

Big Data Analytics Capability and Firm Performance: The Mediating Role of Marketing Agility

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ABSTRACT

As digital transformation accelerates, big data analytics has become an important strategic means for firms to enhance competitiveness and improve performance. However, existing research remains inconclusive regarding how big data analytics capability translates into firm performance, particularly from a marketing agility perspective. Drawing on the Resource-Based View and Dynamic Capability Theory, this study examines the relationship between big data analytics capability and firm performance, with a specific focus on the mediating role of marketing agility. Big data analytics capability is conceptualized as a higher-order capability comprising tangible resource capability, human resource capability, and intangible resource capability, while marketing agility is modeled through customer agility and decision agility. Using online survey data from 425 senior executives or employees aged 20 years and above who possessed knowledge of big data analytics or its applications and were familiar with marketing activities and structural equation modeling, the study finds that big data analytics capability has a significant positive effect on firm performance. The results further show that big data analytics capability positively affects both customer agility and decision agility, and that these two dimensions of marketing agility significantly mediate the relationship between big data analytics capability and firm performance. These findings extend the literature by clarifying the capability–agility–performance mechanism through which firms derive value from big data analytics. The study also contributes to marketing and dynamic capability research by showing that the performance value of analytics depends not only on data-related resources, but also on the firm’s ability to translate analytics-based insights into responsive marketing action and timely decision-making.

Keywords: Big Data Analytics Capability, Marketing Agility, Customer Agility, Decision Agility, Firm Performance

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บทคัดย่อ

6 เนื่องจากการเปลี่ยนแปลงทางดิจิทัลเกิดขึ้นอย่างรวดเร็ว การวิเคราะห์ข้อมูลขนาดใหญ่จึงกลายเป็นกลยุทธ์สำคัญสำหรับบริษัทต่าง ๆ ในการเพิ่มขีดความสามารถในการแข่งขันและปรับปรุงประสิทธิภาพ อย่างไรก็ตาม งานวิจัยที่มีอยู่ยังคงไม่สามารถสรุปได้ว่า ความสามารถในการวิเคราะห์ข้อมูลขนาดใหญ่ส่งผลต่อประสิทธิภาพของบริษัทอย่างไร โดยเฉพาะอย่างยิ่งจากมุมมองของการจัดการด้านการตลาด งานวิจัยนี้ใช้แนวคิดมุมมองตามทรัพยากร (Resource-Based View) และทฤษฎีความสามารถเชิงพลวัต (Dynamic Capability Theory) มาศึกษาความสัมพันธ์ระหว่างความสามารถในการวิเคราะห์ข้อมูลขนาดใหญ่และประสิทธิภาพของบริษัท โดยเน้นที่บทบาทตัวกลางของความคล่องตัวทางการตลาด ความสามารถในการวิเคราะห์ข้อมูลขนาดใหญ่ถูกกำหนดให้เป็นความสามารถระดับสูงที่ประกอบด้วยความสามารถด้านทรัพยากรที่จับต้องได้ ความสามารถด้านทรัพยากรมนุษย์ และความสามารถด้านทรัพยากรที่จับต้องไม่ได้ ในขณะที่ความคล่องตัวทางการตลาดถูกจำลองผ่านความคล่องตัวของลูกค้าและความคล่องตัวในการตัดสินใจ จากการใช้ข้อมูลจากการสำรวจออนไลน์จากผู้บริหารระดับสูงหรือพนักงานจำนวน 425 คน อายุ 20 ปีขึ้นไป ที่มีความรู้เกี่ยวกับการวิเคราะห์ข้อมูลขนาดใหญ่หรือการประยุกต์ใช้ และคุ้นเคยกับกิจกรรมทางการตลาดและการสร้างแบบจำลองสมการโครงสร้าง งานวิจัยพบว่า ความสามารถในการวิเคราะห์ข้อมูลขนาดใหญ่มีผลเชิงบวกอย่างมีนัยสำคัญต่อประสิทธิภาพของบริษัท ผลการวิจัยแสดงให้เห็นเพิ่มเติมว่า ความสามารถในการวิเคราะห์ข้อมูลขนาดใหญ่ส่งผลต่อทั้งความคล่องตัวของลูกค้าและความคล่องตัวในการตัดสินใจ และมีอิทธิพลของสองความคล่องตัวทางการตลาดนี้เป็นตัวกลางสำคัญในความสัมพันธ์ระหว่างความสามารถในการวิเคราะห์ข้อมูลขนาดใหญ่กับผลการดำเนินงานของบริษัท ข้อค้นพบนี้ช่วยขยายขอบเขตงานวิจัยที่มีอยู่โดยการชี้แจงกลไกความสามารถ ความคล่องตัว ผลการดำเนินงานที่บริษัทได้รับคุณค่าจากการวิเคราะห์ข้อมูลขนาดใหญ่ งานวิจัยนี้ยังช่วยสนับสนุนงานวิจัยด้านการตลาดและความสามารถเชิงพลวัตโดยแสดงให้เห็นว่า คุณค่าของผลการดำเนินงาน

จากการวิเคราะห์นั้นไม่ได้ขึ้นอยู่กับทรัพยากรที่เกี่ยวข้องกับข้อมูลเท่านั้น แต่ยังขึ้นอยู่กับความสามารถของบริษัทในการแปลงข้อมูลเชิงลึกจากการวิเคราะห์ ไปสู่การดำเนินการทางการตลาดที่ตอบสนองและตัดสินใจได้อย่างทัน่วงที่ด้วย

คำสำคัญ : ความสามารถในการวิเคราะห์ข้อมูลขนาดใหญ่ ความคล่องตัวทางการตลาด ความคล่องตัวของลูกค้า ความคล่องตัวในการตัดสินใจ ผลการดำเนินงานของบริษัท

INTRODUCTION

As digital transformation accelerates across industries, firms are increasingly relying on big data analytics to improve market responsiveness, optimize strategic decisions, and sustain competitive advantage. Over the past decade, big data has evolved from a technical issue of storage and processing into a strategic organizational resource with implications for marketing, innovation, and performance (McAfee & Brynjolfsson, 2012; Chen et al., 2012; Rialti et al., 2019). In particular, big data analytics capability (BDAC) has attracted growing scholarly attention because it enables firms to integrate data, technology, managerial knowledge, and organizational learning into actionable insights that support business value creation (Gupta & George, 2016; Akter et al., 2016; Mikalef et al., 2020). From a resource-based perspective, BDAC is increasingly recognized as a strategic capability that allows firms to deploy and reconfigure valuable resources in ways that improve efficiency, market intelligence, and organizational outcomes (Barney, 1991; Dubey et al., 2019). This logic is particularly relevant in marketing contexts, where firms must continuously sense customer needs, interpret market signals, and respond to competitive changes with speed and precision.

Despite this growing interest, the literature has not yet reached consensus on whether, and more importantly how, BDAC improves firm performance. A substantial stream of prior research reports positive effects of big data analytics on organizational outcomes such as profitability, market share, innovation, and decision quality (Wamba et al., 2017; Rialti et al., 2019; Yasmin et al., 2020; Morimura & Sakagawa, 2023). However, other studies suggest that investments in big data do not automatically translate into superior performance, because firms may lack the organizational conditions, complementary capabilities, or managerial mechanisms needed to convert analytics outputs into effective action (Ghasemaghaei et al., 2018; Ghasemaghaei & Calic, 2020; Mikalef et al., 2019). This tension indicates that the value of BDAC cannot be fully understood through a simple direct-effect logic. Instead, the performance implications of BDAC likely depend on the intervening organizational processes through which data-based insights are transformed into market-facing actions.

