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Data-driven disruptive competitiveness: Exploring the role of big data analytics capability and entrepreneurial marketing in disruptive innovation

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Abstract

Big data analytics capability has garnered significant attention in both academic and managerial circles as a major driver of innovation-driven competitive advantage. However, the existing literature on the BDAC-innovation relationship is still inconclusive, with industry reports highlighting that many firms struggle to derive significant value from it. Rooted in resource-based theory and dynamic capabilities, this study examines the role of big data analytics capability in disruptive innovation, considering the mediation of entrepreneurial marketing, a strategic orientation representing the interface of entrepreneurship and marketing. The proposed relationships are validated through the analysis of 216 manufacturers in Pakistan using partial least squares-based structural equation modeling. The results reveal that big data analytics capability positively influences both entrepreneurial marketing and disruptive innovation, while entrepreneurial marketing also positively influences disruptive innovation. Moreover, entrepreneurial marketing fully mediates the relationship between big data analytics capability and disruptive innovation. These findings have significant implications for both theory and practice.

Keywords: *Big data analytics capability, Entrepreneurial marketing, Disruptive innovation, Emerging economy firms, Structural equation modeling*

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1. INTRODUCTION

We are currently thriving in the 'Age of Data', where industries and public entities are generating a staggering amount of new data daily, exceeding 2.5 quintillion bytes, thanks to the widespread internet usage by over 4.9 billion global users (Flynn, 2023). This expansive data, known for its high volume, variety, and velocity, primarily comprises consumer information (Erevelles et al., 2016). Consequently, businesses are investing significantly in big data analytics capabilities (BDAC) to analyze this data, derive valuate insights and enhance innovation capabilities (Dean et al., 2023). Statistics show that investments in BDAC are projected to grow to $665.7 billion by 2033, up from $225.3 billion in 2023 (Kashinath et al., 2023). These significant investments in BDAC are based on the belief that they can drive superior performance (Gupta et al., 2020), facilitate business transformation (Loebbecke & Picot, 2015) and catalyze disruptive innovation (DI) (Wessel, 2016). This trend is observable across various industries, where BDAC is reshaping the dynamics of the customer-firm relationship, challenging existing value propositions (Ciampi et al., 2021), and fostering DI (Wessel, 2016). Well-known companies like Uber, 23andMe, Airbnb, Xiaomi, and Amazon exemplify how BDAC has allowed them to revolutionize their industries by offering more convenient, simpler, and affordable products (Guttentag, 2013; Johnson et al., 2017; Willis & Tranos, 2021). By leveraging vast market data from diverse sources in real-time, these companies have gained unparalleled insights into consumers, competitors, and supply chains, thereby stimulating DI and overturning traditional sources of innovation and competitive advantages (Johnson et al., 2017; Wessel, 2016).

Identified as the next frontier of productivity, innovation, and competition (Manyika et al., 2011), scholars have begun exploring how BDAC influences various types of firm innovation, including incremental, radical, and frugal innovations (Al-Omoush et al., 2024; Mikalef et al., 2020). Scholars also conceptually refers to its role in fostering DI, enabling firms quickly adjust to market shifts and disrupt industries by offering more affordable, convenient, and competitive products (Johnson et al., 2017; Wessel, 2016). However, despite these compelling arguments and corporate examples highlighting the significance of BDAC for DI, the extant literature has not yet empirically examined this relationship. Additionally, while earlier studies have suggested a direct role of BDAC in firm innovation outcomes, recent literature and industry reports highlight a significant disparity between the accelerating rate of investments and the actual value that BDAC yields (Bean & Davenport, 2019; Mikalef et al., 2019b). This disparity underscores the necessity for a deeper comprehension of the BDAC value-creation process, which has led scholars to investigate the mechanisms by which BDAC can enhance firm innovation (Huynh et al., 2023; Mikalef et al., 2019b). However, there is limited theoretical knowledge on the mechanisms by which BDAC can be effectively harnessed to foster DI.

This study intends to address two critical questions: (1) Does BDAC foster DI? (2) If so, through what facilitating mechanisms does BDAC promote DI? To address these questions, this study build on the resource-based theory (RBT) and the dynamic capabilities view (DCV), examining how BDAC influences DI. Drawing on recent literature, BDAC is defined as the firm's ability to gather, store, and analyze highly voluminous, varied, and rapidly generating data to extract insights (Olabode et al., 2022). DI is defined as "a new product with a different set of performance attributes that are initially attractive to new and emerging market segments who are not the current focal point of the business" (Zhang & Zhu, 2021, p. 184). This form of innovation creates new functionalities and markets (Kraus et al., 2023), outperforming established products by being comparatively cheaper, simpler, and usually more convenient (Govindarajan et al., 2011).

The current knowledge of the mechanisms through which BDAC lead to superior value creation is informed by two closely related streams: entrepreneurship and marketing (Ciampi et al., 2021; Gnizy, 2019; Mazzei & Noble, 2017). Recently, entrepreneurship scholars have begun to explore how a firm's entrepreneurial orientation, enabled by BDAC, can lead to enhanced innovation (Ciampi et al., 2021). Similarly, marketing academics have analyzed the revolutionary influence of big data investments on firm marketing strategies, specifically on market orientation within the BDAC-value creation processes (Gnizy, 2019). BDAC allow firms to approach market from a different perspective, fostering a proactive and entrepreneurial approach (Erevelles et al., 2016; Liu, 2014). Building on this, some recent studies advocate for a more integrative approach to examining the value creation process of BDAC, focusing on the convergence of different orientations, namely entrepreneurship and marketing, referred to as entrepreneurial marketing (EM) (Alqahtani & Uslay, 2022; Erevelles et al., 2016). Researchers across these perspectives build on RBT and its extension, the DCV, utilizing the resource-strategy-performance framework, to elucidate the pathway from BDAC to superior innovation outcomes. However, up until now, how EM, a unique strategic orientation which also fits the RBT/DCV framework (Alqahtani & Uslay, 2020), facilitates the relationship between BDAC and DI remains unexplored.

EM is conceptualized as a strategic orientation that combines entrepreneurial traits—such as innovativeness, proactiveness, risk-taking, opportunity-seeking, and resource leveraging—and marketing traits—like value creation and customer focus (Morris et al., 2002). EM represents not just the combination but also the synergy of entrepreneurial and marketing traits, making a firm innovative, change-driven, and market-driving (Eggers et al., 2020). Since DI possesses distinct attributes compared to other kinds of innovation, such as radical innovation (Govindarajan et al., 2011), it necessitates a firm to redefine its traditional market orientation by incorporating an entrepreneurial dimension (Zhou et al., 2005). DIs are more focused on achieving market superiority by creating new functionalities and markets, rather than solely on technological advancements (Kraus et al., 2023). Relying on traditional market or customer orientation, which centers on existing markets, is insufficient for fostering DI (Govindarajan et al., 2011). Instead, integrating entrepreneurial traits is advocated (Zhou et al., 2005). This integration, encapsulated as EM, is critical when pursuing high-risk, innovative endeavors like DI (Eggers et al., 2020). These considerations emphasize the efficacy of EM for fostering DI, and researchers also conceptually refer to the role of customer information, particularly digital information, in shaping a firm's EM strategy (Fink et al., 2020; Polas & Raju, 2021; Schulte & Eggers, 2010). However, no studies have empirically explored how BDAC fosters EM or whether EM mediates the BDAC-DI relationship.

This study aims to fill these gaps by exploring the impact of BDAC on DI and the mediating role of EM in this relationship. By applying RBT and the DCV, particularly the resource-strategy-performance framework, we adopt a stepwise approach to examine the roles of BDAC in both DI and EM, as well as how EM mediates the BDAC and DI relationship. Thus, this study makes numerous key contributions to the literature by offering novel insights into the BDAC-value creation process. Firstly, by explicating the role of BDAC in DI, this study extends the understanding of BDAC's role in DI. By demonstrating how firms can nurture DI by leveraging BDAC, it expands the literature on the capabilities' antecedents of DI. Secondly, by investigating the role of BDAC in EM and the consequent impact of EM on DI, it enriches the burgeoning literature on the antecedents and consequences of EM, which has primarily been conceptual. Third, by considering the mediating function of EM in the BDAC-DI relationship, we contribute to the scholarly discourse focused on understanding the mechanisms of BDAC value creation. Based on our understanding, this is the pioneering study that examines the BDAC value-creation processes from an EM perspective.

The remaining article is structured as follows: Section 2 presents the literature review and theoretical framework, Section 3 explains the methodology, Section 4 presents the results, Section 5 discusses the findings and implications, and Section 6 offers the conclusion.

2. LITERATURE REVIEW AND THEORETICAL BACKGROUND

2.1 Resource-based theory of the firm

Prior studies have employed various theoretical frameworks to understand how BDAC leads to superior value creation, with the RBT and its extension, the DCV, being the most prominent (Ciampi et al., 2021; Dean et al., 2023). We use RBT and its extension DCV as the theoretical foundations for several reasons: (1) their widespread applicability in information systems (BDAC) and marketing research (Akter et al., 2016; Kozlenkova et al., 2014); (2) their emphasis on firm-internal factors to explain differential outcomes (Suoniemi et al., 2020) ; and (3) their conceptual mapping of how information and marketing-related resources can be leveraged to develop value-creating strategies (Kozlenkova et al., 2014). According to RBT, a firm's competitive edge arises from owning valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). However, researchers claim that merely possessing such resources does not guarantee competitive advantage (Priem & Butler, 2001). While RBT highlights the essential characteristics of resources for competitive advantage, it fails to explain the management of these resources in response to external changes (Eisenhardt & Martin, 2000). This limitation led to the development of DCV, which asserts that certain capabilities are necessary to manage and deploy resources effectively (Ali et al., 2024). Capabilities are described as unique resources, routines, and knowledge that allow firms to modify resources and implement value-generating strategies (Kozlenkova et al., 2014). While knowledge is recognized as the most influential strategic resource, the capability to manage and deploy it effectively is thought as a key driver of competitive advantage (Grant, 1996). In the modern business landscape, acquiring knowledge has evolved into managing extensive datasets, or big data (Johnson et al., 2017). Thus, BDAC, reflecting a firm proficiency in gathering, storing, and analyzing extensive datasets, has emerged as a key knowledge-based resource and capability (Olabode et al., 2022), positioning itself as key source of innovation-driven competitiveness (Mikalef et al., 2019b).

While early research shows that BDAC directly influences firm innovation (Mikalef et al., 2020), the latest studies and industry reports indicate that many firms fail to effectively leverage BDAC for superior value (Bean & Davenport, 2019; Huynh et al., 2023). Scholars argue that while BDAC provides insights, these insights do not lead to value creation unless they are applied to develop an effective strategy (Gnizy, 2019; Mazzei & Noble, 2017). Researchers argue that DCV, particularly its widely acknowledged "resource-strategy-performance" framework, offers comprehension of the mechanisms through which BDAC can be effectively leveraged to realize superior outcomes (Gnizy, 2019). Recent studies explore how insights from BDAC can inform a firm's strategic orientation, which leads to superior value creation and innovation outcomes (Ciampi et al., 2021; Gnizy, 2019; Mazzei & Noble, 2017). For example, Gnizy, (2019), drawing on RBT, shown how BDAC shapes strategic orientations (market and entrepreneurial orientations), leading to improved performance. Relatedly, Ciampi et al. (2021), building on DCV, have exhibited how BDAC shapes the firm's entrepreneurial orientation, which consequently leads to business model innovation. Although some researchers have emphasized the influence of digital information in shaping EM (Fink et al., 2020) and the efficacy of EM for nurturing breakthrough innovation such as DI (Zhou et al., 2005), much of this literature remains conceptual or case-based, lacking empirical support. Thus, we use RBT and DCV to explore the relationships between BDAC, EM, and DI.

