked to participate. The managers who agreed to participate in the study requested the e-mail addresses of the department managers. In the second stage, information about the research was sent to all e-mail addresses (417 in total), and permission was requested for voluntary participation. Forty-six refused to participate in the survey, and fifty-eight did not answer. In the third stage, an online survey form link was sent to 313 participants who agreed to participate. In the last stage, the data was cross-checked for missing values or outliers. While preparing the online questionnaire, all questions were required to be marked so there was no risk of receiving missing values. Ultimately, the survey yielded an effective response rate of 75%.

The study comprised 74.1% males and 25.9% females, with an average age of 36.4 years. Remarkably, 87.2% of the participants have obtained a bachelor's degree or higher and have more than ten years of professional experience in the tourism sector. 12.4% of the participants were General Managers, 16.7% were Assistant General Managers, 12.4% were Front Office Managers, 12.4% were Human Resources Managers, 12.4% Food and Beverage Managers, 12.4% were Housekeepers, 8.4% were Kitchen Chefs, 3.8% were Sales and Marketing Managers, 3.3% were Technical Managers, and 5.8% were other Department Managers. Additionally, all participants have experience using hotel automation systems, professional digital tools and applications, as well as digital hotel management systems.

3.2 Measures

Data were obtained using a four-dimensional measurement tool. The scales were adapted from prior literature and measured using a five-point Likert scale (1 = strongly disagree, to 5 = strongly agree). Before administering the questionnaire, two pre-tests were performed, and statistically appropriate and acceptable values were achieved. The reliability of all dimensions exceeds 0.85; according to Nunnally (1978), an internal consistency reliability of 0.70 or higher is recommended.

The BDAC scale developed by Demir *et al.* (2022) was used to measure BDAC. The scale consists of four dimensions: BD collection, processing, analysis, interpretation, and transformation capability. The Cronbach's alpha value for the items was 0.88. *The DT scale* was adapted from Demir *et al.* (2023). The scale includes items related to digital systems, networks, tools, and technology management. The Cronbach's alpha value for the scale items was 0.91. *The TBMI scale* was developed from the Six-generation Innovation Models, including the "Technology-Driven Model," "System Integration/Network Model," and "Innovation Environment Model." This model gains digital functionality by integrating technological features into the innovative business model (Demir & Demir 2015:28). The Cronbach's alpha value for the scale items was 0.93. *The DBE scale* was developed from existing literature (Graça & Camarinha-Matos, 2017; Tsai & Zdravkovic, 2020). The scale includes items related to the digital aspect of business collaboration based on the internet and network technologies. The Cronbach's alpha value for the items was 0.89.

3.3 Control variables

This study included two control variables: managerial experience and experience with DT technologies. These control variables were measured using a nominal scale and "yes-no" responses related to participants' a) experience in the hospitality industry and b) use of digital technology, tools, applications, and networks. These control variables were used to accurately measure the TBMI goals of selected businesses (Demir & Demir, 2015; Yuan & Wen, 2018).

4. Results

For the hypotheses of the study, the convergent and discriminant validity were first tested. Confirmatory factor analysis (CFA) was performed using AMOS 23. The four-factor model, including BDAC, DT, DBE, and TBMI ($\chi 2/df=1.812$; GFI=0.913; NFI=0.904; CFI=0.921; TLI=0.915; RMSEA=0.041; SRMR=0.039; $p < 0.01$) was compared with the one-factor model ($\chi 2/df=2.402$; GFI=0.711; NFI=0.789; CFI=0.806; TLI=0.808; RMSEA=0.246; SRMR=0.539; $p<0.1$). The findings of the CFA indicated that the fit indices of the four-factor model have a better range than those of the one-factor model, thus confirming the discriminant validity of the variables. The average variance extracted (AVE) and composite reliability (CR) were checked. All AVEs are above 0.7 and CRs above 0.8 (Table 2); the CR test showed that the internal consistency values exceeded the acceptable threshold of 0.70 while AVE values exceeded the acceptable threshold of 0.50 (Bagozzi & Yi, 1988; Hair *et al.*, 2010). Second, Harman's single-factor test was employed to identify potential concerns regarding common method bias (Podsakoff *et al*., 2003). The findings indicated that a single factor (BDAC) accounted for 23.33%, which suggests no substantial common method bias since it is less than 50% of the variance (James *et al.*, 1984; Lindell & Whitney, 2001; Podsakoff *et al.*, 2003). The mediating role of DT in the relationship between BDAC and TBMI was examined using a bootstrapping analysis with a multi-step approach proposed by Baron and Kenny (1986). Additionally, hierarchical regression analysis was employed to investigate the moderating effect of DBE in the research model. Table 3 shows the correlation coefficients of the variables. Using a moderated mediation model allows the study to capture both the indirect and conditional effects, providing a more comprehensive understanding of how these variables interact in driving TBMI.