One important limitation of the existing literature is that most studies examine BDAC from a broad organizational or information systems perspective, while paying insufficient attention to the marketing function as a key site where analytics-driven value is created and realized. Although prior research has identified dynamic capabilities as an important explanatory mechanism linking analytics capability to performance (Mikalef & Pateli, 2017; Mikalef et al., 2020), these explanations are often conceptually broad and do not clearly specify the more fine-grained managerial processes through which BDAC shapes firm outcomes. In particular, the role of marketing agility remains underexplored. Marketing agility refers to a firm's ability to rapidly sense and respond to customer needs, competitor moves, and market changes through timely strategic and tactical adjustments (Kalaighnam et al., 2021; Zhou et al., 2019). Recent studies imply that agility may serve as a critical bridge between IT-related capabilities and performance (Roberts & Grover, 2012; Tseng et al., 2022; Wamba et al., 2022), yet

evidence on marketing agility in the specific context of big data analytics remains limited. Moreover, marketing agility itself is often treated as a unitary construct, leaving insufficient understanding of its internal dimensions and their distinct roles in translating BDAC into performance outcomes.

To address these gaps, this study develops and tests a capability–agility–performance framework grounded in the resource-based view and dynamic capability theory. Specifically, BDAC is conceptualized as a higher-order capability composed of three dimensions: tangible resource capability, human resource capability, and intangible resource capability. Marketing agility is further decomposed into customer agility and decision agility, allowing a more fine-grained examination of how analytics capability is translated into market-oriented action and, ultimately, firm performance.

By positioning marketing agility as the mediating mechanism, this study seeks to answer the following research question: how does big data analytics capability influence marketing agility, a key dynamic capability within the marketing management function, in ways that enhance firm performance? In doing so, this study has three objectives: first, to examine the direct effect of BDAC on firm performance; second, to investigate the effects of BDAC on the two dimensions of marketing agility, namely customer agility and decision agility; and third, to test the mediating roles of these two dimensions of marketing agility in the BDAC–performance relationship.

This study focuses on firms operating in China for several theoretically and practically relevant reasons. First, China represents one of the world’s largest and fastest-growing big data markets, with the country’s data generation volume expected to reach 48.6 zettabytes by 2025 (CAICT, 2023). Chinese firms have made substantial investments in big data analytics infrastructure, yet evidence on how these investments translate into marketing and performance outcomes remains limited. Second, the Chinese market is characterized by high velocity of digital transformation, particularly in marketing-related functions such as e-commerce, social media, and mobile payments, making it an ideal context to examine marketing agility. Third, prior research on BDAC has predominantly drawn samples from Western economies (e.g., United States, Europe, Australia), leaving a geographical gap in understanding how these capabilities operate in different institutional and cultural contexts. By focusing on Chinese firms, this study extends the generalizability of the BDAC–agility–performance framework beyond Western settings. Accordingly, the survey was administered to senior executives and employees in Chinese firms that had engaged in big data analytics and marketing activities.

This study contributes to literature in three ways. First, it refines the conceptualization of BDAC by distinguishing among tangible, human, and intangible resource capabilities, thereby clarifying the internal structure of BDAC beyond its broad treatment in prior studies. Second, it extends research on the business value of big data analytics by shifting the analytical lens from the firm level in general to the marketing agility domain in particular. Third, it introduces a more granular view of marketing agility by separating customer agility from decision agility and examining their mediating roles between

BDAC and firm performance. In this way, the study offers a more precise explanation of how firms convert data-based resources and insights into market responsiveness, strategic action, and performance gains in digitally competitive environments.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The present study is grounded in the Resource-Based View (RBV) (Barney, 1991) and Dynamic Capability Theory (Teece et al., 1997; Teece, 2007). In recent big data analytics research, these two perspectives are frequently combined to explain how data-related assets become sources of superior performance only when firms are able to orchestrate, integrate, and reconfigure them into actionable organizational capabilities (Wamba et al., 2017; Mikalef et al., 2020; Huynh et al., 2023). From an RBV perspective, data, analytics infrastructure, managerial know-how, and data-driven routines may constitute strategically valuable resources. However, RBV alone is insufficient to explain how such resources are mobilized and transformed into performance outcomes in turbulent environments. Dynamic Capability Theory complements this logic by emphasizing the firm's capacity to renew and reconfigure its resource base in response to market change. Specifically, Teece (2007) articulated three core dynamic processes: sensing market opportunities and threats, seizing new opportunities through investment and decision-making, and reconfiguring organizational resources to maintain strategic alignment. The present study maps these three processes onto the proposed framework as follows: Big data analytics capability (BDAC) primarily contributes to the sensing process by enabling firms to identify customer needs and market signals through data analysis. Marketing agility, in turn, embodies the seizing and reconfiguring processes within the marketing function, customer agility corresponds to seizing (rapidly responding to customer needs), while decision agility corresponds to reconfiguring (swiftly adjusting marketing mix and resource allocation). This theoretical mapping is illustrated in Figure 1. In this sense, BDAC can be understood as an organizational capability rooted in data-related resources, while agility-related capabilities represent the mechanism through which analytics-based insights are translated into timely market action and, ultimately, performance gains (Wamba et al., 2017; Mikalef et al., 2020; Rialti et al., 2019).

Big Data Analytics Capability and Firm Performance

Big data analytics has been widely recognized as a potential driver of business value because it enables firms to capture, process, and interpret large volumes of structured and unstructured data for strategic and operational purposes. Prior studies suggest that BDAC helps firms improve decision quality, identify market opportunities, support innovation, and enhance both operational and market outcomes. At the same time, the empirical literature is not entirely uniform. While many studies report a positive relationship between BDAC and firm performance, others note that data investments alone do not automatically generate value unless they are embedded in organizational processes and

complementary capabilities. This inconsistency suggests that BDAC should be viewed not as simple technology possession, but as an organizational capability built through the coordinated deployment of multiple resource categories (Gupta & George, 2016; Wamba et al., 2017; Mikalef et al., 2020; Ansari & Ghasemaghaei, 2023).

Following this logic, BDAC is conceptualized here as a higher-order capability composed of three lower-order dimensions: tangible resource capability, human resource capability, and intangible resource capability. This specification is consistent with the established BDAC literature, which conceptualizes analytics capability as being built from technological and data infrastructure, analytics-related human skills, and intangible organizational enablers such as a data-driven culture and organizational learning (Gupta & George, 2016; Aziz et al., 2023; Huynh et al., 2023). Tangible resource capability refers to the firm's ability to deploy analytics-related infrastructure, platforms, and data resources. Human resource capability reflects the technical and managerial skills required to analyze data and apply insights to business problems. Intangible resource capability captures the organizational conditions that support analytics use, especially data-driven culture, managerial support, and organizational learning routines. This multidimensional view sharpens the construct by distinguishing BDAC from big data resources per se and by emphasizing capability formation rather than mere resource possession (Gupta & George, 2016; Aziz et al., 2023).