2.1.1 Big data analytics capability

The notion of BDAC has been widely discussed across different management domains, including strategic management, information systems, innovation, and marketing. To date, researchers have defined and operationalized BDAC's concept in different ways, resulting in a lack of agreement on a universally accepted definition or operationalization. Building upon DCV, Mikalef et al. (2019b) defined BDAC as a firm's ability to utilize talent and technology to gather, manage, and analyze data to extract valuable insights. Others claim that BDAC relates to the firm's technological infrastructure, management, and human resources capabilities to analyze data for insights (Yasmin et al., 2020). However, a central theme among them is that BDAC reflects a firm's capability to gather, manage, and analyze extensive datasets for insights. Building on RBT and DCV, a significant stream of literature also defines and operationalizes BDAC based on its 3Vs dimensions: volume capability, variety capability, and velocity capability (Dean et al., 2023; Olabode et al., 2022).

Dean et al. (2023) define volume capability as a firm's proficiency in analyzing large datasets to generate insights. Advances in cloud computing and big data tools like Hadoop and NoSQL databases have enabled firms to store and analyze large-scale consumer and market data to extract new insights (Johnson et al., 2017). Analyzing this data lets firms explore new market opportunities (Erevelles et al., 2016). Variety capability reflects a firm's ability to manage and analyze data from diverse sources (Ghasemaghaei & Calic, 2020). Today, various digital platforms like social media, shopping, and live-streaming websites generate consumer data in different forms such as text, audios, and videos (Olabode et al., 2022). The availability of advanced analytical tools (e.g., Apache Spark and Tableau) has allowed firms to manage this diverse data, identify new correlations, and visualize complex patterns (Ghasemaghaei & Calic, 2019). However, this big data is generated instantly and a has shorter lifecycle (Mikalef et al., 2019b). Velocity capability is the firm's ability to speedily analyze this voluminous and diverse data in real-time (Dean et al., 2023). This capability allows the quick transformation of raw data into knowledge, and knowledge into actionable strategies (Olabode et al., 2022). Thus, a strong velocity capabilities facilitate firms quickly commit decisions and adjust to market fluctuations (Hajli et al., 2020). While most scholars agree on these three core dimensions, some have proposed additional factors such as veracity, value, viability, and visualization (Ghasemaghaei & Calic, 2019; 2020). Nonetheless, the three core dimensions—volume, variety, and velocity—are considered sufficient for operationalizing the BDAC construct (Ghasemaghaei et al., 2018; Olabode et al., 2022). Thus, we consider this three-dimensional framework and define BDAC as a firm's ability to acquire, manage, and analyze vast, varied, and rapidly generated data to extract valuable insights.

2.1.2 Entrepreneurial marketing

In today's dynamic business environment, shaped by technological advances and shifting consumer behavior, traditional marketing approaches have become obsolete (Eggers et al., 2020; Morgan & Anokhin, 2020). EM, which merges entrepreneurship and marketing, has emerged as a strategic approach to thrive in such an environment (Alqahtani & Uslay, 2020). First conceptualized in the 1980s, EM has since become widely discussed across management literature (Eggers et al., 2020). The literature presents four perspectives on EM: exploring commonalities between entrepreneurship and marketing, addressing entrepreneurial challenges from a marketing viewpoint, examining marketing challenges through an entrepreneurial lens, and integrating both fields for unique insights (Sadiku-Dushi et al., 2019). Among these different perspectives, a common theme is that EM operates at the intersection of entrepreneurship and marketing (Bachmann et al., 2021). EM was initially perceived as a cost-effective strategy for small firms. However, recent literature has also established its effectiveness for larger firms (Alqahtani & Uslay, 2020). In their foundational work, Morris et al. (2002, p. 5) defined EM as "the proactive identification and exploitation of opportunities for acquiring and retaining profitable customers through innovative approaches to risk management, resource leveraging, and value creation." Building on this work, EM encompasses seven key components, with four—innovativeness, proactiveness, risk-taking, and opportunity-focus—stemming exclusively from entrepreneurship. Two components, customer-intensity and value creation, originate solely from marketing, while resource-leveraging overlaps both domains (Bachmann et al., 2021).

Innovativeness mirrors a firm's readiness to embrace novel ideas, foster creativity, and experiment (Morgan & Anokhin, 2020). Innovation-oriented firms challenge the status quo, promoting unconventional thinking to turn new opportunities into innovative solutions (Sadiku-Dushi et al., 2019). Proactiveness entails taking preemptive action to anticipate future problems, needs, and changes (Eggers et al., 2020). Proactive firms shape their environments rather than react passively, gaining first-mover advantage by pioneering new products, services, and markets (Bachmann et al., 2021).

Risk-taking mirrors a firm’s willingness to undertake uncertain ventures with potentially high failure costs (Ciampi et al., 2021). Risk-taking firms accept higher risks for potentially greater profits, provided these risks are well-managed (Bachmann et al., 2021). Opportunity-focused behavior involves scanning the environment to uncover untapped market opportunities and unmet customer needs (Sadiku-Dushi et al., 2019). Such firms explore new avenues for continuous profitability, beyond exploiting existing opportunities (Alqahtani & Uslay, 2020). However, regardless of their size, firms face resource scarcity when pursuing innovative, risky marketing opportunities (Eggers et al., 2020). They must be proficient in resource-leveraging, using limited internal and external resources in a manner to attain above-average results with below-average investments (Eggers et al., 2020).

Customer focus, or customer orientation, involves engaging with customers to understand their existing and future needs (Bachmann et al., 2021). It is characterized by a responsive approach that prioritizes addressing current market needs but also differs from a market-pull approach by adopting a market-driven perspective, considering future market needs as well (Zhou et al., 2005). Customer focus is considered a critical component of the EM concept, assisting in the successful implementation of highly innovative and risky moves by firms (Eggers et al., 2020). Researchers argue that firms adopting EM strategically gain advantages from the synergies between entrepreneurial and marketing traits. These synergies make EM a disruptive strategy, enabling firms to pursue risky, breakthrough innovations that can disrupt markets and significantly impact consumer behavior (Eggers et al., 2020; Zhou et al., 2005).

2.1.3 Disruptive innovation

DI has recently attracted considerable focus and importance (Antonio & Kanbach, 2023), stemming from Christensen’s influential concept of disruptive technology in *The Innovator’s Dilemma* (Christensen, 1997). This concept, built upon Schumpeter’s theory of “creative destruction,” recognizes the continuous cycle of obsolescence and innovation. However, recognizing that technology alone does not drive disruption, the term “disruptive technology” was replaced with DI, encompassing disruptive product, process, and business model innovations. DI refers to a novel product featuring distinct performance characteristics, initially appealing to untapped or new markets that are not the primary focus of the business (Zhang & Zhu, 2021). It disrupts the market by initially targeting new or non-mainstream customers by offering less expensive and more convenient alternatives to established products (Kraus et al., 2023). Since it initially underperforms in the attributes that mainstream customers value, it is often rejected by them, at least initially (Govindarajan et al., 2011). Such a product may not essentially contain groundbreaking technologies, like radical innovation, but appeals to both price-sensitive mainstream and new-market customers through key features like simplicity, convenience, and cost-effectiveness (Zhang & Zhu, 2021). However, through gradual improvements and technological advancements, it reaches a point where it starts attracting mainstream customers (Antonio & Kanbach, 2023). In essence, DI initially faces resistance from mainstream customers, capturing only a small portion of the existing market. However, with time, it finds acceptance among mainstream customers who initially dismissed it (Zhang & Zhu, 2021). Consequently, DI leads to the creation of new markets and functionalities, ultimately resulting in the disruption of established markets (Kraus et al., 2023).

2.2 Hypotheses

2.2.1 Big data analytics capability and disruptive innovation

Market data has consistently been acknowledged to be a pivotal driver of innovation (Johnson et al., 2017). Recent advancements in information technology and digitalization have transformed traditional data acquisition into comprehensive big data management (Erevelles et al., 2016). This evolution requires businesses to develop BDAC to effectively acquire, store, and analyze voluminous, varied, and swiftly generated data to extract insights (Olabode et al., 2022). Many studies report BDAC's positive role in fostering innovation (Al-Omoush et al., 2024; Dean et al., 2023), with some notting its power to disrupt markets through DI (Hopp et al., 2018; Olabode et al., 2022; Wessel, 2016).

Firms with high-volume capabilities can store and analyze large datasets (Dean et al., 2023). Advances in cloud computing and tools like Hadoop and NoSQL databases have enabled firms to extract valuable insights from these datasets (Calic & Ghasemaghaei, 2021). Scholars argue that immersion in this data helps firms better understand current and future customer needs (Erevelles et al., 2016), detect hidden patterns, identify market gaps (Olabode et al., 2022), and discover novel opportunities (Cappa et al., 2021). However, high volume alone is insufficient and can lead to 'infobesity' and counterproductive outcomes (Cappa et al., 2021). Firms must also possess high variety and velocity capabilities for informed, timely decision-making (Urbinati et al., 2019). These combined capabilities allow firms to deliver superior value (Olabode et al., 2022). Data now flows from different sources like social media and shopping websites, offering insights into purchase history, demographics, and intentions. These platforms, where customers, businesses, and stakeholders share ideas and feedback, are crucial sources of novel ideas and innovation (Erevelles et al., 2016). Firms with high variety capability to manage and analyze this data diversity gain profound insights into customer problems and future preferences (Olabode et al., 2022). Adeptness in both data volume and variety allows firms to triangulate findings from multiple sources and make confident decisions backed by sufficient data (Ghasemaghaei & Calic, 2019). This proficiency empowers them to overcome market challenges, minimize costs, and associated risks, enabling them to venture beyond existing markets and unlock new solutions to meet customers' future needs (Johnson et al., 2017). Given that data is rapidly generated and has a short lifespan, firms also need velocity capability to extract timely insights (Erevelles et al., 2016). Without it, firms risk lagging behind competitors in detecting market opportunities (Dean et al., 2023). High velocity capability enables firms to quickly detect and respond early to market signals (Erevelles et al., 2016), reducing time gaps and fostering agility, which is critical for developing DIs and achieving a first-mover advantage (Ganguly et al., 2024; Tseng et al., 2022).