4.1 Mediating effect of DT

The results indicate that BDAC has a positive and significant association with TBMI ($\beta=0.48$; $t=6.19$; $p<0.001$) and DT ($\beta=0.43$; $t = 5.73$; $p < 0.001$). DT is also positively and significantly associated with TBMI ($\beta = 0.51$; $t = 8.27$; $p < 0.001$). The results are crucial for validating the hypotheses. Accordingly, H_1, H_2, and H_3 are statistically supported. The effect of BDAC remains valuable and significant, but its impact, in terms of volume, variety, veracity, velocity, and value, can be overlooked when businesses have insufficient DT efforts. Hence, the mediating effect of DT is confirmed ($\beta=0.18$; $p<0.01$). Furthermore, the indirect impact of BDAC on TBMI was also positively and significantly determined by bootstrapping analysis (as seen in Table 4). As a result, it can be concluded that DT mediates the relationship between BDAC and TBMI; hence, H_4 is also statistically supported.

4.2 Moderating effect of DBE

H_5 assumes that the effect of DT on TBMI would be positive for businesses with robust DBE. The result of the hierarchical regression analysis indicates that the indirect relation between power and the interaction of DT and DBE increases in the regression equation. Table 5 illustrates that the relationship between DT and TBMI strengthens in the case of high DBE ($\beta=0.32$, $p<0.001$), as compared with low DBE ($\beta=0.09$, $p<0.001$). The direct effects of DT (Table 4) and the moderating effect of DBE (Table 5) on TBMI are also positive and significant. As seen in Figure 3, the result of the slope test shows that businesses' DT has a more substantial impact on TBMI when DBE are vital, and the slope is relatively weak for DBE. The interaction effect between DT and TBMI is statistically positive and significant. Hence, H_5 is supported.