Empirical evidence also supports the performance relevance of these constituent capability dimensions. Studies have shown that infrastructure-related capabilities are foundational for extracting value from data, that human and managerial analytics skills are critical for interpreting and applying insights, and that intangible organizational conditions such as culture and learning significantly strengthen the conversion of analytics capability into superior firm outcomes (Yasmin et al., 2020; Upadhyay & Kumar, 2020; Karaboğa et al., 2023). In addition, recent empirical work continues to show that BDAC contributes positively to firm-level outcomes such as competitive performance, market performance, and operational performance (Aziz et al., 2023; Olabode et al., 2022). When tangible, human, and intangible resource capabilities are effectively combined, firms are better positioned to generate valuable insights, align strategic decisions, and realize superior performance. Accordingly, the following hypotheses are proposed:

H1a: Tangible resource capability has a significant positive impact on firm performance.

H1b: Human resource capability has a significant positive impact on firm performance.

H1c: Intangible resource capability has a significant positive impact on firm performance.

Big Data Analytics Capability and Marketing Agility

Although BDAC may improve firm performance directly, its value is more likely to emerge when analytics-based insights are converted into responsive market behavior. This is where marketing agility becomes central. Marketing agility refers to the firm's capacity to sense market developments, interpret customer and competitor signals, and rapidly adjust marketing actions, plans, and resource allocations. In line with Dynamic Capability Theory, marketing agility is treated here as a higher-order dynamic capability that allows firms to reconfigure market-facing activities under conditions of uncertainty. Recent studies support this view by showing that data analytics enhances firms' market responsiveness and that marketing agility serves as an important mechanism linking data-related capabilities to competitive and market outcomes (Tarn & Wang, 2023; Alghamdi & Agag, 2024).

Existing literature indeed offers varying perspectives on the dimensionality of marketing agility. For instance, some studies conceptualize marketing agility as a three-dimensional construct comprising customer agility, competitor agility, and channel agility (Roberts & Grover, 2012). Others embed it within a broader strategic agility framework encompassing sensing, seizing, and reconfiguring processes (Teece, 2007; Mikalef et al., 2020). However, the theoretical focus of this study is specifically on "how big data analytics capability translates into firm performance through the marketing function." Within this particular context, a two-dimensional distinction offers both theoretical parsimony and analytical specificity. The study further decomposes marketing agility into two dimensions: customer agility and decision agility. Customer agility captures the ability to sense and respond to evolving customer needs (Roberts & Grover, 2012; Day, 1994). Decision agility refers to the ability to make timely and effective marketing decisions and strategic adjustments. This two-dimensional specification offers a more fine-grained account of how firms operationalize agility in marketing contexts. Prior literature on customer agility and analytics-enabled responsiveness indicates that customer-related sensing and responding routines are a critical manifestation of market-facing agility, while analytics-supported decision quality and speed are central to strategic adaptation in turbulent environments (Agag et al., 2024; Tseng, 2023; Shamim et al., 2020).

BDAC is expected to enhance customer agility for several reasons. From the perspective of Teece's (2007) sensing–seizing–reconfiguring framework, BDAC first strengthens the firm's sensing capability: analytics infrastructure and data resources enable firms to gather richer and timelier information about customer behavior, preferences, and emerging demand patterns. Second, skilled analytics personnel (human resource capability) can transform these data into actionable insights for segmentation, personalization, and market sensing which corresponds to the initial stage of seizing opportunities. Third, a data-driven culture and organizational learning (intangible resource capability) facilitate the dissemination and use of customer knowledge across functions, further enabling seizing by ensuring that sensed opportunities are translated into coordinated responses. Together, these elements improve the firm's ability to identify changes in customer needs and respond more effectively. Existing empirical studies

lend direct support to this logic. Research has shown that marketing analytics use positively affects customer agility over time, and that big data analytics tools strengthen customer sensing and responding capability, which in turn improves market-related outcomes (Agag et al., 2024; Tseng, 2023). In addition, case-based and survey evidence suggests that big data analytics plays an important role in helping firms address changing customer needs and develop market agility in dynamic environments (Hajli et al., 2020; Tarn & Wang, 2023). From a dynamic capability perspective, BDAC therefore enables the sensing and seizing routines that underpin customer agility. Therefore, the following hypotheses are proposed:

H2a: Tangible resource capability has a significant positive impact on customer agility.

H2b: Human resource capability has a significant positive impact on customer agility.

H2c: Intangible resource capability has a significant positive impact on customer agility.

BDAC is also expected to strengthen decision agility. Decision agility corresponds more directly to the seizing and reconfiguring processes in Teece's (2007) framework. Once market signals have been sensed, firms must make rapid marketing decisions (seizing opportunities) and adjust resource allocations (reconfiguring actions). In marketing environments characterized by volatility and information overload, timely and accurate decision-making depends on the firm's ability to acquire, integrate, interpret, and communicate relevant information. Analytics infrastructure improves information accessibility and processing speed, thereby enabling faster seizing. Human resource capability enhances the quality of analysis and managerial interpretation which supports more effective reconfiguring of marketing strategies. Intangible resource capability, especially a data-driven culture, encourages evidence-based coordination and faster decision cycles. Recent empirical evidence supports this argument. Studies have shown that BDA capability significantly contributes to decision-making performance, and that data-driven culture strengthens the effect of analytics capability on better decisions (Shamim et al., 2020). Related research also indicates that analytics-driven capabilities improve marketing agility by enabling firms to process market intelligence more effectively and respond more quickly to external change (Tarn & Wang, 2023; Alghamdi & Agag, 2024). Accordingly, firms with stronger BDAC should be better able to adjust marketing strategies, reallocate resources, and respond quickly to market shifts. Accordingly, the following hypotheses are proposed:

H3a: Tangible resource capability has a significant positive impact on decision agility.

H3b: Human resource capability has a significant positive impact on decision agility.

H3c: Intangible resource capability has a significant positive impact on decision agility.

Marketing Agility and Firm Performance

A substantial body of literature suggests that agility is positively associated with firm performance because it enables firms to respond quickly and effectively to market turbulence. In marketing settings, agility enhances the firm's ability to identify opportunities, refine offerings, tailor communication, and

align actions with changing customer expectations. Recent empirical research has shown that marketing agility is positively associated with both short- and long-term firm performance, while earlier evidence also indicates that marketing agility contributes to superior financial performance by strengthening the effectiveness of market-facing capabilities under turbulent conditions (Agag et al., 2025; Zhou et al., 2019). However, treating marketing agility as a single undifferentiated construct may obscure the distinct mechanisms through which it contributes to performance. The present study therefore separately examines customer agility and decision agility.

Customer agility is expected to improve firm performance because firms that sense and respond to customer needs more effectively are better able to increase satisfaction, retention, loyalty, and product–market fit. Customer agility also supports iterative learning and rapid refinement of products and services, which can improve market outcomes and strengthen competitive position. Direct empirical support for this argument is available in recent studies. For example, Ngo and Vu (2020) found that customer agility has significant positive consequences for firm performance in the tourism context, while Tseng (2023) showed that customer sensing and responding capability significantly enhances new product success. Related platform-based research also suggests that customer agility enables firms to exploit customer knowledge more effectively and improve competitive action in dynamic markets (Huang & Rust, 2021). Prior work therefore indicates that customer sensing and customer responding jointly shape the quality of market adaptation, with important consequences for product performance and customer-related outcomes. Therefore, the following hypothesis is proposed.