Thus, these three capabilities at the core of BDAC (Olabode et al., 2022) improve firms' clarity, accuracy, and timeliness in sensing and seizing opportunities (Zeng & Glaister, 2018). Empirical research confirms the positive influence of BDAC on innovation. Recent literature also highlights BDAC's role in recognizing new concepts and opportunities leading to DI (Urbinati et al., 2019; Wessel, 2016). BDAC equips firms to detect opportunities in real-time and allocate resources to convert them into innovation (Al-Omoush et al., 2024). It enables them to disrupt markets, value propositions, and competition by promoting customer-led and customer-driven innovation (Ciampi et al., 2021). Researchers claim BDAC emerges as a novel source of DI (Wessel 2016) and that insights extracted through BDAC equip firms with the ability to create new products offering lower costs, increased consumer convenience, and significant product changes (Johnson et al., 2017). Such products not only have the power to create new functionalities and markets, disrupting established products and markets, but also result in a profound shift in consumer behaviors (Olabode et al., 2022; Wessel, 2016). Thus, we hypothesize that

H1 BDAC positively influences DI.

2.2.2 Big data analytics capability and entrepreneurial marketing

The role of BDAC in shaping firm strategy has recently gained recognition in scholarly literature (Talaoui et al., 2023). While previous research often implied that strategy dictates data use, in the current data-driven environment, the analysis of big data is increasingly influencing firms' strategies (Gnizy, 2019; Mazzei & Noble, 2017). This shift has been particularly evident within the marketing discipline, where BDAC is transforming firms' strategic approaches (Erevelles et al., 2016). Researchers suggest that BDAC allows firms to approach markets through a novel perspective, fostering entrepreneurial and proactive marketing behaviors (Ciampi et al., 2021). Scholars also emphasize the crucial role of digital market information in shaping EM (Fink et al., 2020; Polas & Raju, 2021; Schulte & Eggers, 2010). However, the role of BDAC in shaping EM remains underexplored, despite calls for further research (Alqahtani & Uslay, 2022). We posit that the effective utilization of BDAC can fosters an EM behavior within firms based on the following considerations.

Scholars posit that BDAC provides insights that enhance firms' analytical capabilities, market knowledge, and knowledge-sharing, leading to the adoption of entrepreneurial and market-oriented strategies (Akter et al., 2021; Gnizy, 2019, 2020). In their study of the long-term impact of EM on purchase intentions, Fink et al. (2020) suggest that extensive data reach, frequent engagement, and rapid communication through social media platforms promote firm EM behavior. Likewise, Schulte and Eggers (2010) discovered that large-scale market data on customers, competitors, and trends foster an entrepreneurial mindset, facilitating EM strategies. Ghasemaghaei and Calic (2019) argue that BDAC fosters firms' inclination towards predicting future events and reacting to new opportunities, e.g., mindset nurtured through BDAC promotes proactivity, risk-taking, innovativeness (Ciampi et al., 2021) and opportunity-seeking behaviors, enabling firms to seek groundbreaking entrepreneurial marketing strategies (Zeng & Khan, 2019). Further, real-time interactions on digital platforms such as social media and e-commerce, which generate diverse data, break traditional barriers, fostering value creation by connecting firms, customers, and partners (Urbinati et al., 2019; Xie et al., 2016). By integrating these actors, these platforms support a synergistic value-creation process that surpasses what firms can achieve alone (Pera et al., 2016). BDAC through these engagements thus becomes a critical source of value creation (Urbinati et al., 2019). Gnizy (2019) argues that analyzing the interaction data generated from these data reservoirs broadens a customer focus to create value that addresses the customers' existing and future needs. Meanwhile, it is argued that BDAC, by leveraging internal and external resources, alleviates resource burdens and promotes resource leveraging (Xie et al., 2016). Scholars argued that resources and capabilities shared by firms, customers, and other stakeholders in the big data environment, such as social media and e-commerce platforms, let firms achieve more with fewer resources, overcoming resource shortages and minimizing costs in value creation processes (Al-Omoush et al., 2024; Xie et al., 2016).

To combine, we claim that BDAC lets firms look at the market through an entrepreneurial lens, identifying and exploiting market opportunities through innovative and proactive approaches to risk management, resource utilization, and value creation. Hence, we propose that

H2 BDAC positively influences EM.

2.2.3 Entrepreneurial marketing and disruptive innovation

The theoretical underpinnings of both EM and DI originate from Schumpeterian theory, specifically the concept of "creative destruction," which views innovation as a continuous cycle of replacing the old with the new (Antonio & Kanbach, 2023; Sadiku-Dushi et al., 2019). DI disrupts market equilibrium by introducing new markets and functionalities, displacing established products, and disrupting industries (Kraus et al., 2023). It involves unconventional value propositions, carrying inherent uncertainty and risk (Zhang & Zhu, 2021), and requires a significant shift in customers' behavior and perceptions of the innovation as a superior alternative (Govindarajan et al., 2011). DI requires firms to embrace an entrepreneurial and market-driving approach (Schindehutte et al., 2008; Zhang & Zhu, 2021). Scholars argue that EM allows for that (Eggers et al., 2020).

Rooted in Schumpeter's entrepreneurial philosophy, EM embodies a relentless drive to disrupt market equilibrium (Sadiku-Dushi et al., 2019). It enables firms to proactively identify and seize new opportunities, creating value and driving transformative change in consumer behavior (Eggers et al., 2020). Its entrepreneurial dimensions, such as innovativeness, proactiveness, and risk-taking, epitomize a mindset that fosters bold actions despite uncertain outcomes (Bachmann et al., 2021). These dimensions encourage firms to transform uncertain opportunities into innovative solutions (Ciampi et al., 2021). The opportunity-focused dimension allows firms to examine the external environment and identify unexploited markets (Alqahtani & Uslay, 2020). The combination of opportunity-seeking behavior and entrepreneurial traits enables firms to act on innovation opportunities before competitors (Yang & Gabrielsson, 2017). Thus, these components of EM help firms develop new products targeting unmet customer needs, crucial for handling DI (Kraus et al., 2023). However, firms often face resource constraints when pursuing bold innovations like DI (Eggers et al., 2020). The resource-leveraging aspect of EM optimizes limited resources through strategic management of internal and external resources, including those from partners, customers, and other stakeholders (Alqahtani & Uslay, 2020). By leveraging and sharing resources, firms alleviate constraints and mitigate risks in bold innovations (Srivastava & Gnyawali, 2011). Value creation dimension is also critical, facilitating a bilateral process where firms and customers co-create value (Morris et al., 2002). Customers perceive value when the product meets expectations relative to its price, while firms achieve value through customer acceptance (Alqahtani & Uslay, 2020). Since DIs target unexplored segments and require mainstream acceptance, involving customers in value creation is vital for market success (Zhou et al., 2005). This builds confidence in both firms and customers regarding the innovation's viability. However, Sadiku-Dushi et al. (2019) claim that successful value creation also requires firms to exhibit strong customer focus to understand their current problems and needs. While some argue that customer focus is limited to existing needs, others emphasize its role in anticipating future demands (Eggers et al., 2020). When synergized with an entrepreneurial mindset, a strong customer orientation becomes a market-driving approach, essential for innovations like DI (Govindarajan et al., 2011; Zhou et al., 2005). Thus, the strategic fusion of the entrepreneurial and marketing aspects of EM fosters disruptive behavior, enabling firms to develop DI and shape consumer behavior towards embracing these innovations (Eggers et al., 2020). Conclusively, we hypothesize that

H3 EM positively influences DI

2.2.4 Mediating role of entrepreneurial marketing

Scholars argue that while having BDAC is important, it may not alone be sufficient to enhance firm innovation outcomes (Mikalef et al., 2019b). Anecdotal evidence has been provided by the literature, as some studies report its direct influence on firm innovation (Mikalef et al., 2020), while others suggest that such a relationship occurs through the mediation of various strategic orientations like market and entrepreneurial orientation (Ciampi et al., 2021; Gnizy, 2019). Building on this, we argue that EM, as a potent strategic orientation, seems to be an ideal intervening channel through which BDAC influences DI. Scholars posit that BDAC, an unapparelled source of market intelligence, enables firms to redefine and transform their traditional marketing strategies (Mazzei & Noble, 2017) and to see markets through an entrepreneurial lens (Liu, 2014). Marketing and information systems scholars posit that insights gleaned through BDAC evoke a firm's propensity to revolutionize their marketing strategy and promote entrepreneurial and proactive marketing behavior (Erevelles et al., 2016; Gnizy, 2020). This, in turn, empowers firms to devise innovative solutions and create significant value that caters to emerging and future market needs (Gnizy, 2019; Zeng & Khan, 2019). Specifically, in the case of DIs that can overturn competition by creating new markets and functionalities, scholars assert that firms must abandon traditional processes and strategies and adopt more innovative and proactive marketing strategies that enable them to disrupt market circumstances (Zhang & Zhu, 2021; Zhou et al., 2005). Prior literature demonstrates that BDAC, which contains predictive insights about future markets, acts as a catalyst for developing a firm's strategic orientation intended for such market disruptions through innovation (Olabode et al., 2022). Importantly, scholars posit that adept management of extensive and diverse market information serves as a crucial input for developing EM strategies (Fink et al., 2020; Schulte & Eggers, 2010). Moreover, EM, as an important type of firm strategic orientation, allows firms to approach marketing issues with an entrepreneurial mindset, serving as an innovative and proactive marketing strategy that can disrupt market equilibrium through innovation (Sadiku-Dushi et al., 2019). Building on these insights and the earlier established positive role of BDAC in both EM and DI, we assume that EM operates as a mediator in the BDAC and DI relationship. So, we suppose that

H4 EM mediates the positive relationship between BDAC and DI.

3. METHODOLOGY

While BDAC has been posited as a key factor of innovation-driven competitiveness, the literature remains constrained by the question of whether and how BDAC leads to DI. Building on current literature, this study employs a deductive approach to examine two complementary questions: (1) Does BDAC foster DI? (2) If so, through what mechanisms does BDAC promote DI? To answer these, the study builds on RBT and its extension, DCT, to develop a novel framework for empirically examining BDAC's role in DI through the mediation of EM. Adopting a stepwise approach, the goal is to use statistical analysis to test four hypotheses: the role of BDAC in DI (H1) and EM (H2), the role of EM in DI (H3), and the mediating role of EM in the BDAC-DI relationship (H4).

3.1 Sample and data collection

For empirical analysis, manufacturing firms from Pakistan, an emerging economy, was selected for several key reasons. First, emerging economies are recognized as hotbeds for DI due to their unique socio-economic conditions, where people, because of comparatively lower purchasing power, tend to favor cost-effective alternatives over premium products such as DI (Zhang & Zhu, 2021). Second, manufacturing firms in these economies, particularly in Pakistan, face a dynamic business environment marked by rapid shifts in customer preferences, technological disruptions, and fierce competition from both local and international counterparts (Ali et al., 2024). Studies show that these firms are increasingly adopting data analytics, entrepreneurial approaches, and relying on innovations (Bhatti et al., 2024; Khan et al., 2022). Yet, empirical research on this study's objectives is limited, making Pakistan's manufacturing industry a compelling setting.