Table 2. Exploratory factor analysis

Constructs and items	Pre-test-1				Pre-test-2				Final construct			
	FL	α	AVE	CR	FL	α	AVE	CR	FL	α	AVE	CR
Big Data Analytics Capabilities		**0.72**	**0.54**	**0.73**		**0.77**	**0.61**	**0.79**		**0.88**	**0.72**	**0.88**
Our organization uses diverse and reliable sources to collect big data.	0.76				0.81				0.92			
Our organization is agile in collecting data for innovative opportunities.	0.73				0.76				0.86			
Our organization has structured processes for managing and processing big data.	0.69				0.71				0.81			
Our organization has the tools and expertise to analyze complex data.	0.61				0.68				0.79			
Our organization extracts meaningful insights by interpreting data in context.	0.55				0.63				0.78			
Our organization uses data knowledge and skills for strategic planning.	0.52				0.60				0.77			
Our organization applies big data insights to strengthen stakeholder collaboration.	0.49				0.55				0.75			
Our organization develops innovative methods for analyzing big data.	0.46				0.51				0.72			
Our technological infrastructure efficiently handles large and varied data sets.	*0.41*				*0.44*				*Removed*			
Our organization effectively evaluates and uses insights from big data.	*0.39*				*Removed*				*Removed*			
Digital Transformation		**0.71**	**0.63**	**0.70**		**0.78**	**0.66**	**0.78**		**0.91**	**0.79**	**0.92**
Our organization considers digital technologies to be a strategic advantage.	0.83				0.88				0.94			
The digital transformation process is strongly supported by top management.	0.64				0.72				0.89			
Our employees have the necessary skills to use digital tools effectively.	0.62				0.71				0.86			
Digital transformation has made our business processes more efficient.	0.58				0.67				0.79			
Our organization can adapt to digital changes quickly and flexibly.	0.51				0.59				0.74			
Digital transformation holds a significant place in our organizational culture.	*0.42*				*0.46*				*Removed*			
Our organization uses technological tools in some services instead of the employees.	*0.37*				*Removed*				*Removed*			
Tech-Business Model Innovation		**0.74**	**0.62**	**0.75**		**0.79**	**0.64**	**0.80**		**0.93**	**0.81**	**0.92**
Our organization integrates technologies into its business model to create new value.	0.86				0.93				0.93			
We frequently redesign our business model in response to technological advancements.	0.68				0.84				0.84			
Technology plays a central role in interacting with all our stakeholders.	0.53				0.78				0.81			
We experiment with new digital business models to stay competitive.	0.48				0.76				0.78			
Technological innovation has significantly transformed revenue generation methods.	*0.40*				*Removed*				*Removed*			
Digital Business Ecosystem		**0.69**	**0.58**	**0.71**		**0.76**	**0.62**	**0.77**		**0.89**	**0.74**	**0.89**
Our organization collaborates effectively in the digital ecosystem.	0.77				0.83				0.91			
Digital technologies make our processes more flexible and adaptive.	0.72				0.76				0.85			
Our organization uses digital innovations to stay competitive.	0.64				0.71				0.81			
The digital ecosystem helps us respond quickly to customer needs	0.59				0.68				0.78			
Our organization strategically assesses digital ecosystem opportunities.	*0.48*				*0.49*				*Removed*			
Our organization efficiently shares data with businesses through digital platforms.	*0.36*				*Removed*				*Removed*			

α = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted; FL = Factor Loading
α = 90; KMO=0.972; Bartlett's test of sphericity/Approx. chi-square=15,282.16 / df=701 / p= 0.001 (Final construct)

Table 3. Means, standard deviations, and correlations among the variables

	Mean	Std. Dev.	1	2	3	4	5	6
1. Pro.Ex.	11.75	5.16	-					
2. Tech-Ex	1.00	0.00	0.39**	-				
3. BDAC	4.09	0.62	0.27*	0.43**	*0.84*			
4. DT	4.18	0.69	0.19*	0.48**	0.51**	*0.88*		
5. TBMI	4.29	0.65	0.34**	0.21*	0.56**	0.58**	*0.90*	
6. DBE	4.11	0.61	0.36**	0.17*	0.44**	0.42**	0.55**	*0.86*

*Correlation is significant at the 0.05 level (two-tailed).
**Correlation is significant at the 0.01 level (two-tailed).
#1 Diagonal values (italic) are the square roots of AVE.
#2 Pro.Ex, Professional experiences; Tech-Ex, Digital technology, networks, tools usage experiences; BDAC, Big Data Analytics Capabilities; DT, Digital Transformation, TBMI, Tech-Business Model Innovation; DBE, Digital Business Ecosystem

Table 4. Mediated regression analysis results

	Effect	**SE**	**t**	**p**
Control variables				
Pro.Ex	0.07	0.09	2.03	0.00
Tech-Ex	0.15	0.31	2.29	0.00
Relationships				
BDAC×TBMI	0.30	0.09	4.18	0.00
BDAC×DT	0.43	0.22	5.73	0.00
DT×TBMI	0.51	0.12	8.27	0.00
	Effect	**SE**	**LL 95% CI**	**UL 95% CI**
Bootstrap results for indirect effects (Mediator: DT)				
Direct effect	0.30	0.09	0.173	0.425
Indirect effect	0.18	0.06	0.117	0.263
Total effect	0.48	0.10	0.341	0.599

n=313; Bootstrap Sample Size, 5000; LL, Lower Limit; CI, Confidence Interval; UL, Upper Limit; Pro.Ex, Professional experiences; Tech-Ex, Digital technology, networks, tools usage experiences; BDAC, Big Data Analytics Capabilities; DT, Digital Transformation; TBMI, Tech-Business Model Innovation