H4: Customer agility has a significant positive impact on firm performance.

Decision agility is likewise expected to enhance firm performance. In fast-moving markets, decision speed is a critical source of advantage (Eisenhardt, 1989). Firms must frequently revise pricing, promotion, channel strategy, and resource allocation under uncertainty. Decision agility improves the speed and quality of such adjustments by reducing information delays, facilitating coordinated action, and allowing the firm to act before opportunities dissipate or competitive threats intensify. Although the literature more often examines decision agility as one dimension of broader organizational or marketing agility, existing evidence remains supportive. Zhou et al. (2019) showed that marketing agility improves financial performance, implying that timely market-aligned decision adjustment is performance relevant. More recently, Bekos et al. (2025) found that organizational agility is positively associated with performance when supported by effective marketing implementation capability, and Kyriakopoulos et al. (2025) reported that new product development decision-making agility contributes positively to performance outcomes. These findings collectively suggest that decision agility is not merely speed for its own sake, but the capability to make timely and effective decisions that preserve strategic fit and improve firm outcomes. Hence, the following hypothesis is proposed.

H5: Decision agility has a significant positive impact on firm performance.

The Mediating Role of Marketing Agility

The central argument of this study is that the business value of BDAC is not fully realized at the point of data analysis itself. Rather, analytics-derived insights must be translated into market-facing capabilities and actions. This is precisely the function of marketing agility. Prior research has suggested that dynamic capabilities mediate the relationship between analytics capability and performance, but such explanations often remain broad and do not specify the relevant functional mechanism. For example, Mikalef et al. (2020) found that the effect of BDAC on competitive performance is not direct, but is fully mediated by dynamic capabilities, which then enhance marketing and technological capabilities. More recent evidence also shows that agility-related capabilities can mediate the effect of data-based capabilities on performance outcomes in dynamic environments (Alyahya et al., 2023). By introducing marketing agility, and by distinguishing between customer agility and decision agility, this study specifies a more precise mediating pathway between BDAC and firm performance.

Customer agility mediates the BDAC–performance relationship because analytics capabilities help firms perceive customer signals more accurately and respond to them more effectively. Tangible analytics resources provide the information base, human resources provide interpretive capacity, and intangible resources create the organizational conditions for coordinated customer response. These effects should improve customer-oriented adaptation, which in turn enhances performance. Existing studies provide support for both links in this mediation chain. Tseng et al. (2022) showed that big data analytics supports customer agility in the new product context, while Tseng (2023) further found that the effective use of big data analysis tools enhances customer sensing and responding capabilities, and that these capabilities significantly improve new product success. In addition, Wamba (2022) reported that customer agility significantly mediates the relationship between AI assimilation and firm performance, offering parallel dynamic-capability evidence that customer-facing agility is a valid mechanism through which analytics-related capabilities are translated into performance gains. Therefore, the following hypotheses are proposed.

H6a: Customer agility mediates the relationship between tangible resource capability and firm performance.

H6b: Customer agility mediates the relationship between human resource capability and firm performance.

H6c: Customer agility mediates the relationship between intangible resource capability and firm performance.

Decision agility also mediates the BDAC–performance relationship. BDAC equips firms with the information, skills, and routines required to support timely and evidence-based marketing decisions. These capabilities help managers interpret market developments, coordinate responses across functions, and implement strategic adjustments more effectively. In turn, better and faster marketing decisions

improve market performance and financial outcomes. Prior research supports this logic. Mikalef et al. (2020) demonstrated that BDAC improves performance through dynamic capabilities rather than through a direct path alone. Alyahya et al. (2023) further showed that strategic agility partially mediates the relationship between big data analytics capabilities and sustainable performance. In addition, evidence from analytics research indicates that data-analytic capability enhances decision-making performance by improving the firm's ability to process information and act effectively under uncertainty. Accordingly, decision agility represents a second, distinct mechanism through which BDAC contributes to firm performance. Thus, the following hypotheses are proposed.

H7a: Decision agility mediates the relationship between tangible resource capability and firm performance.

H7b: Decision agility mediates the relationship between human resource capability and firm performance.

H7c: Decision agility mediates the relationship between intangible resource capability and firm performance.

Taken together, the proposed framework conceptualizes BDAC as a multidimensional capability that influences firm performance both directly and indirectly through two dimensions of marketing agility. This capability–agility–performance logic not only clarifies the internal mechanism through which firms derive value from big data analytics but also repositions marketing agility as a central domain in which that value is realized. The conceptual framework was shown in Figure 1.

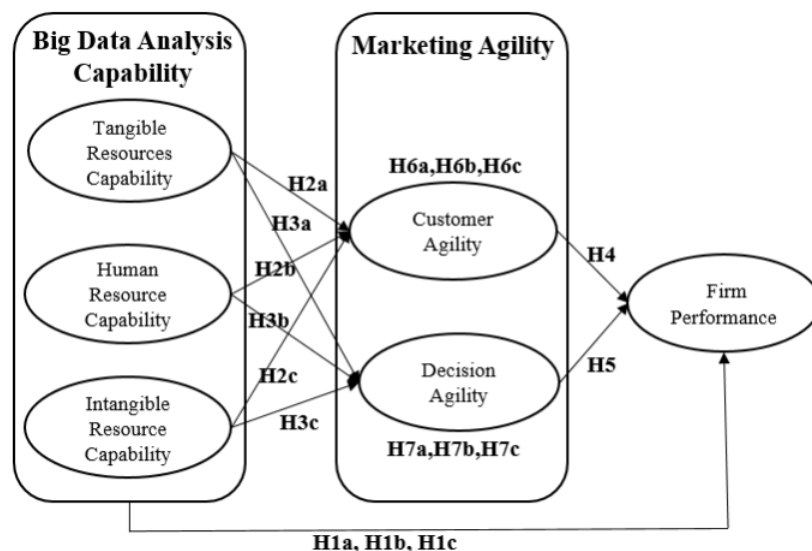


Figure 1: Conceptual Framework

METHODOLOGY

Research Design

This study adopts a quantitative research design to test the proposed relationships among big data analytics capability, marketing agility, and firm performance. More specifically, the research examines the direct effects of the three dimensions of BDAC on firm performance, the effects of BDAC on the two dimensions of marketing agility, and the mediating roles of customer agility and decision agility in the BDAC–performance relationship. The study explicitly states that the study uses a structured questionnaire survey and Structural Equation Modeling (SEM) to analyze the relationships among the six key constructs in the model.

Sample and Data Collection

The target respondents were Chinese senior executives or employees aged 20 years and above who possessed knowledge of big data analytics or its applications and were familiar with marketing activities. To improve respondent relevance, the study applied two screening criteria at the firm level: first, the firm must have engaged in big data analytics, applications, or investment activities within the previous three years; second, the firm must have emphasized marketing-related activities or strategic adjustments, including market or customer sensing, response efforts, and marketing decision-making practices. The sample was not restricted to a single industry, and firms from sectors such as manufacturing and retail e-commerce were included as long as they met the selection criteria. Purposive sampling was employed to target respondents who met two firm-level screening criteria. Potential respondents were recruited through three online channels between January and March 2026. First, a commercial online panel provider (Credamo, a widely used platform for academic survey research in China) was engaged to identify eligible respondents from its pre-screened pool of professionals. Second, professional networking platform LinkedIn was used to target senior executives and marketing professionals with self-reported big data analytics experience. Third, industry-specific online communities (e.g., marketing analytics forums on Tencent QQ and WeChat groups focused on digital transformation) were used to distribute the survey invitation. To avoid overlap, the same unique respondent identifier was tracked across channels, and duplicate responses were removed.