Table 1- Sample Characteristics (N = 216). Source: own research

	Frequency	Percent	Cumulative Percent
Industrial Sector			
Automobile	24	11.1	11.1
Garments/Apparels/Leather processing/Footwear	29	13.4	24.5
Engineering Manufacturing	22	10.2	34.7
FMCG/Food/Retail	42	19.4	54.2
Pharmaceuticals	32	14.8	69.0
Textile	32	14.8	83.8
Telecom/IT	35	16.2	100.0
Firm Size			
1-100	16	7.4	7.4
101-300	44	20.4	27.8
301-500	64	29.6	57.4
501-1000	83	38.4	95.8
> 1000	09	4.2	100.0
Firm Age			
6-10	39	18.1	18.1
11-15	45	20.8	38.9
16-20	55	25.5	64.4
21-25	44	20.4	84.7
> 25	33	15.3	100.0
Respondent Department			
Marketing/Sales	74	34.26	34.26
Manufacturing/Operations	33	15.28	49.54
Research and Development (R&D)	46	21.30	70.84
Information Technology (IT)	57	26.39	97.23
Other	06	2.77	100.0
Respondent Gender			
Male	135	62.5	62.5

Female	81	37.5	100.0

Given the lack of comprehensive databases, difficulty in obtaining managerial responses, and the unavailability of innovation-related secondary data, a non-random convenience sampling technique was employed. Although non-random sampling limits equal participation, it is effective in emerging economies like Pakistan for gathering informed responses (Ali et al., 2023). A survey team consisting of a professor, two research assistants, and one industry expert was formed to compile a list of manufacturing firms from major industrial zones, ensuring representativeness. Firms' data and contacts were retrieved from company websites, personal contacts, and chambers of commerce of different industrial zones.

Data collection took place over three months, from 01/2024 to 03/2024. Only one senior manager per firm, holding a strategic position and well-informed about the research subject, was selected as a participant. To maximize responses, the survey was administered both online (via Google Forms and WhatsApp) and offline (through personal contacts). In the first phase, 792 questionnaires were distributed, followed by a reminder six weeks later. In total, 225 responses were collected (response rate = 27.27%). After removing invalid responses, 216 valid responses were analyzed, with a gender distribution of 135 male and 81 female participants from key functional areas like marketing/sales, manufacturing/operations, R&D, and IT. Like other studies (Ali et al., 2024; Khan et al., 2022), our sample exhibited a good representation of Pakistan's manufacturing industry, including firms of different sizes and ages, covering all key sectors, such as automobile (11.1%), garments (13.4%), FMCG (19.4%), pharmaceuticals (14.8%), textile (14.8%), and telecom/IT (16.2%). The characteristics of the analyzed firms are detailed in Table 1.

3.2 Survey instrument

A closed-end survey questionnaire, complemented by a cover letter explaining the research aim and key concepts with examples, was utilized for data gathering. The questionnaire was comprised of two parts. Part one encompassed a participant's information (gender, department) and firm characteristics (industry sector, age, size). No personal information was requested to ensure unbiased responses. Part two measured key concepts such as BDAC, EM, DI, and control variables like R&D expenditure, technological turbulence, and market turbulence. A seven-point scale (1 = strongly disagree, 7 = strongly agree) was utilized to record responses. We employed widely validated instruments to assure their reliability and validity. The detail of survey items and their coding are given in Table 2. Following Olabode et al. (2022), BDAC was defined as a second-order construct having three formative dimensions: volume capability, variety capability, and velocity capability. Twelve items (four per dimension) were adapted from Johnson et al. (2017). EM was assessed with a total of 35 items representing seven dimensions. Specifically, items for proactiveness (five items), innovativeness (five items), and risking (four items) were sourced from Eggers et al. (2013). Customer focus (7 items) were adopted from Narver et al. (2004) with two items (CSF3 and CFS6) dropped due to weak loading (below 0.5). Resource leveraging (4 items) were derived from Eggers et al. (2020). Opportunity focus and value creation scales (5 items each) were sourced from Sadiku-Dushi et al. (2019) with one item (OPF5) dropped due to weak loading (below 0.5). After removing weak items, 32 items remained. DI was evaluated using five items from Govindarajan et al. (2011) and Zhang and Zhu (2021). Control variables involved firm-level factors (size, age, R&D expenditure) and external factors (market and technological turbulence), known to influence EM and DI (Bachmann et al., 2021; Govindarajan et al., 2011). Firm age and size were quantified using natural logs, while R&D expenditure was evaluated with three items derived from Kim et al. (2013). Technological turbulence and market turbulence were evaluated with four items each derived from Jaworski and Kohli (1993) and Guo et al. (2018), respectively.

Table 2 - Measurement scales description

Construct/Item code	Item description
Big data analytics capability	
1. Volume capability	
VOC1	"In my firm, we analyze large amounts of data about our customers."
VOC2	"The quantity of data we explore about our customers is substantial."
VOC3	"We use a great deal of customer data."
VOC4	"We scrutinize copious volumes of customer data."
2. Variety capability	
VAC1	"We use several different sources of customer data to gain customer insights."
VAC2	"In my firm, we analyze many types of customer data."
VAC3	"We have many customer databases from which we can run data."
VAC4	"We examine customer data from a multitude of sources."
3. Velocity capability	
VEC1	"We analyze customer data as soon as we receive it."
VEC2	"The time period between when my firm gets customer data and when they analyze it is short."
VEC3	"My firm is lightning fast in exploring our customer data."
VEC4	"My firm analyzes customer data speedily."
Entrepreneurial marketing	
1. Proactiveness	
PRO1	"We continuously try to discover additional needs of our customers of which they are unaware."
PRO2	"We consistently look for new business opportunities."
PRO3	"Our marketing efforts try to lead customers, rather than respond to them."
PRO4	"We incorporate solutions to unarticulated customer needs in our products and services."
PRO5	"We work to find new businesses or markets to target."
2. Innovativeness	
INN1	"We highly value new product lines"
INN2	"When it comes to problem solving, we value creative new solutions more than solutions that rely on conventional wisdom"
INN3	"We consider ourselves to be an innovative company."
INN4	"Our business is often the first to market with new products and services."
INN5	"Competitors in this market recognize us as leaders in innovation."

3. Risk taking	
RSK1	"We value new strategies/plans even if we are not certain that they will work."
RSK2	"To make effective changes to our offering, we are willing to accept at least a moderate level of risk of significant losses."
RSK3	"We encourage people in our company to take risks with new ideas."
RSK4	"We engage in risky investments (e.g., new employees, facilities, debt, stock options) to stimulate future growth."
4. Opportunity focus	
OPF1	"We look beyond current customers and markets for more opportunities for our firm."
OPF2	"We are good at recognizing and pursuing opportunities for our firm."
OPF3	"Our firm is characterized as opportunity-driven."
OPF4	"Our firm is always looking for new opportunities."
OPF5	"Our firm will do whatever it takes to pursue a new opportunity."
5. Resource leveraging	
RSL1	"In our business, we use connections to friends, business partners, etc. to get cost-efficient access to information and advice."
RSL2	"In our business, we explore options to operate in cost-efficient ways."
RSL3	"We work with other firms to refer business in order to save on marketing costs."
RSL4	"We use connections to other firms to increase our offerings in cost-efficient ways."
6. Customer focus	
CSF1	"We constantly monitor our level of commitment and orientation to serving customer needs."
CSF2	"We freely communicate information about our successful and unsuccessful customer experiences across all business functions."
CSF3	"Our strategy for competitive advantage is based on our understanding of customers' needs."
CSF4	"We measure customer satisfaction systematically and frequently."
CSF5	"We are more customer focused than our competitors."
CSF6	"We believe this business exists primarily to serve customers."
CSF7	"Data on customer satisfaction are disseminated at all levels in this business unit on a regular basis."
7. Value creation	
VAC1	"We make sure that our firm creates value for consumers with excellent customer service."

VAC2	"We make sure that our firm does an excellent job of creating value for customers."
VAC3	"We make sure that our firm's pricing structure is designed to reflect value created for customers."
VAC4	"We, as managers, ensure that our employees understand how they contribute to value for customers."
VAC5	"Providing value for our customers is the most important thing our firm does."
Disruptive innovation	
DI1	"Our firm frequently introduces products that are disruptive in nature."
DI2	"Our firm lead in introducing disruptive product innovations."
DI3	"Our new products are very attractive to a different customer segment at the time of product introduction."
DI4	"Our new products are those where the mainstream customers found the innovations attractive over time as they were able to satisfy the requirements of the mainstream market."
DI5	"The introduction of our new products helps us open up a new market."
R & D expenditure	
RD1	"Compared with major competitors in the industry, our company engages in R&D expenditures very well."
RD2	"Compared with major competitors in the industry, our company emphasizes R&D activities very well."
RD3	"Compared with other activities, our company engage in R&D expenditures very well."
Market turbulence	
MT1	"It is difficult to predict market and customer preference changes."
MT2	"In our business, customers' product preferences change quite a bit overtime."
MT3	"Constant changes in consumer demands bring hidden opportunities for our company business development."
MT4	"It is very difficult to forecast where customer demand in our industry will be in 5 years."
Technological turbulence	
TT1	"The technology in our industry is changing rapidly."
TT2	"It is very difficult to forecast where the technology in our industry will be in the next five years."
TT3	"Technological changes provide big opportunities in our industry."
TT4	"A large number of new product ideas have been made possible through technological breakthroughs in our industry."

3.3 Data analysis Procedure

Partial least squares-based structural equation modeling (PLS-SEM) was employed to analyze the research model of this study, as it contains both reflective and reflective-formative type higher-order constructs (Sarstedt et al., 2019). Because of its capability to analyze both reflective and formative constructs, PLS-SEM supersedes other techniques such as CB-SEM (Hair et al., 2017). Furthermore, PLS-SEM is suitable for complex models, examining direct and indirect relationships (Guenther et al., 2023). We used WarpPLS 8.0 for the analysis.

As per Hair et al. (2017), PLS-SEM evaluates research models in two steps. In step one, confirmatory factor analysis (CFA) is implemented to examine the measurement model. In step two, PLS-SEM-based path analysis is deployed for structural model evaluation and hypothesis testing. As our study involved first-order reflective and second-order reflective-formative constructs, we used a two-stage approach for CFA (Sarstedt et al., 2019). In stage one, the first-order reflective constructs are assessed by examining factor loadings (> 0.7), construct reliability (composite reliability and Cronbach's alpha > 0.7), and construct convergent validity (average variance extracted, AVE > 0.5). The constructs discriminant validity is evaluated through the Fornell-Larcker criterion (square root of the AVE greater than its correlation with other constructs) and the heterotrait-monotrait (HTMT) ratios (≤ 0.85).

In stage two, higher-order formative constructs are evaluated using latent variable scores from stage one (Ali et al., 2024). Reflective construct evaluation criteria cannot be used for formative constructs due to their distinct nature, where each formative construct is explained by individual formative indicators (Sarstedt et al., 2019). As per Sarstedt et al. (2019) and Ali et al. (2024), formative constructs are validated by examining the significance of outer weights ($p < 0.5$), multicollinearity among formative indicators using variance inflation factors (VIF < 3.3), and discriminant validity of all constructs (formative and reflective) through full-collinearity statistics (FVIF < 3.3).