Table 5. Hierarchical moderated regression analysis

Predictors		TBMI		
	R	R^2	Estimate	SE
Step 1	0.36***	0.25***		
Constant			6.24	0.07
DT			0.52**	0.16
DBE			0.29**	0.11
Step 2	ΔR^2	0.06		
DT x DBE			0.19*	0.23
Moderator		**TBMI**		
DBE	**Effect**	**Boot SE**	**LLCI**	**ULCI**
Conditional direct effects of TD on TBMI at values of the DBE (moderator)				
DBE - 1SD	0.09	0.12	0.08	0.15
DBE mean	0.21	0.19	0.14	0.26
DBE + 1SD	0.32	0.24	0.21	0.37
n=313; Bootstrap Sample Size, 5000; LL, Lower Limit; CI, Confidence Interval; UL, Upper Limit; DT, Digital Transformation; TBMI, Tech-Business Model Innovation; DBE, Digital Business Ecosystem				

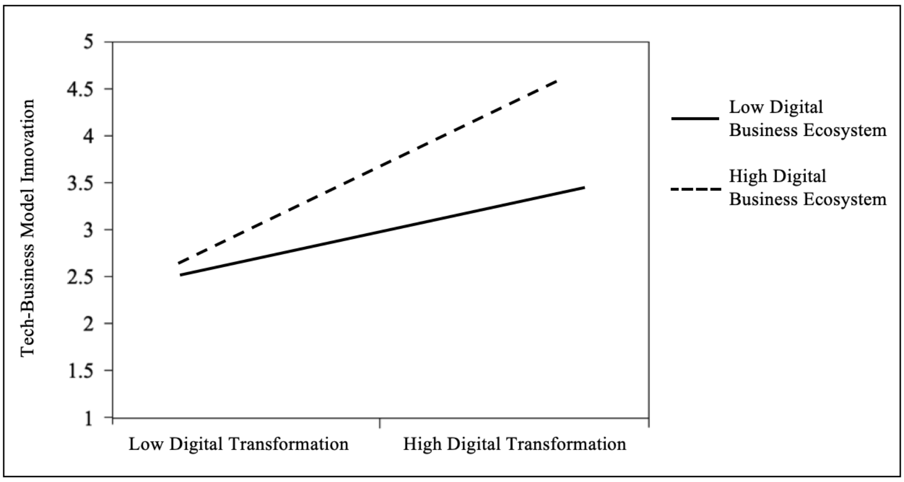

Figure 3. Interaction effects of DT and DBE on TBMI.

As DT increases, TBMI also increases, as indicated by the upward trend in both lines. However, the rate of increase differs depending on the level of the DBE. A high DBE strengthens DT's positive impact on TBMI. This suggests that businesses operating in a more digitally advanced ecosystem benefit more from DT efforts, leading to greater innovation in their business models. Conversely, in a low DBE, the same level of DT yields comparatively lower innovation outcomes (Figure 3).

5. Conclusion, Implications, and Future Research

5.1 Conclusion

This study advances understanding of how BDAC drive TBMI by revealing the mediating role of DT and the moderating effect of DBE. Using survey data from 313 hotel managers and a moderated mediation model, the findings show that BDAC enhances TBMI directly and indirectly through DT, highlighting that data analytics serves as a catalyst for reconfiguring business models rather than solely an operational tool.

The results further demonstrate that robust digital ecosystems strengthen the DT–TBMI link, underscoring the importance of external collaboration and ecosystem engagement in amplifying internal transformation. These insights extend the DCV and RBV by conceptualizing BDAC as a transformative capability when dynamically leveraged within supportive ecosystems.