The data collection procedure followed a two-phase design. A pilot survey involving 40 respondents from different industries was conducted first to assess the questionnaire’s design and improve measurement quality. The pilot phase was used to refine the wording, structure, and content of the instrument. The formal survey was then administered online by purposive sampling. Respondents who completed the full survey received a monetary incentive of approximately RMB 5 yuan or an equivalent digital voucher. A total of 472 responses were received from the 600 invited respondents. After data cleaning (removal of questionnaires with missing values, contradictory responses, outliers,

and repetitive answering patterns), 425 valid responses remained. Following established guidelines for structural equation modeling (SEM), the required sample size was evaluated prior to data collection. With six latent constructs and 30 measurement items, the minimum recommended sample size ranges from 200 to 300 for models of moderate complexity (Kline, 2016; Hair et al., 2019). The final sample of 425 valid responses exceeds this threshold and provides sufficient statistical power for detecting hypothesized effects.

Measurement

All focal constructs were measured using established multi-item scales adapted from prior studies. The questionnaire included six first-order constructs and 30 items in total. Big data analytics capability was operationalized through three dimensions: tangible resource capability, human resource capability, and intangible resource capability, with five items for each dimension adapted from Gupta and George (2016), Mikalef et al. (2019), and Li et al. (2021). Marketing agility was captured through two dimensions: customer agility and decision agility. Customer agility was measured with five items adapted from Roberts and Grover (2012) and Hu et al. (2022), while decision agility was measured with five items adapted from Zhou et al. (2019) and Khan (2020). Firm performance was measured with five items adapted from Wamba et al. (2017) and Chen et al. (2012). All items were rated on a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”).

Data Analysis

The study used SPSS 28 and AMOS 29 for empirical analysis. Descriptive statistics were employed first to summarize the sample profile and provide an overview of respondent characteristics. Reliability and validity assessments were then conducted through Cronbach’s alpha, confirmatory factor analysis (CFA; recommended thresholds from Hu & Bentler, 1999), and related psychometric checks. After the adequacy of the measurement model was established, SEM (using maximum likelihood estimation; Kline, 2016) was used to test the hypothesized direct and indirect relationships among the constructs. To test mediation, the study employed the bootstrap method in AMOS with 5,000 resamples (Preacher & Hayes, 2008).

Before testing the hypothesized paths, the fit of the structural model was assessed using the same set of fit indices as the measurement model. The structural model yielded acceptable fit: $\chi^2/df = 1.412$, RMSEA = 0.031, SRMR = 0.042, CFI = 0.984, TLI = 0.981, IFI = 0.984, GFI = 0.921. These values meet or exceed commonly recommended thresholds (Hu & Bentler, 1999; Hair et al., 2019), indicating that the structural model adequately represents the observed data.

Common Method Bias Testing

Because all variables were measured using self-reported data from single respondents, common method bias (CMB) could potentially inflate the observed relationships. Following established recommendations (Podsakoff et al., 2003; Podsakoff et al., 2012), two complementary approaches were employed to assess CMB. First, Harman's single-factor test was conducted using unrotated exploratory factor analysis on all 30 measurement items. The results showed that a single factor accounted for 28.6% of the total variance, well below the conventional threshold of 50%. This indicates that no single factor explains the majority of the covariance among the items. Second, the marker variable technique was applied. A theoretically unrelated marker variable ("attitude toward workplace physical environment") was included in the questionnaire. The average correlation between this marker variable and the six focal constructs was $r = 0.04$ (non-significant), and the significance pattern of the hypothesized paths remained unchanged after controlling for the marker variable. Together, these tests suggest that common method bias does not pose a serious threat to the validity of the findings.

RESULTS

Sample Characteristics

The final 425 sample covered 27 provinces and four direct-administered municipalities in China. The largest industry sectors were manufacturing (32.5%), retail and e-commerce (28.9%), financial services (15.3%), and information technology (12.0%). The remaining 11.3% came from other sectors including healthcare, education, and logistics. This distribution suggests that the sample captures a reasonable cross-section of Chinese firms engaged in big data analytics and marketing activities. In terms of gender, the sample was relatively balanced, with 51.3% female and 48.7% male respondents. Most respondents were between 26 and 45 years old, with the largest group aged 36–45 years (43.5%), followed by those aged 26–35 years (32.2%). These characteristics suggest that the respondents were appropriate informants for evaluating big data analytics capability, marketing agility, and firm performance.

Measurement Model

Before testing the structural relationships, confirmatory factor analysis (CFA) was conducted to assess the measurement model. The overall six-factor measurement model showed a very good fit to the data ($\chi^2/df = 1.027$, RMSEA = 0.008, SRMR = 0.036, IFI = 0.998, TLI = 0.998, CFI = 0.998, GFI = 0.940, AGFI = 0.928), indicating satisfactory construct representation. At the construct level, the CFA results also showed acceptable to excellent fit across all six latent variables. Standardized factor loadings were consistently strong, ranging from 0.729 to 0.803 across the six constructs. In addition, all constructs demonstrated adequate convergent validity (Table 1), with composite reliability (CR) values above 0.70 and average variance extracted (AVE) values above 0.50. Fornell–Larcker tests further supported

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discriminant validity, as the square root of the AVE for each construct exceeded its correlations with the other constructs (Table 2). Furthermore, the Cronbach's alpha values for tangible resource capability, human resource capability, and intangible resource capability, customer agility, decision agility, and firm performance. were all above 0.70, ranging from 0.872 to 0.892 (Table 1), exceeding the conventional threshold of 0.70 (Nunnally, 1978), indicating satisfactory internal consistency reliability. Overall, these results indicate that the measurement model was psychometrically sound and suitable for subsequent hypothesis testing.

Table 1: Convergent Validity of Scales for Each Variable in the Formal Survey

Variable	Ustd.	S.E.	C.R.	P	Factor Loading	CR	AVE	α
TRC1 $\leftarrow$ TRC	1.000				.776	.876	.585	.876
TRC2 $\leftarrow$ TRC	.973	.063	15.353	***	.738			
TRC3 $\leftarrow$ TRC	1.044	.065	15.953	***	.764			
TRC4 $\leftarrow$ TRC	1.049	.064	16.387	***	.782			
TRC5 $\leftarrow$ TRC	1.026	.064	15.984	***	.765			
HRC1 $\leftarrow$ HRC	1.000				.765	.872	.576	.872
HRC2 $\leftarrow$ HRC	.956	.063	15.216	***	.744			
HRC3 $\leftarrow$ HRC	.996	.064	15.666	***	.764			
HRC4 $\leftarrow$ HRC	.948	.062	15.244	***	.745			
HRC5 $\leftarrow$ HRC	1.039	.065	15.926	***	.776			
IRC1 $\leftarrow$ IRC	1.000				.729	.880	.594	.880
IRC2 $\leftarrow$ IRC	1.005	.067	14.899	***	.758			
IRC3 $\leftarrow$ IRC	1.136	.072	15.738	***	.802			
IRC4 $\leftarrow$ IRC	1.077	.071	15.238	***	.776			
IRC5 $\leftarrow$ IRC	1.094	.071	15.482	***	.788			
CA1 $\leftarrow$ CA	1.000				.791	.892	.624	.892
CA2 $\leftarrow$ CA	.958	.056	17.140	***	.783			
CA3 $\leftarrow$ CA	.994	.056	17.662	***	.803			
CA4 $\leftarrow$ CA	.950	.056	17.093	***	.781			
CA5 $\leftarrow$ CA	.955	.055	17.314	***	.790			

Table 1: Convergent Validity of Scales for Each Variable in the Formal Survey (Cont.)