In step two, the structural model is assessed using PLS-SEM path analysis with bootstrapping. Researchers first evaluate the structural model fitness via R-square (> 0.20) and Q-square (> 0), reflecting the model's explanatory and predictive power, respectively. Then, the structural paths (hypotheses) are tested at a 95% confidence level ($p < 0.05$).

4. RESULTS

4.1 Response bias and common method bias

Since we gathered data from individual respondents at one time, we analyzed the collected responses for the potential of response bias and common method bias (CMB) before CFA. Response bias was evaluated by comparing the means of the main constructs using early and late responses, and by examining differences across gender, business sectors, and firm size (large > 250 vs. small-medium ≤ 250). No significant differences were found ($p > 0.05$), suggesting no response bias concerns in our data. For CMB, Harman's single-factor test was performed, revealing that only 22.10% of the total variance was explained by a single common factor. Furthermore, we employed more conservative measures, such as full collinearity variance inflation factors (FVIFs) and the nonlinear bivariate causality direction ratio (NLBCDR), as recommended by Kock (2015) and Rasoolimanesh et al. (2015), to evaluate CMB. The calculated average FVIFs for all first-order constructs remained comfortably below the 3.3 limit (see Table 2), and the NLBCDR value was 0.970, surpassing the 0.7 threshold. This analysis confirms that CMB is not a critical matter in our data.

4.2 Measurement model evaluation

As this research involved a combination of single-order reflective and second-order reflective formative type constructs, we applied the widely used two-stage approach for analyzing the measurement model (Sarstedt et al., 2019). In the first stage, we evaluated single-order reflective constructs and the first-order reflective dimensions of second-order constructs by analyzing items loadings, constructs reliability, convergent validity, and discriminant validity (Sarstedt et al., 2019).

4.2.1 Reliability and validity of first-order constructs

The reliability and validity results of our first-order constructs are shown in Table 3. First, as per Hair et al. (2017), item loadings ≥ 0.7 confirm its valid representation of the respective construct. Our results show that all items have loading values ≥ 0.7, indicating good item-level reliability. Only two items of the customer-focus construct (CUF3 and CUF6) and one item of the opportunity-focus construct (OPF 5) showed loadings below the more lenient threshold (≥ 0.5). Therefore, given the reflective nature of both constructs, these three items were excluded from further analysis (Hair et al., 2017). Second, the reliability of all constructs is confirmed, as every construct shows composite reliability (CR) and Cronbach's alpha (α) values above the minimum value of 0.7 These values indicate that all the items of a given construct are internally consistent and measuring the same concept (Sarstedt et al., 2019). Third, the AVE (average variance extracted) value of each construct is ≥ 0.50. This shows that more than 50% of the variance in the construct is explained by its items, thus establishing convergent validity (Hair et al., 2017).

Table 3-Measurement statistics of first-order constructs (first stage) Source: own research

Construct/Item code	Loading	Composite reliability (CR)	Cronbach's Alpha (α)	Average variance extracted (AVE)	Full collinearity (FVIFs)
Volume capability		0.922	0.888	0.748	1.648
VOC1	0.862				
VOC2	0.875				
VOC3	0.842				
VOC4	0.879				
Variety capability		0.894	0.842	0.677	1.661
VAC1	0.812				
VAC2	0.795				
VAC3	0.842				
VAC4	0.843				
Velocity capability		0.925	0.891	0.754	1.840
VEC1	0.889				
VEC2	0.879				
VEC3	0.853				
VEC4	0.851				
Proactiveness		0.910	0.877	0.670	1.536
PRO1	0.787				

PRO2	0.816				
PRO3	0.833				
PRO4	0.830				
PRO5	0.825				
Innovativeness		0.908	0.873	0.663	1.666
INN1	0.823				
INN2	0.842				
INN3	0.797				
INN4	0.829				
INN5	0.780				
Risk taking		0.894	0.844	0.679	1.412
RSK1	0.815				
RSK2	0.831				
RSK3	0.839				
RSK4	0.812				
Opportunity focus		0.926	0.894	0.759	1.672
OPF1	0.900				
OPF2	0.849				
OPF3	0.864				
OPF4	0.870				
Resource leveraging		0.921	0.886	0.744	1.326
RSL1	0.831				
RSL2	0.869				
RSL3	0.888				
RSL4	0.861				
Customer focus		0.910	0.876	0.669	1.265
CSF1	0.845				
CSF2	0.812				
CSF4	0.814				
CSF5	0.836				
CSF7	0.781				
Value creation		0.909	0.875	0.665	1.355
VAC1	0.851				
VAC2	0.801				
VAC3	0.782				
VAC4	0.829				
VAC5	0.814				
Disruptive innovation		0.921	0.893	0.701	1.677
DI1	0.834				
DI2	0.852				
DI3	0.866				
DI4	0.846				
DI5	0.787				
R & D expenditure		0.867	0.779	0.685	1.112
RD1	0.835				
RD2	0.870				
RD3	0.775				
Market turbulence		0.865	0.792	0.615	1.222

MT1	0.791				
MT2	0.745				
MT3	0.768				
MT4	0.831				
Technological turbulence		0.908	0.878	0.713	1.247
TT1	0.830				
TT2	0.793				
TT3	0.938				
TT4	0.810				

4.2.2 Discriminant validity of the first-order constructs

According to Sarstedt et al., (2019), all constructs must exhibit sufficient discriminant validity. Following the recommendations of Hair et al. (2017), we evaluated the discriminant validity of our constructs using the Fornell-Larcker criterion and HTMT ratios. As presented in Table 4, the square root of the AVE for each construct exceeds its correlation with other constructs, confirming discriminant validity as per the Fornell-Larcker criterion. The HTMT values of all the constructs are also below the limit of 0.85. These results confirm the discriminant validity of the constructs.

Table 4 - First-order correlations and discriminant validity (first-stage) Source: own research

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Volume capability	**.87**	.49	.63	.40	.27	.36	.27	.35	.29	.30	.38	.06	.10	.05
2. Variety capability	.43	**.82**	.58	.41	.35	.37	.47	.30	.33	.30	.40	.12	.17	.18
3. Velocity capability	.56	.50	**.87**	.47	.31	.35	.35	.35	.30	.21	.39	.08	.07	.06
4. Proactiveness	.36	.35	.42	**.82**	.37	.34	.24	.36	.36	.34	.45	.21	.13	.05
5. Innovativeness	.24	.31	.28	.33	**.81**	.48	.56	.22	.23	.40	.49	.27	.09	.08
6. Risk taking	.32	.32	.32	.30	.41	**.82**	.44	.26	.26	.28	.44	.16	.07	.10
7. Opportunity focus	.25	.41	.31	.21	.50	.38	**.87**	.25	.27	.39	.44	.15	.13	.10
8. Resource leveraging	.31	.26	.32	.32	.19	.23	.22	**.86**	.33	.33	.39	.06	.15	.06
9. Customer focus	.26	.29	.27	.32	.20	.23	.24	.29	**.82**	.24	.38	.16	.14	.07
10. Value creation	.27	.26	.18	.30	.35	.24	.35	.29	.20	**.82**	.42	.12	.06	.07
11. Disruptive innovation	.34	.35	.35	.40	.43	.39	.40	.35	.33	.38	**.84**	.19	.07	.12
12. R & D expenditure	.01	.10	.04	.18	.23	.14	.12	.05	.13	.08	.17	**.83**	.12	.19

13. Market turbulence	.00	.11	.00	.11	-.06	-.01	.10	.13	.12	.02	.06	.04	**.78**	.40
14. Technological turbulence	.03	.17	.00	.02	-.01	-.03	-.05	.04	.02	-.02	.13	.12	.31	**.85**

Notes: Values in bold on the diagonal are the square root of the AVE; Values above the diagonal are the HTMT ratios (best if < 0.85); Values below the diagonal are the correlations among constructs.

4.2.3 Reliability and validity of second-order constructs

During the second stage, we utilized factor scores from the first stage to evaluate second-order formative constructs. Specifically, the reliability and validity of seven formative dimensions of EM and three formative dimensions of BDAC were evaluated. We analyzed their respective indicators weight significance ($p < 0.05$) and multicollinearity (VIF < 3.3) as well as the discriminant validity (FVIF < 3.3) among all the reflective and formative constructs (Ali et al., 2024). Table 5 shows the results. All the formative factors of EM and BDAC have statistically significant outer weights ($p < 0.05$), establishing that they significantly explain their respective constructs. The VIF values for these formative indicators are below the threshold of 3.3. This shows that all the formative indicators are distinctively explaining their given constructs. Moreover, the FIVIF values for all the reflective and formative constructs are below the limit of 3.3, confirming all of the constructs' discriminant validity and allowing us to analyze the structural model.

Table 5 - Measurement statistics of second-order constructs (second stage) Source: own research

Construct	Construct type	Weight	P-value	Multi-collinearity (VIF)	Full collinearity (FVIF)
Big data analytics capability	Formative				1.620
Item 1: Volume capability		0.335	<0.001	1.513	
Item 2: Variety capability		0.506	<0.001	1.396	
Item 3: Velocity capability		0.385	<0.001	1.658	
Entrepreneurial marketing	Formative				2.186
Item 1: Proactiveness		0.353	<0.001	1.323	
Item 2: Innovativeness		0.151	0.012	1.543	
Item 3: Risk taking		0.242	<0.001	1.332	
Item 4: Opportunity focus		0.280	<0.001	1.480	
Item 5: Resource leveraging		0.225	<0.001	1.226	
Item 6: Customer focus		0.189	0.002	1.202	
Item 7: Value creation		0.140	0.018	1.284	
Disruptive innovation	Reflective				1.656
R & D expenditure	Reflective				1.071
Market turbulence	Reflective				1.049
Technological turbulence	Reflective				1.074
Firm age	---				1.198
Firm size	---				1.190

Note: VIF < 3.0 are required for retaining a formative indicator

4.3 Structural model evaluation

4.3.1 Model quality and fitness

To evaluate the quality and fitness of our structural model, we first examined its explanatory and predictive capabilities using R^2 and Q^2 values, respectively. We found that the R^2 values for EM and DI are 0.430 and 0.366, suggesting that our structural model has substantial explanatory power. The Q^2 values for EM and DI were found to be 0.438 and 0.420, respectively, demonstrating the strong predictive capacity of our structural model. Furthermore, we also examined six key statistical metrics produced by WarpPLS. In particular, we evaluated our structural model by assessing its average R-squared (ARS), average adjusted R-squared (AARS), average path coefficient (APC), Tenenhaus GoF (GoF), average block VIF (AVIF), and average full collinearity VIF (AFVIF) statistics (Ali et al., 2024; Kock, 2017). As is shown, we found all these statistical metrics acceptable for our structural model:

ARS = 0.374, $P < 0.001$
AARS = 0.354, $P < 0.001$
APC = 0.152, $P < 0.001$
GoF = 0.520, small ≥ 0.1, medium ≥ 0.25, large ≥ 0.36
AVIF = 1.136, acceptable if ≤ 5, ideally ≤ 3.3
AFVIF = 1.406, acceptable if ≤ 5, ideally ≤ 3.3

These structural model quality and fitness metrics confirm the eligibility of our structural model for hypotheses testing.