Managerially, firms should pair investments in data analytics with organizational culture, processes, and inter-firm networks to maximize innovation and competitiveness. The study contributes theoretically and methodologically by validating a moderated mediation framework in an underexplored hospitality context and invites future research across industries and cultural settings.

5.2 Theoretical implications

This study makes several important contributions to research on BDAC, DT, and TBMI, addressing key gaps and enriching theoretical understanding. The findings align with and extend prior scholarship while challenging conventional assumptions.

First, the results support the DCV and RBV, confirming BDAC as a dynamic capability that enhances TBMI. While prior studies emphasize BDAC's role in agility and competitive advantage (Teece, 2018; Mikalef et al., 2020), few empirically examine its direct impact on TBMI in digital contexts. This study validates DCV's core premise by demonstrating how BDAC enables firms to reconfigure resources, adapt to market change, and drive innovation.

Second, the findings extend RBV by conceptualizing BDAC not as a static resource but as a transformative capability that yields sustained advantage when combined with DT (Barney, 1991). Consistent with Ciampi et al. (2021) and Cui et al. (2022), our integrated model incorporates both internal capabilities (BDAC) and external ecosystems (DBE), refining existing theories.

Third, this research addresses an underexplored area by empirically testing BDAC's effect on TBMI in hospitality. Prior work largely links BDAC to operational efficiency or general performance (Naz et al., 2024; Dremel et al., 2017). Our findings demonstrate BDAC's strategic role in innovation and identify DT as a mediating mechanism, answering calls to move beyond viewing BDAC and DT as parallel constructs (Hanelt et al., 2021). This supports Warner and Wäger's (2019) view of DT as business model reconfiguration rather than mere technology adoption.

Fourth, the study introduces DBE as a moderator of the DT–TBMI link, a contribution previously untested in hospitality. Results show that firms embedded in stronger digital ecosystems experience amplified DT–TBMI effects, positioning innovation as ecosystem-driven rather than purely internal. These findings extend ecosystem theory (Adner & Kapoor, 2010) and align with prior research emphasizing that digital co-creation environments magnify transformational outcomes (Fernández-Portillo et al., 2024). Our results quantify this effect within hospitality, where ecosystem integration remains uneven, and highlight that even incremental moderation can have meaningful implications. Consistent with Masucci et al. (2020), the study underscores that ecosystem maturity—beyond firm-level digital capabilities—is critical for scaling innovation outcomes.

Finally, this study advances methodology by validating a moderated mediation model that captures indirect (DT) and conditional (DBE) effects, using SEM to test complex relationships and controlling for managerial experience and digital proficiency to enhance generalizability. These choices address calls for more nuanced analytical approaches in digital innovation research (Hair et al., 2010; Demir et al., 2023). While prior studies link BDAC to innovation (Mikalef et al., 2020; Ciampi et al., 2021), they often treat this relationship as direct. Our findings challenge this view, aligning with emerging evidence that DT capabilities are essential intermediaries unlocking BDAC's potential (Cui et al., 2022; Su et al., 2021). This study further shows DT is not merely concurrent with BDAC but a critical mechanism driving TBMI, especially in complex service contexts like hospitality. Collectively, these contributions refine theory, broaden empirical understanding, and offer a foundation for future research on digital innovation pathways.

5.3 Managerial implications

The findings of this study provide actionable guidance for hospitality managers, industry stakeholders, and technology developers seeking to leverage BDAC, DT, and DBE to drive TBMI. Central to this is investing in BDAC training for managers and executives by developing in-house expertise in data collection, processing, and interpretation (Demir et al., 2023) and forging partnerships with universities or certification programs to enhance analytic capabilities (Cui et al., 2022). Fostering a digital-first culture is equally important; adopting AI-driven analytics and IoT solutions can embed innovation into daily operations (Naz et al., 2024), while recognition programs that reward data-based initiatives align individual performance with organizational innovation goals (Warner & Wäger, 2019). Agile leadership practices, such as cross-functional teams connecting IT, marketing, and operations, enable the rapid translation of BDAC insights into action (Hanelt et al., 2021). Real-time dashboards monitoring key metrics like guest satisfaction and revenue per available room facilitate dynamic decision-making (Mikalef *et al.,* 2020).