Variable	Ustd.	S.E.	C.R.	P	Factor Loading	CR	AVE	α
DA1 $\leftarrow$ DA	1.000				.798	.876	.585	.876
DA2 $\leftarrow$ DA	.926	.057	16.349	***	.758			
DA3 $\leftarrow$ DA	.953	.057	16.674	***	.771			
DA4 $\leftarrow$ DA	.931	.057	16.371	***	.759			
DA5 $\leftarrow$ DA	.892	.056	15.833	***	.738			
FP1 $\leftarrow$ FP	1.000				.763	.874	.580	.874
FP2 $\leftarrow$ FP	1.001	.065	15.472	***	.755			
FP3 $\leftarrow$ FP	1.025	.065	15.868	***	.773			
FP4 $\leftarrow$ FP	.994	.064	15.449	***	.754			
FP5 $\leftarrow$ FP	.973	.062	15.655	***	.764			

Note: TRC = Big Data Tangible Resources Capability; HRC = Big Data Human Resource Capability; IRC = Big Data Intangible Resources Capability; CA = Customer Agility; DA = Decision Agility; FP = Firm Performance.

Table 2: Discriminant Validity

	FP	DA	CA	IRC	HRC	TRC
FP	.762					
DA	.521	.765				
CA	.514	.532	.790			
IRC	.488	.489	.493	.771		
HRC	.505	.490	.509	.489	.759	
TRC	.497	.474	.485	.473	.468	.765

Note: Bolded text on the diagonal is the square root of AVE, and below the diagonal is the correlation coefficient between the latent variables

Structural Model and Hypothesis Testing

The structural model results provided full support for the proposed hypotheses in Table 3. First, all three dimensions of big data analytics capability had significant positive effects on firm performance. Tangible resource capability positively influenced firm performance ($\beta = 0.174$, $p = 0.004$), supporting H1a. Human resource capability also had a significant positive effect on firm performance

($\beta = 0.172$, $p = 0.006$), supporting H1b. Likewise, intangible resource capability positively affected firm performance ($\beta = 0.143$, $p = 0.019$), supporting H1c. These findings indicate that the development of tangible, human, and intangible big data-related capabilities directly contributes to improved organizational performance. Second, the three dimensions of big data analytics capability were all positively associated with customer agility. Tangible resource capability had a significant effect on customer agility ($\beta = 0.242$, $p < 0.001$), supporting H2a. Human resource capability also significantly enhanced customer agility ($\beta = 0.283$, $p < 0.001$), supporting H2b. Similarly, intangible resource capability had a significant positive effect on customer agility ($\beta = 0.247$, $p < 0.001$), supporting H2c. These results suggest that firms with stronger analytics-related resources are better able to sense and respond to customer needs. Third, all three dimensions of big data analytics capability also significantly improved decision agility. Tangible resource capability positively affected decision agility ($\beta = 0.237$, $p < 0.001$), supporting H3a. Human resource capability positively affected decision agility ($\beta = 0.264$, $p < 0.001$), supporting H3b. Intangible resource capability likewise had a significant positive effect on decision agility ($\beta = 0.255$, $p < 0.001$), supporting H3c. These findings indicate that stronger analytics-related capabilities enable firms to make faster and more effective marketing-related decisions. Fourth, both dimensions of marketing agility were positively related to firm performance. Customer agility significantly improved firm performance ($\beta = 0.172$, $p = 0.004$), supporting H4, while decision agility also had a significant positive effect on firm performance ($\beta = 0.195$, $p = 0.001$), supporting H5. Taken together, these results confirm that marketing agility is an important performance-enhancing capability in the big data analytics context.

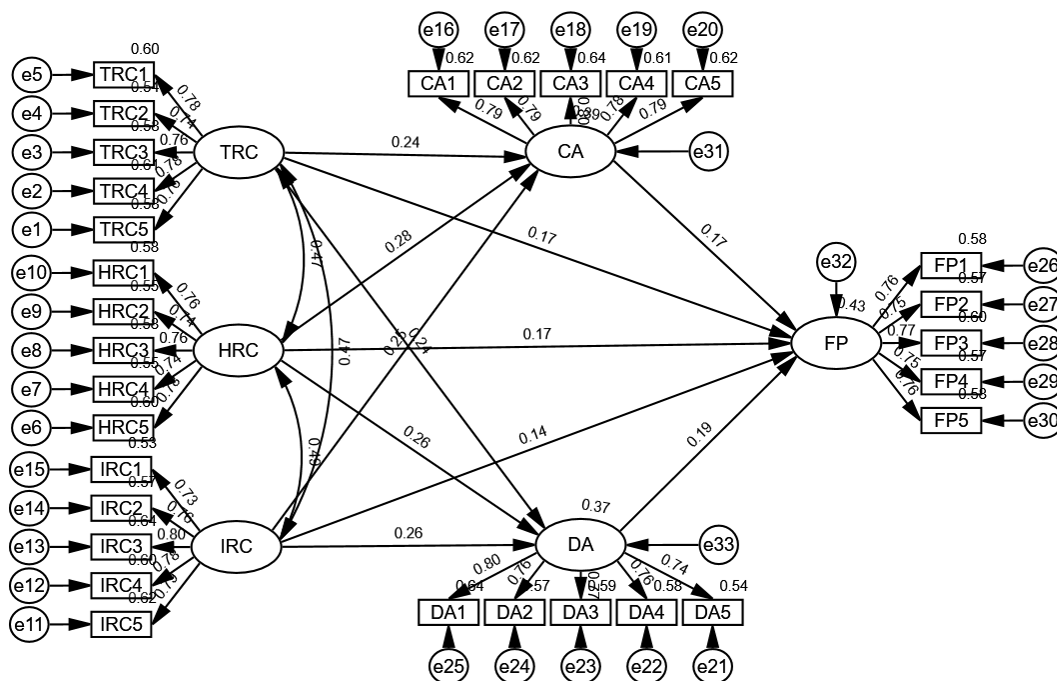


Figure 2: Results of Analysis of Structural Modeling with Hypotheses

Table 3: Direct Hypothesis Effect Analysis

Hypothesis	Path	β	B	S.E.	C.R.	P	Result
H1a	FP $\leftarrow$ TRC	.174	.167	.058	2.892	.004	Accepted
H1b	FP $\leftarrow$ HRC	.172	.162	.059	2.754	.006	Accepted
H1c	FP $\leftarrow$ IRC	.143	.134	.057	2.340	.019	Accepted
H2a	CA $\leftarrow$ TRC	.242	.260	.062	4.188	***	Accepted
H2b	CA $\leftarrow$ HRC	.283	.298	.062	4.790	***	Accepted
H2c	CA $\leftarrow$ IRC	.247	.259	.061	4.227	***	Accepted
H3a	DA $\leftarrow$ TRC	.237	.218	.055	3.994	***	Accepted
H3b	DA $\leftarrow$ HRC	.264	.238	.055	4.360	***	Accepted
H3c	DA $\leftarrow$ IRC	.255	.230	.054	4.245	***	Accepted
H4	FP $\leftarrow$ CA	.172	.154	.054	2.851	.004	Accepted
H5	FP $\leftarrow$ DA	.195	.203	.063	3.223	.001	Accepted