4.3.2 Hypotheses results

We used the bootstrapping method with 999 samples for hypotheses testing (Kock, 2017; Rasoolimanesh et al., 2015). For each hypothesized relationship, the path coefficient (β) was examined at a 95% confidence level ($P < 0.05$). The results of the direct relationships are shown in Table 6 and Fig. 1.

In H1, we stated that BDAC positively influences DI. The results show that the path coefficient of the relationship between BDAC and DI is β = 0.375, which is statistically significant at a 99% confidence level ($P < 0.001$). The R-square value shows that BDAC explains 26% of the variance in DI. Therefore, H1 is supported. In H2, we proposed that BDAC positively influences EM. The results reveal that the path coefficient between BDAC and EM is β = 0.514, which is statistically significant at a 99% confidence level ($P < 0.001$). The R-square value shows that BDAC explains 43% of the variance in EM. Thus, H2 is supported. Moreover, in H3, we hypothesized that EM positively influences DI. The findings show that the path coefficient between EM and DI is β = 0.555, which is statistically significant at a 99% confidence level ($P < 0.001$). The R-square value reveals that EM explains 36.6% of the variance in DI. Thus, H3 is also supported.

Table 6 - Direct relationship results Source: own research

Structural Paths	β	SE	P-value	R-Square	Remarks
Path (C) BDAC → DI	0.375	0.064	<0.001	0.260	H1 supported
path a: BDAC → EM	0.514	0.072	<0.001	0.430	H2 supported
path b: EM → DI	0.555	0.054	<0.001	0.366	H3 supported

Next, in H4, we stated that EM mediates the relationship between BDAC and DI. In the mediation model, we examined both the direct effect (c') and the indirect effect (path a × b) of BDAC on DI. The mediation results are shown in Table 7 and Fig. 1. In the mediated model, the indirect effect (BDAC → EM → DI) path coefficient is β = 0.285, which is statistically significant at a 99% confidence level ($P < 0.001$). Meanwhile, the direct effect path coefficient (c') between BDAC and DI is β = 0.082, which is not statistically significant ($P = 0.105$). This confirms that EM fully mediates the relationship between BDAC and DI. Therefore, H4 is also supported.

Table 7 - Mediation results Source: own research

Direct effect (path c'): BDAC → DI	0.082	0.065	0.105		
Indirect effect (path a x b): BDAC → EM → DI	0.285	0.049	<0.001		H4 supported
Total effect [path c' + (path a x b)]	0.367	0.058	<0.001		

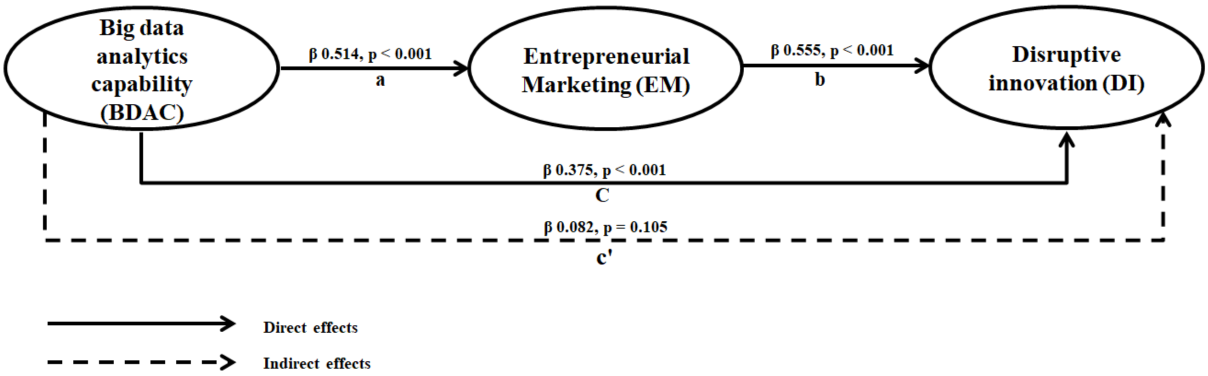

Fig. 1 - Structural model Source: own research

5. DISCUSSION

BDAC has garnered widespread recognition as a valuable resource and capability within the contemporary business landscape, capable of disrupting established sources and creating new avenues for competition by stimulating DIs (Johnson et al., 2017; Wessel, 2016). However, due to limited theoretical understanding and empirical evidence on this thriving topic, the potential value of BDAC on firm performance drivers is still to be fully comprehended (Mikalef et al., 2019a). Therefore, it is urgent to comprehend the fundamental mediating mechanisms through which the potential of BDAC can be realized, particularly in terms of enhancing performance outcomes, especially innovation outcomes (Johnson et al., 2017; Mikalef et al., 2019b). Our study addressed this gap. Building on the RBT, particularly its resource-strategy-performance framework, this study examined how and to what extent BDAC enhances DI. By collecting data from 216 manufacturing firms in Pakistan, our results reveal that BDAC has a significantly positive influence on DI. These results provide support for prior conceptual claims that, in today's digitalized world, BDAC serves as a new source of DI (Wessel, 2016). Firms that are equipped with robust BDAC can disrupt existing markets and industries through the development of cost-effective, convenient, and advantageous innovations (Johnson et al., 2017). Our results further show that BDAC plays an important role in shaping the firm's EM strategy. Our findings endorse the increasingly prevalent debate that, in today's data-driven business environment, BDAC transcends its traditional role as a subordinate element of a firm's strategy; instead, it assumes a primary role (Gnizy, 2019; Mazzei & Noble, 2017). This finding marks a shift from the traditional view that a chosen strategy determines the type of data to be analyzed. Our results support the notion that, in the current business environment, it is the data itself that shapes and informs the firm's strategy. While previous research has illustrated how BDAC separately influences strategic orientations such as market and entrepreneurial orientation (Ciampi et al., 2021; Gnizy, 2019), our study extends this by highlighting that insights derived through BDAC play a key role in promoting synergies between the entrepreneurial and marketing aspects of a firm's strategy, thereby influencing EM. Additionally, we find that EM positively influences DI. These results offer empirical support for prior conceptual claims that emphasized the interface of entrepreneurship and marketing for the successful development and commercialization of DI (e.g., Eggers et al., 2020; Hills et al., 2010). Lastly, our results show that EM fully mediates the relationship between BDAC and DI. Our mediation results support previous studies that built on the resource-strategy-performance framework and argue that BDAC is indeed essential; however, its benefit could be better realized in terms of superior innovative outcomes through organizational strategies informed by the insights gleaned through BDAC (Ciampi et al., 2021; Gnizy, 2019; Mazzei & Noble, 2017). By demonstrating that EM acts as a key mediator, our study offers new evidence on how BDAC's value-creation potential can be effectively harnessed from an EM perspective.

5.1 Theoretical contributions

Our study makes noteworthy contributions to the literature on BDAC, EM, and DI by demonstrating how various concepts from the fields of big data and marketing can be interlinked and leveraged to stimulate DI.

First, we contribute to the literature on the drivers of DI by examining how firms can foster it through the utilization of BDAC. DI has been widely discussed in the scholarly literature; however, the literature remains mainly conceptual, lacking empirical investigation of its antecedents (Antonio & Kanbach, 2023; Christensen et al., 2018). Some conceptual works highlight the importance of digitalization and the use of abundant, highly diverse, and real-time data for DI (Bstieler et al., 2018; Wessel, 2016). However, the literature did not explicitly and empirically examine the role of BDAC in DI. Thus, our study is the first, to the best of our knowledge, to empirically examine the role of BDAC in fostering DI, advancing the current literature on DI from a firm capabilities perspective. Further, emerging economies are thought to be hotbeds of DI due to their evolving business environment and consumers' preferences for cheaper, more convenient, and more advantageous products (Wan et al., 2015). However, most of the previous literature on BDAC and DI has focused on developed economies. This study offers valuable theoretical insights, highlighting how firms in these economies, like Pakistan, can utilize BDAC to drive DI.

Second, our study makes an important contribution to the field of marketing by examining the role of BDAC in EM strategies within firms. Previous research in EM has been predominantly limited to case studies and theoretical frameworks, leaving a substantial gap in understanding the factors that affect it (Alqahtani & Uslay, 2020; Yang & Gabrielsson, 2017). Some studies have acknowledged the role of market information, including data from social media, in shaping EM behaviors (Fink et al., 2020; Schulte & Eggers, 2010), but the impact of BDAC, which serves as a vast source of market intelligence, has been largely overlooked. Our study addresses this gap by finding a positive relationship between BDAC and EM, thus enriching the literature on the determinants of EM.

Third, this study adds to the literature on the outcomes of EM by delving into its influence on DI. We built upon of conceptualization by Morris et al. (2002) and the recommendation of Zhou et al. (2005) to examine how EM influences DI, a topic that has received scant attention. Although previous research has associated EM with Schumpeter's theory of creative destruction, underscoring its potential to disrupt market equilibrium by promoting innovative approaches (Hills et al., 2010; Sadiku-Dushi et al., 2019), its precise effects on DI have remained uncharted. To our understanding, our study is the first to directly probe into this relationship, addressing the calls from researchers to study the relationship between EM and relevant outcome variables.

Fourth, this research adds to the emerging streams of literature that call for exploring the mechanisms through which the innovative potential of BDAC can be realized within firms (Calic & Ghasemaghaei, 2021; Johnson et al., 2017; Mikalef et al., 2019a). Anecdotal evidence was provided in previous literature on the direct role of BDAC in enhancing firm performance drivers such as innovation, leading to a lack of research on the mechanisms through which it can be translated into innovative outcomes (Ghasemaghaei & Calic, 2019; 2020). By establishing the mediation role of EM, this study contributes by offering new insights that the full potential of BDAC for DI can be realized when a firm pursues an EM strategy.

5.2 Practical implications

Our study underscores significant implications for firms engaged in data-driven innovation amidst a dynamic business environment, particularly in emerging economies. The findings highlight the imperative of viewing BDAC as an unparalleled source of market intelligence for achieving exceptional innovation, notably DI. To achieve this, firms need to invest in developing robust systems and capabilities to timely collect, process, and analyze both structured and unstructured market data in real-time. Contrary to past concerns about big data causing information overload and stifling innovation, our study recommends that firms should not solely rely on big data storage capabilities like Hadoop. To attain market leadership through innovation, they must concurrently possess the capabilities and technologies (e.g., Storm and SQLstream) to rapidly collect, analyze, and derive insights from diverse big data in real-time. This enables managers to extend knowledge beyond familiar domains, discern evolving market dynamics cost-effectively, surpassing traditional market research methods. Insights gleaned from such a real-time analysis can help them develop a more nuanced and multidimensional view of the existing and future market, spot existing loopholes and new patterns, and identify and take advantage of new market opportunities for DI.