Hotels can further enhance competitiveness by personalizing guest experiences through predictive analytics that tailor services to preferences such as room selection or dining habits (Demir & Demir, 2025). Integrating BDAC with CRM systems enables effective segmentation and targeted loyalty programs (Verhoef & Bijmolt, 2019). Accelerating DT enhances operational efficiency through automation of back-office tasks like inventory and staff scheduling via cloud-based ERP systems (Buhalis & Leung, 2018). Participation in DBEs offers additional opportunities; collaboration with technology startups, local attractions, and online travel agencies supports bundled service offerings (Gretzel *et al.,* 2023), while consortia such as Hotel Technology Next Generation facilitate best-practice sharing and standardization (Khatami et al., 2024).

Technology developers also play a pivotal role in enabling innovation. Designing integrated BDAC platforms tailored for hospitality is crucial, incorporating user-friendly dashboards to visualize occupancy and guest sentiment (Li et al., 2022) and AI chatbots to manage routine inquiries (Wirtz, 2022). Ensuring interoperability through open APIs allows integration of property management systems with third-party services such as ride-sharing or restaurant reservations (Tsai & Zdravkovic, 2020), while blockchain technologies can secure and verify shared data like guest reviews (Wang et al., 2022). Addressing data privacy concerns requires embedding privacy-by-design principles into BDAC tools to ensure compliance with regulations such as the GDPR (Pathak *et al.,* 2023). Hotels can operationalize this by implementing secure data storage, obtaining explicit guest consent, providing transparency dashboards, conducting audits, and training staff on data ethics. Finally, offering scalable Software-as-a-Service solutions lowers adoption costs, making advanced analytics accessible to small and mid-sized hotels (Orero-Blat *et al.,* 2024). Together, these measures enable hospitality firms to innovate and sustain competitiveness in dynamic digital environments.

5.4 Limitations and future research directions

While this study offers valuable insights into the interplay between BDAC, DT, DBE, and TBMI, several limitations warrant attention and suggest avenues for future research. First, the analysis focused solely on five-star hotels in Antalya, Türkiye, limiting generalizability to other hospitality segments (e.g., budget hotels, resorts) and industries (e.g., retail, healthcare). Replicating this study in diverse sectors and geographies could test the robustness of the proposed model. Second, the Turkish hospitality market's distinct regulatory and cultural characteristics may shape results. Comparative studies across regions with varying institutional environments (e.g., digital infrastructure, government policies) could clarify contextual moderators.

Third, reliance on managerial self-reports risks response bias (e.g., social desirability). Future research should triangulate findings with objective data such as financial performance and IoT-based operational metrics. Fourth, the cross-sectional design limits causal inference; longitudinal studies tracking BDAC adoption and TBMI outcomes over time would strengthen causality claims.

Fifth, psychological and organizational factors (e.g., employee resistance, digital literacy) were not examined. Incorporating behavioral frameworks (e.g., Technology Acceptance Model) could reveal barriers and enablers of DT adoption. Moreover, despite controlling for managerial experience and digital usage, key contextual variables—such as firm size, competitive intensity, and regulatory pressures—were omitted due to data limitations. Their exclusion may introduce omitted-variable bias, as differences in resources and market conditions can shape both predictors and outcomes. For instance, larger firms typically possess greater capacity for innovation, while firms in highly competitive markets may adopt different strategies than those in less dynamic environments. These unmeasured influences may partially account for some observed effects, limiting internal validity. Future research should incorporate such contextual and organizational factors to enhance model robustness and offer a more comprehensive understanding of the dynamics underpinning TBMI.

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