*** P < 0.001

Mediation Analysis

The mediating effects were assessed using bootstrap estimation with 5,000 resamples and 95% bias-corrected confidence intervals. The results in Table 4 showed that customer agility significantly mediated the relationships between all three dimensions of big data analytics capability and firm performance. Specifically, the indirect effect of tangible resource capability on firm performance through customer agility was 0.040 (95% CI [0.011, 0.084], $p = 0.006$), supporting H6a. The indirect effect of human resource capability through customer agility was 0.046 (95% CI [0.012, 0.094], $p = 0.007$), supporting H6b. The indirect effect of intangible resource capability through customer agility was 0.040 (95% CI [0.010, 0.090], $p = 0.006$), supporting H6c.

Decision agility also significantly mediated the effects of big data analytics capability on firm performance. The indirect effect of tangible resource capability through decision agility was 0.044 (95% CI [0.016, 0.090], $p = 0.002$), supporting H7a. The indirect effect of human resource capability through decision agility was 0.048 (95% CI [0.018, 0.094], $p = 0.002$), supporting H7b. The indirect effect of intangible resource capability through decision agility was 0.047 (95% CI [0.015, 0.096], $p = 0.002$), supporting H7c. The total indirect effect was 0.265 (95% CI [0.150, 0.386], $p < 0.001$), while the direct effect remained significant at 0.463 (95% CI [0.301, 0.642], $p < 0.001$). The total effect was 0.728 (95% CI [0.617, 0.849], $p < 0.001$). Because both the indirect and direct effects were significant, the findings

support a pattern of partial mediation. In other words, big data analytics capability improves firm performance not only directly, but also indirectly through customer agility and decision agility.

Table 4: Mediation Effect Test

NO.	Mediating path	Effect	95% Confidence Interval		P	Result
			LLCI	ULCI		
H6a	TRC → CA → FP	.040	.011	.084	.006	Accepted
H6b	HRC → CA → FP	.046	.012	.094	.007	Accepted
H6c	IRC → CA → FP	.040	.010	.090	.006	Accepted
H7a	TRC → DA → FP	.044	.016	.090	.002	Accepted
H7b	HRC → DA → FP	.048	.018	.094	.002	Accepted
H7c	IRC → DA → FP	.047	.015	.096	.002	Accepted
	Indirect Effect	.265	.150	.386	.000	Accepted
	Direct Effect	.463	.301	.642	.000	Accepted
	Total Effect	.728	.617	.849	.000	Accepted

DISCUSSION

This study sets out to explain how BDAC contributes to firm performance by examining the mediating role of marketing agility. The findings provide consistent support for the proposed capability–agility–performance framework. All hypothesized paths were significant, indicating that BDAC enhances firm performance both directly and indirectly through customer agility and decision agility. This pattern of results offers a more fine-grained explanation of how firms convert data-related resources into market-facing action and performance gains. The findings of this study can be further interpreted through Teece’s (2007) sensing–seizing–reconfiguring framework. BDAC primarily contributes to the sensing process by enabling firms to more accurately identify market signals and customer needs. The two dimensions of marketing agility correspond, respectively, to seizing (customer agility) and reconfiguring (decision agility). Customer agility allows firms to rapidly act upon sensed opportunities, while decision agility enables the swift reallocation of marketing resources and adjustment of strategic actions. The empirical support for this capability–agility–performance chain provides novel evidence for the applicability of dynamic capability theory in the context of data-driven marketing. It also suggests that the value of big data analytics lies not only in superior sensing but also, and perhaps more critically, in the firm’s capacity to seize and reconfigure based on those sensed insights.

First, the results confirm that BDAC has a direct positive effect on firm performance. More specifically, tangible resource capability, human resource capability, and intangible resource capability all significantly improved firm performance. This finding is consistent with prior studies suggesting that big data analytics generates business value by improving market insight, decision quality, operational efficiency, and strategic responsiveness (Akter et al., 2016; Gupta & George, 2016; Rialti et al., 2019; Wamba et al., 2017). At the same time, the present study contributes to the ongoing debate over whether investments in big data necessarily yield performance benefits. Rather than treating analytics as a purely technological asset, the findings suggest that performance gains depend on a broader capability configuration that includes infrastructure, human expertise, and organizational conditions. In this sense, the study supports the resource-based view that competitive advantage arises not from isolated resources, but from their coordinated deployment and recombination (Barney, 1991).

Second, the results show that all three dimensions of BDAC significantly enhance both customer agility and decision agility. This finding extends prior work on dynamic capabilities by showing that data-related capabilities are not only valuable in themselves, but also serve as enabling conditions for higher-order market-facing capabilities. Firms with stronger tangible analytics resources are better able to capture and process market information; firms with stronger human resource capability are better positioned to interpret data and translate it into action; and firms with stronger intangible resource capability, such as data-driven culture and organizational learning, are more likely to embed analytics into everyday strategic and marketing processes. Together, these effects strengthen the firm's ability to sense customer needs, respond to market changes, and make timely strategic adjustments. This is consistent with prior research suggesting that analytics capability improves organizational responsiveness, decision effectiveness, and strategic adaptation (Ghasemaghaei et al., 2018; Mikalef & Pateli, 2017; Tseng, 2023).

Third, both customer agility and decision agility significantly improve firm performance. This finding reinforces the argument that marketing agility is an important performance-enhancing capability in turbulent environments. Customer agility allows firms to better anticipate and respond to shifting customer needs, thereby improving satisfaction, retention, and product-market fit. Decision agility, in turn, enables firms to adjust pricing, promotion, resource allocation, and strategic priorities more rapidly and effectively, which is particularly important when market conditions are volatile and competitive windows are narrow. These results are aligned with earlier studies showing that agility strengthens market performance, innovation outcomes, and financial returns by enabling firms to act on emerging opportunities more quickly than competitors (Khan, 2020; Zhou et al., 2019).

Most importantly, the mediation results indicate that marketing agility constitutes a key mechanism through which BDAC is translated into firm performance. Both customer agility and decision agility significantly mediated the relationships between the three BDAC dimensions and firm performance, and the direct effects of BDAC remained significant. This pattern suggests partial mediation rather than

full mediation. Substantively, the findings imply that BDAC does not create value only through direct improvements in information processing or resource utilization. Its business value also depends on whether firms can transform analytics output into customer-oriented responsiveness and timely marketing decisions. This result helps address the “big data paradox” noted in prior research, namely, that firms often invest heavily in analytics but struggle to realize measurable performance gains (Ghasemaghaei et al., 2018; Mikalef et al., 2019). The present study suggests that one reason for this gap is the absence of an effective marketing conversion mechanism. When firms develop marketing agility, they are better able to turn data-based knowledge into concrete strategic and operational action.