Meanwhile, our mediation results suggest that it is critical for such firms to adopt an EM strategy to convert insights gleaned through BDAC into significant outputs such as DI. It suggests that firms need to shift their focus from traditional inside-out and myopic marketing strategies, which are considered hindrances, to sense and seize highly uncertain and vague market opportunities for DI. Remaining stuck to traditional marketing market orientation strategies in the current highly dynamic data-driven business environment can lead them to the tyranny of the served market, confining their abilities to sense and seize vague, riskier, and forthcoming market opportunities. Recent literature suggests that the source of market disruption indeed originates from big data. However, despite increased investments in BDAC, a limited number of firms have successfully translated these investments into tangible market advantages. Our mediation results posit that firms, to optimize the potential of BDAC for DI, have to institute an EM strategic posture. DI, theoretically linked to Schumpeter's theory of creative destruction, requires firms to abandon their traditional innovative strategies. The theoretical trace of EM is also argued to be rooted in the Schumpeterian theory of creative destruction, emphasizing looking at the market through an entrepreneurial prism. Thus, our study underscores that it is imperative for firms to not only invest in BDAC but also institute

EM as a strategic posture to fully realize it greater benefits, like DI. It proposes that insights derived through BDAC enable firms to be entrepreneurial and customer value-oriented, making them able to see the market through an entrepreneurial prism for sensing and seizing market opportunities for DI.

6. CONCLUSION

BDAC has been widely acknowledged as a critical driver of innovation-driven competitiveness, and the latest literature positions it as a key source of disruptive innovation. However, the literature lacked an empirical investigation of how and through which mechanisms BDAC influences DI. Building on the tenets of RBT and DCV, this study developed a novel framework that examined both the direct role of BDAC in DI and its mediation through EM. The theoretical model was empirically validated using survey data of 216 Pakistani manufacturers. Results confirmed that BDAC positively influences both DI and EM, and EM positively influences DI. Furthermore, EM fully mediates the relationship between BDAC and DI. These results offer new theoretical insights into BDAC's value-creation potential from an EM perspective and provide practical takeaways for firms seeking to leverage BDAC for high-impact innovations, such as DI, to disrupt existing markets. Despite these significant implications, the study has some limitations that offer avenues for further research. Firstly, the generalizability of the results is constrained to the manufacturing sector in Pakistan, an emerging economy, potentially limiting its applicability to firms in diverse countries and economies. Therefore, future investigations should validate the proposed theoretical relationships in developed economies and other nations. Secondly, the reliance on data from a single source at a single point in time introduces the likelihood of common method bias and response bias. Subsequent research could address this limitation by employing mixed-method and longitudinal approaches for a better understanding. Thirdly, while we operationalized BDAC as a higher-order concept comprised of three lower-order capabilities (i.e., volume capability, variety capability, and velocity capability), which is not uncommon (Olabode et al., 2022), future studies may explore other operationalizations of BDAC as proposed by Akter et al. (2016). Lastly, while the effectiveness of EM has been acknowledged across various firm types and sizes (Eggers et al., 2020), it is often perceived as more relevant for small-sized enterprises (Bachmann et al., 2021). Future studies could extend our model by conducting comparative research across different industries and firm sizes to gain deeper insights into the conditions that enhance or diminish its effectiveness in capturing superior value from BDAC.

References

1. Akter, S., Hossain, M. A., Lu, Q. (Steven), & Shams, S. M. R. (2021). Big data-driven strategic orientation in international marketing. *International Marketing Review*, *38*(5), 927–947. https://doi.org/10.1108/IMR-11-2020-0256/FULL/PDF
2. Akter, S., et al. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, *182*, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018
3. Al-Omoush, K. S., Garcia-Monleon, F., & Mas Iglesias, J. M. (2024). Exploring the interaction between big data analytics, frugal innovation, and competitive agility: The mediating role of organizational learning. *Technological Forecasting and Social Change*, *200*, 123188. https://doi.org/10.1016/j.techfore.2023.123188

4. Ali, S., et al. (2024). Marketing capabilities, market ambidexterity and product innovation outcomes: A yin-yang of inside-out and outside-in. *Industrial Marketing Management*, *118*, 27–43. https://doi.org/10.1016/J.INDMARMAN.2024.02.003
5. Ali, S., Wu, W., & Ali, S. (2023). Managing the product innovations paradox: The individual and synergistic role of the firm inside-out and outside-in marketing capability. *European Journal of Innovation Management*, *26*(2), 504–530. https://doi.org/10.1108/EJIM-05-2021-0234
6. Alqahtani, N., & Uslay, C. (2020). Entrepreneurial marketing and firm performance: Synthesis and conceptual development. *Journal of Business Research*, *113*, 62–71. https://doi.org/10.1016/J.JBUSRES.2018.12.035
7. Alqahtani, N., & Uslay, C. (2022). Marketing/entrepreneurship interface research priorities (2023–2026). *Journal of Research in Marketing and Entrepreneurship*, *24*(2), 405–419. https://doi.org/10.1108/JRME-11-2021-0151
8. Antonio, J. L., & Kanbach, D. K. (2023). Contextual factors of disruptive innovation: A systematic review and framework. *Technological Forecasting and Social Change*, *188*, 122274. https://doi.org/10.1016/j.techfore.2022.122274
9. Bachmann, J. T., Ohlies, I., & Flatten, T. (2021). Effects of entrepreneurial marketing on new ventures' exploitative and exploratory innovation: The moderating role of competitive intensity and firm size. *Industrial Marketing Management*, *92*, 87–100. https://doi.org/10.1016/j.indmarman.2020.10.002
10. Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108
11. Bean, R., & Davenport, T. (2019). *Companies are failing in their efforts to become data-driven*. *Harvard Business Review*. https://hbr.org/2019/02/companies-are-failing-in-their-efforts-to-become-data-driven
12. Bhatti, S. H., et al. (2024). Exploring data-driven innovation: What's missing in the relationship between big data analytics capabilities and supply chain innovation? *Annals of Operations Research*, *333*(2–3), 799–824. https://doi.org/10.1007/s10479-022-04772-7
13. Bstieler, L., et al. (2018). Emerging research themes in innovation and new product development: Insights from the 2017 PDMA-UNH doctoral consortium. *Journal of Product Innovation Management*, *35*(3), 300–307. https://doi.org/10.1111/JPIM.12447
14. Calic, G., & Ghasemaghaei, M. (2021). Big data for social benefits: Innovation as a mediator of the relationship between big data and corporate social performance. *Journal of Business Research*, *131*, 391–401. https://doi.org/10.1016/j.jbusres.2020.11.003
15. Cappa, F., Oriani, R., Peruffo, E., & McCarthy, I. (2021). Big data for creating and capturing value in the digitalized environment: Unpacking the effects of volume, variety, and veracity on firm performance*. *Journal of Product Innovation Management*, *38*(1), 49–67. https://doi.org/10.1111/JPIM.12545
16. Christensen, C. M. (1997). *The innovator's dilemma: When new technologies cause great firms to fail*. Harvard Business School Press.
17. Christensen, C. M., McDonald, R., Altman, E. J., & Palmer, J. E. (2018). Disruptive innovation: An intellectual history and directions for future research. *Journal of Management Studies*, *55*(7), 1043–1078. https://doi.org/10.1111/joms.12349
18. Ciampi, F., et al. (2021). Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation. *Journal of Business Research*, *123*, 1–13. https://doi.org/10.1016/j.jbusres.2020.09.023
19. Dean, T., Zhang, H., & Xiao, Y. (2023). Use big data to leverage customer need diversity

for radical innovation. *Journal of Marketing Management*, *39*(15–16), 1620–1644. https://doi.org/10.1080/0267257X.2023.2273277

20. Eggers, F., et al. (2013). Implications of customer and entrepreneurial orientations for SME growth. *Management Decision*, *51*(3), 524–546. https://doi.org/10.1108/00251741311309643
21. Eggers, F., Niemand, T., Kraus, S., & Breier, M. (2020). Developing a scale for entrepreneurial marketing: Revealing its inner frame and prediction of performance. *Journal of Business Research*, *113*, 72–82. https://doi.org/10.1016/J.JBUSRES.2018.11.051
22. Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, *21*(10–11), 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11<1105::AID-SMJ133>3.0.CO;2-E
23. Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big data consumer analytics and the transformation of marketing. *Journal of Business Research*, *69*(2), 897–904. https://doi.org/10.1016/J.JBUSRES.2015.07.001
24. Fink, M., et al. (2020). Effective entrepreneurial marketing on Facebook – A longitudinal study. *Journal of Business Research*, *113*, 149–157. https://doi.org/10.1016/j.jbusres.2018.10.005
25. Flynn, J. (2023). *How many people use the Internet? [2023]: 35 facts about Internet usage in America and the World*. Zippia: The Career Expert. https://www.zippia.com/advice/how-many-people-use-the-internet/
26. Ganguly, A., Talukdar, A., & Kumar, C. (2024). Absorptive capacity and disruptive innovation: The mediating role of organizational agility. *IEEE Transactions on Engineering Management*, *71*. https://doi.org/10.1109/TEM.2022.3205922
27. Ghasemaghaei, M., & Calic, G. (2019). Does big data enhance firm innovation competency? The mediating role of data-driven insights. *Journal of Business Research*, *104*, 69–84. https://doi.org/10.1016/j.jbusres.2019.07.006
28. Ghasemaghaei, M., & Calic, G. (2020). Assessing the impact of big data on firm innovation performance: Big data is not always better data. *Journal of Business Research*, *108*, 147–162. https://doi.org/10.1016/j.jbusres.2019.09.062
29. Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *Journal of Strategic Information Systems*, *27*(1), 101–113. https://doi.org/10.1016/J.JSIS.2017.10.001
30. Gnizy, I. (2019). Big data and its strategic path to value in international firms. *International Marketing Review*, *36*(3), 318–341. https://doi.org/10.1108/IMR-09-2018-0249/FULL/XML
31. Gnizy, I. (2020). Applying big data to guide firms' future industrial marketing strategies. *Journal of Business and Industrial Marketing*, *35*(7), 1221–1235. https://doi.org/10.1108/JBIM-06-2019-0318/FULL/XML
32. Govindarajan, V., Kopalle, P. K., & Danneels, E. (2011). The effects of mainstream and emerging customer orientations on radical and disruptive innovations. *Journal of Product Innovation Management*, *28*(s1), 121–132. https://doi.org/10.1111/J.1540-5885.2011.00865.X
33. Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, *17*(S2), 109–122. https://doi.org/10.1002/smj.4250171110
34. Guenther, P., et al. (2023). Improving PLS-SEM use for business marketing research. *Industrial Marketing Management*, *111*, 127–142.