A further contribution to the findings lies in the disaggregation of marketing agility into customer agility and decision agility. Prior studies often treat agility as a broad or unitary construct, which makes it difficult to identify the specific channels through which analytics capability affects performance. By separating customer agility from decision agility, this study shows that the mediating role of marketing agility is multidimensional. Customer agility captures the firm’s external responsiveness to customer and market signals, whereas decision agility captures the internal capacity to make fast and effective marketing adjustments. This distinction is theoretically useful because it shows that the value of BDAC unfolds through both market-sensing and decision-execution mechanisms. It also suggests that firms may underperform not because they lack data, but because they are weak either in customer-oriented responsiveness or in organizational decision speed. In this sense, the findings extend the literature on big data analytics and dynamic capabilities by repositioning marketing agility as a key domain in which data-driven competitive advantage is realized.

Rather than merely confirming the hypothesized relationships, several theoretically meaningful patterns deserve explicit interpretation. First, the partial mediation observed (indirect effect = 0.265, direct effect = 0.463) suggests that BDAC operates through multiple parallel pathways beyond marketing agility, approximately 64% of its total effect on performance bypasses the two agility dimensions. This implies that BDAC functions as a “meta-capability” that directly enhances resource utilization while simultaneously enabling lower-level dynamic capabilities. Second, the consistently stronger effects of human resource capability ($\beta = 0.283$ for customer agility; $\beta = 0.264$ for decision agility) relative to tangible and intangible capabilities indicate that the “last mile” of analytics value creation lies in human interpretation and judgment, not infrastructure. Third, the slightly stronger effect of decision agility ($\beta = 0.195$) compared to customer agility ($\beta = 0.172$) on firm performance may reflect temporal dynamics: decision agility (e.g., pricing, budget reallocation) affects current-period financial outcomes more immediately, whereas customer agility operates through longer chains of customer satisfaction and retention. These interpretations move beyond mere restatement and offer actionable insights for both theory development and managerial practice.

Implications

This study offers three main theoretical contributions to literature. First, it refines the conceptualization of big data analytics capability by modeling it as a higher-order capability composed of tangible, human, and intangible resource capabilities. This specification helps reduce the conceptual ambiguity that often surrounds related constructs such as big data resources, analytics capability, and IT capability. Second, the study extends the business value of analytics literature by shifting attention to the marketing agility domain. Prior research has largely examined big data analytics capability at a broad organizational level, while giving less attention to the functional processes through which analytics creates value. The findings show that analytics-derived value is realized not only through resource deployment, but through market-facing managerial capabilities. Third, this study advances Dynamic Capability Theory by identifying marketing agility as a specific mediating mechanism linking big data analytics capability to firm performance. By further distinguishing customer agility from decision agility, it offers a more fine-grained explanation of how analytics capability is converted into performance gains. This multidimensional view improves theoretical precision and clarifies the capability–agility–performance chain.

Moreover, it has some managerial implications as well. First, prioritize human resource capability as the most powerful driver of marketing agility. Among the three dimensions of BDAC, human resource capability exhibited the strongest total effect on both customer agility ($\beta = 0.283$, $p < 0.001$) and decision agility ($\beta = 0.264$, $p < 0.001$), surpassing the effects of tangible and intangible resource capabilities. This finding suggests that hiring, training, and retaining analytics talent, data scientists, marketing analysts, and insight translators who can bridge technical analysis and business decisions, should be the top priority. Concretely, firms should consider: (a) establishing cross-functional “analytics translator” roles that sit at the intersection of marketing and IT; (b) implementing rotational programs that expose analysts to frontline marketing problems; and (c) tying a portion of marketing managers’ compensation to their team’s data literacy improvement, not just campaign outcomes. Second, invest differentially in the two dimensions of marketing agility based on strategic goals. Firms in stable markets with well-understood customer segments should prioritize decision agility, while firms in turbulent markets with rapidly shifting customer preferences should prioritize customer agility. Third, treat tangible resource capability as a necessary but not sufficient condition. Tangible resource capability (infrastructure, platforms, data resources) showed the smallest direct effect on firm performance ($\beta = 0.174$) among the three BDAC dimensions, yet it remains a prerequisite for human and intangible capabilities to function. Practically, this means: (a) avoid over-investing in expensive analytics platforms before securing analytics talent; (b) prioritize cloud-based or modular analytics solutions that allow incremental scaling rather than large upfront commitments; and (c) conduct a “data readiness audit” to identify which customer-facing data sources (e.g., CRM, social media, transaction logs) are most underutilized relative to their potential. Moreover, retail and e-commerce firms should leverage customer agility to personalize

offers in near real-time, as customer data velocity is highest in this sector. Manufacturing firms may benefit more from decision agility in pricing and channel management, as their customer interaction cycles are typically longer. Financial services firms should prioritize intangible resource capability (data-driven culture and learning routines), given regulatory constraints that limit rapid experimentation with tangible infrastructure. The results also highlight the importance of embedding analytics into marketing processes. Firms gain more from big data analytics when it strengthens customer agility and decision agility, specifically, when it improves customer sensing, customer response, and the speed and quality of marketing decisions. Managerially, this implies two priorities. Firms should improve the capture and use of customer information to support personalized and timely market responses, and they should reduce internal decision delays by strengthening cross-functional coordination and accelerating the translation of analytics outputs into action. In competitive markets, the value of analytics lies less in data possession than in the firm's ability to respond quickly and effectively.

CONCLUSION

This study examined how big data analytics capability (BDAC) influences firm performance through the mediating role of marketing agility. Drawing on the Resource-Based View and Dynamic Capability Theory, it conceptualized BDAC as a higher-order capability composed of tangible, human, and intangible resource capabilities, and modeled marketing agility through customer agility and decision agility. The findings show that BDAC improves firm performance both directly and indirectly through these two dimensions of marketing agility. In doing so, the study clarifies that the value of big data analytics lies not only in data-related resources themselves, but in the firm's ability to translate analytics-based insights into responsive marketing action and timely decision-making.

LIMITATIONS AND FUTURE RESEARCH

This study has several limitations. First, the sample was limited to Chinese firms, which may constrain the generalizability of the findings across institutional and market contexts. Second, the use of a cross-sectional survey limits causal inference. Third, all variables were measured using self-reported data, which may introduce same-source bias despite the procedural and statistical checks applied. Fourth, the absence of industry-level and firm-level control variables represents a methodological limitation of the present study. Future research could incorporate these variable such as industry sector, firm size, firm age, environmental turbulence, competitive intensity, or prior firm performance, as either control variables or moderators to further refine the model. Fifth, the use of self-reported perceptual measures rather than objective data represents a limitation. While BDAC is inherently perceptual (Gupta & George, 2016) and access to objective financial data from Chinese firms is limited, future research should employ multi-method designs, including archival financial data, objective BDAC indicators (e.g., analytics patents), and behavioral trace data. Finally, the model focused on marketing agility as the

key mediator and did not examine other possible boundary conditions or mechanisms. Future research could test the model in other national settings, use longitudinal or multi-source data, and incorporate moderators such as environmental turbulence, digital leadership, or organizational learning capability to further specify the conditions under which BDAC generates performance gains.

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