https://doi.org/10.1016/j.indmarman.2023.03.010
35. Guo, H., et al. (2018). Comparing the impact of different marketing capabilities: Empirical evidence from B2B firms in China. *Journal of Business Research*, *93*, 79–89. https://doi.org/10.1016/J.JBUSRES.2018.04.010
36. Gupta, S., et al. (2020). Achieving superior organizational performance via big data predictive analytics: A dynamic capability view. *Industrial Marketing Management*, *90*, 581–592. https://doi.org/10.1016/j.indmarman.2019.11.009
37. Guttentag, D. (2013). Airbnb: Disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism*, *18*(12), 1192–1217. https://doi.org/10.1080/13683500.2013.827159
38. Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107. https://doi.org/10.1504/ijmda.2017.087624
39. Hajli, N., Tajvidi, M., Gbadamosi, A., & Nadeem, W. (2020). Understanding market agility for new product success with big data analytics. *Industrial Marketing Management*, *86*, 135–143. https://doi.org/10.1016/j.indmarman.2019.09.010
40. Hills, G. E., Hultman, C. M., Kraus, S., & Schulte, R. (2010). History, theory and evidence of entrepreneurial marketing - An overview. *International Journal of Entrepreneurship and Innovation Management*, *11*(1), 3–18. https://doi.org/10.1504/IJEIM.2010.029765
41. Hopp, C., Antons, D., Kaminski, J., & Oliver Salge, T. (2018). Disruptive innovation: Conceptual foundations, empirical evidence, and research opportunities in the digital age. *Journal of Product Innovation Management*, *35*(3), 446–457. https://doi.org/10.1111/jpim.12448
42. Huynh, M. T., Nippa, M., & Aichner, T. (2023). Big data analytics capabilities: Patchwork or progress? A systematic review of the status quo and implications for future research. *Technological Forecasting and Social Change*, *197*, 122884. https://doi.org/10.1016/J.TECHFORE.2023.122884
43. Jaworski, B. J., & Kohli, A. K. (1993). Market orientation: Antecedents and consequences. *Journal of Marketing*, *57–70*(3), 53–70. https://doi.org/10.2307/1251854
44. Johnson, J. S., Friend, S. B., & Lee, H. S. (2017). Big data facilitation, utilization, and monetization: Exploring the 3Vs in a new product development process. *Journal of Product Innovation Management*, *34*(5), 640–658. https://doi.org/10.1111/JPIM.12397
45. Kashinath, G., Beesetty, Y., & Onkar, S. (2023). *Big data and business analytics market statistics | 2033*. Allied Market Research. https://www.alliedmarketresearch.com/big-data-and-business-analytics-market
46. Khan, H., Mavondo, F., & Zahoor, N. (2022). Integration of outside-in and inside-out entrepreneurial marketing capabilities, marketing agility and resources for entrepreneurial firm performance. *International Journal of Entrepreneurial Behaviour and Research*. https://doi.org/10.1108/IJEBR-02-2022-0193
47. Kim, N., Im, S., & Slater, S. F. (2013). Impact of knowledge type and strategic orientation on new product creativity and advantage in high-technology firms. *Journal of Product Innovation Management*, *30*(1), 136–153. https://doi.org/10.1111/J.1540-5885.2012.00992.X
48. Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration*, *11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101
49. Kock, N. (2017). WarpPLS user manual: Version 6.0. *ScriptWarp Systems*, *141*, 47–60.

https://scriptwarp.com/warppls/UserManual_v_8_0.pdf
50. Kozlenkova, I. V., Samaha, S. A., & Palmatier, R. W. (2014). Resource-based theory in marketing. *Journal of the Academy of Marketing Science*, *42*(1), 1–21. https://doi.org/10.1007/s11747-013-0336-7
51. Kraus, S., et al. (2023). Digital entrepreneurship: The role of entrepreneurial orientation and digitalization for disruptive innovation. *Technological Forecasting and Social Change*, *193*, 122638. https://doi.org/10.1016/j.techfore.2023.122638
52. Liu, Y. (2014). Big Data and Predictive Business Analytics. *Journal of Business Forecasting*, *33*(4), 40–42.
53. Loebbecke, C., & Picot, A. (2015). Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. *Journal of Strategic Information Systems*, *24*(3), 149–157. https://doi.org/10.1016/J.JSIS.2015.08.002
54. Manyika, J., et al. (2011). Big data: The next frontier for innovation, competition, and productivity. *McKinsey Global Institute*, *156*. https://catalog.lib.kyushu-u.ac.jp/ja/recordID/3144682/
55. Mazzei, M. J., & Noble, D. (2017). Big data dreams: A framework for corporate strategy. *Business Horizons*, *60*(3), 405–414. https://doi.org/10.1016/J.BUSHOR.2017.01.010
56. Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019a). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research*, *98*, 261–276. https://doi.org/10.1016/j.jbusres.2019.01.044
57. Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019b). Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management*, *30*(2), 272–298. https://doi.org/10.1111/1467-8551.12343
58. Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2020). The role of information governance in big data analytics driven innovation. *Information and Management*, *57*(7), 103361. https://doi.org/10.1016/j.im.2020.103361
59. Morgan, T., & Anokhin, S. A. (2020). The joint impact of entrepreneurial orientation and market orientation in new product development: Studying firm and environmental contingencies. *Journal of Business Research*, *113*, 129–138. https://doi.org/10.1016/J.JBUSRES.2019.06.019
60. Morris, M. H., Schindehutte, M., & LaForge, R. W. (2002). Entrepreneurial marketing: A construct for integrating emerging entrepreneurship and marketing perspectives. *Journal of Marketing Theory and Practice*, *10*(4), 1–19. https://doi.org/10.1080/10696679.2002.11501922
61. Narver, J. C., Slater, S. F., & MacLachlan, D. L. (2004). Responsive and proactive market orientation and new-product success. *Journal of Product Innovation Management*, *21*(5), 334–347. https://doi.org/10.1111/j.0737-6782.2004.00086.x
62. Olabode, O. E., Boso, N., Hultman, M., & Leonidou, C. N. (2022). Big data analytics capability and market performance: The roles of disruptive business models and competitive intensity. *Journal of Business Research*, *139*, 1218–1230. https://doi.org/10.1016/j.jbusres.2021.10.042
63. Pera, R., Occhiocupo, N., & Clarke, J. (2016). Motives and resources for value co-creation in a multi-stakeholder ecosystem: A managerial perspective. *Journal of Business Research*, *69*(10), 4033–4041. https://doi.org/10.1016/j.jbusres.2016.03.047
64. Polas, M. R. H., & Raju, V. (2021). Technology and entrepreneurial marketing decisions

during COVID-19. *Global Journal of Flexible Systems Management*, *22*(2), 95–112. https://doi.org/10.1007/S40171-021-00262-0
65. Priem, R. L., & Butler, J. E. (2001). Is the resource-based "view" a useful perspective for strategic management research? *Academy of Management Review 26*(1), 22–40. https://doi.org/10.5465/AMR.2001.4011928
66. Rasoolimanesh, S. M., Jaafar, M., Kock, N., & Ramayah, T. (2015). A revised framework of social exchange theory to investigate the factors influencing residents' perceptions. *Tourism Management Perspectives*, *16*, 335–345. https://doi.org/10.1016/j.tmp.2015.10.001
67. Sadiku-Dushi, N., Dana, L. P., & Ramadani, V. (2019). Entrepreneurial marketing dimensions and SMEs performance. *Journal of Business Research*, *100*, 86–99. https://doi.org/10.1016/j.jbusres.2019.03.025
68. Sarstedt, M., et al. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal*, *27*(3), 197–211. https://doi.org/10.1016/j.ausmj.2019.05.003
69. Schindehutte, M., Morris, M. H., & Kocak, A. (2008). Understanding market-driving behavior: The role of entrepreneurship. *Journal of Small Business Management*, *46*(1), 4–26. https://doi.org/10.1111/J.1540-627X.2007.00228.X
70. Schulte, R., & Eggers, F. (2010). Entrepreneurial marketing and the role of information - Evidence from young service ventures. *International Journal of Entrepreneurship and Innovation Management*, *11*(1), 56–74. https://doi.org/10.1504/IJEIM.2010.029768
71. Srivastava, M. K., & Gnyawali, D. R. (2011). When do relational resources matter? Leveraging portfolio technological resources for breakthrough innovation. *Academy of Management Journal*, *54*(4), 797–810. https://doi.org/10.5465/AMJ.2011.64870140
72. Suoniemi, S., et al. (2020). Big data and firm performance: The roles of market-directed capabilities and business strategy. *Information & Management*, *57*(7), 103365. https://doi.org/10.1016/J.IM.2020.103365
73. Talaoui, Y., Kohtamäki, M., Ranta, M., & Paroutis, S. (2023). Recovering the divide: A review of the big data analytics-strategy relationship. *Long Range Planning*, *56*(2). https://doi.org/10.1016/j.lrp.2022.102290
74. Tseng, H. T., Aghaali, N., & Hajli, D. N. (2022). Customer agility and big data analytics in new product context. *Technological Forecasting and Social Change*, *180*, 121690. https://doi.org/10.1016/j.techfore.2022.121690
75. Urbinati, A., Bogers, M., Chiesa, V., & Frattini, F. (2019). Creating and capturing value from big data: A multiple-case study analysis of provider companies. *Technovation*, *84–85*, 21–36. https://doi.org/10.1016/j.technovation.2018.07.004
76. Wan, F., Williamson, P. J., & Yin, E. (2015). Antecedents and implications of disruptive innovation: Evidence from China. *Technovation*, *39–40*(1), 94–104. https://doi.org/10.1016/j.technovation.2014.05.012
77. Wessel, M. (2016). *How big data is changing disruptive innovation*. Harvard Business *Review*. https://hbr.org/2016/01/how-big-data-is-changing-disruptive-innovation
78. Willis, G., & Tranos, E. (2021). Using 'big data' to understand the impacts of Uber on taxis in New York City. *Travel Behaviour and Society*, *22*, 94–107. https://doi.org/10.1016/j.tbs.2020.08.003
79. Xie, K., Wu, Y., Xiao, J., & Hu, Q. (2016). Value co-creation between firms and customers: The role of big data-based cooperative assets. *Information and Management*, *53*(8), 1034–1048. https://doi.org/10.1016/j.im.2016.06.003

80. Yang, M., & Gabrielsson, P. (2017). Entrepreneurial marketing of international high-tech business-to-business new ventures: A decision-making process perspective. *Industrial Marketing Management*, *64*, 147–160. https://doi.org/10.1016/j.indmarman.2017.01.007
81. Yasmin, M., et al. (2020). Big data analytics capabilities and firm performance: An integrated MCDM approach. *Journal of Business Research*, *114*. https://doi.org/10.1016/j.jbusres.2020.03.028
82. Zeng, J., & Glaister, K. W. (2018). Value creation from big data: Looking inside the black box. *Strategic Organization*, *16*(2), 105–140. https://doi.org/10.1177/1476127017697510
83. Zeng, J., & Khan, Z. (2019). Value creation through big data in emerging economies: The role of resource orchestration and entrepreneurial orientation. *Management Decision*, *57*(8), 1818–1838. https://doi.org/10.1108/MD-05-2018-0572/FULL/PDF
84. Zhang, F., & Zhu, L. (2021). Social media strategic capability, organizational unlearning, and disruptive innovation of SMEs: The moderating roles of TMT heterogeneity and environmental dynamism. *Journal of Business Research*, *133*, 183–193. https://doi.org/10.1016/j.jbusres.2021.04.071
85. Zhou, K. Z., Yim, C. K. (Bennett), & Tse, D. K. (2005). The effects of strategic orientations on technology- and market-based breakthrough innovations. *Journal of Marketing*, *69*(2), 42–60. https://doi.org/10.1509/jmkg.69.2.42.60756

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