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Competitive advantage: A longitudinal analysis of the roles of data-driven innovation capabilities, marketing agility, and market turbulence

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ABSTRACT

While data-driven innovation capabilities have received considerable attention from academics and practitioners, there is insufficient longitudinal evidence on how they might contribute to improved marketing agility and competitive advantage. In this study, we make a preliminary effort to address this gap by developing a model based on the dynamic capabilities view. We also explore the moderating effects of market turbulence on the link among marketing agility and competitive advantage. We used two-waves data (T = 677 and T+1 = 569) and the cross-lagged panel approach was utilised to analyse the longitudinal data. Our findings provide robust empirical evidence on the causal and predictive temporal impact of data driven innovation capabilities on marketing agility and competitive advantage. It also indicated that marketing agility mediates this relationship over time. Moreover, the analysis suggested that market turbulence reinforce the influence of marketing agility on competitive advantage. We provided significant implications for theory and practice.

1. Introduction

Due to digitalisation, products, services, processes and entire business models have undergone significant transformations (Bhatti et al., 2022). Due to the technological advancements brought about by the Fourth Industrial Revolution, also known as “Industry 4.0”, organisations from various sectors have utilised digital technology to revolutionise their process (Dubey et al., 2018). Data-driven innovation capabilities (DDICs) enable the development of new operations that can supplement or replace traditional business models. Big data and advanced analytics have been deemed game changers (Sultana et al., 2022) in the realm of operations management (Abdelmoety et al., 2022; Bresciani et al., 2021).

Businesses are investing heavily in the development of digital capabilities to uncover innovative insights and implications that could enhance their competitive advantage (Babu et al., 2021), which may make them more inventive (Riikkinen et al., 2018). Hence, data-driven innovation skills may enhance company performance through direct and indirect collaboration, as well as co-innovation (Aboul-Dahab et al., 2021; Rindfeisch et al., 2017). Data-driven innovation is a fundamental pillar of the global data-centric digital economy (Agag, 2019; Akter et al., 2020; Morimura and Sakagawa, 2023). These innovations equip businesses with the tools necessary to outperform competitors and establish themselves as market leaders (Agag et al., 2023a; Moktadir et al., 2019). Data-driven innovation refers to a collection of processes employing tools, such as “big data analytics”, and methodologies, such as machine learning techniques and artificial intelligence, to generate fresh insights from existing datasets. Firms can maintain a competitive advantage via data-driven innovation, research, and development, as well as the creation of new product and service.

Agility represents the ability to swiftly and effectively adapt to the often-unprecedented shifts that arise in the context of data-driven innovations (Agag et al., 2022; Bhatti et al., 2022). It characterises a firm’s capacity to anticipate and skilfully address shifts in the market (Kozak et al., 2021). Consequently, companies can generate increased value for their ecosystems by obtaining and employing agile marketing competencies (Akhtar et al., 2020; Bresciani et al., 2021; Itani et al., 20220). To meet the constantly evolving demands of contemporary consumers, businesses must be nimble and adaptable (Chatterjee et al., 2022). Academics are arguing that big data capabilities are increasingly important for achieving marketing agility. For example, Medeiros and Maçada (2022) explored the relationship between agility and analytical abilities by investigating the influence of data-driven cultures on competitive advantage. Irfan et al. (2019) explored the effect of big data capabilities

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on business performance and consumer agility from a dynamic capability perspective. Sultana et al. (2022) explored and suggested a 4C conceptual framework of developing strategic agility under the user-driven innovation viewpoint. Similarly, Chan et al. (2017) developed a framework for analysing the impact of supply chain agility on organisational performance. These examinations frequently employ a descriptive research methodology and rely on cross-sectional data from a single source, neither of which shed light on what causes competitive advantage. The extent to which a company explains variances in competitive advantage achieved by enterprises in a certain setting is not well understood, making this an essential area for investigation (e.g., Bhatti et al., 2022; Hajli et al., 2020).

Agility is defined as "the ability to respond quickly and effectively to novel challenges in a data-driven innovation environment" (Agag et al., 2023b; Bresciani et al., 2021). It exemplifies a company's capacity to anticipate market possibilities or threats and respond appropriately (Bhatti et al., 2022). Therefore, businesses can create more value for themselves and their ecosystem partners by acquiring and deploying agile marketing capabilities (Agag et al., 2020; Hajli et al., 2020). To meet the ever-evolving demands of today's consumers, businesses must be nimble (Hajli et al., 2020; Sultana et al., 2022). The importance of big data skills in enabling agility is increasingly being argued by academics. One such study is that conducted by Yang et al. (2023), who probed the connection between organisational nimbleness and analytical prowess in order to assess the effect of a data-driven culture on competitive advantage.

Drawing from the "resource-based view" (RBV; Barney, 1986) and the "dynamic capabilities" (DC; Teece et al., 1997) theories, this research utilises a two-wave survey of Saudi Arabian retail companies to demonstrate the role of data-driven innovation capability and marketing agility in influencing competitive advantage, This paper uses RBV and DC theories to suggest that a company's ability to innovate based on data can increase its marketing agility and, by extension, its competitive advantage. Hence, our examination aims to examine this gap by tackling the following research questions:

RQ1: "What is the influence of data-driven innovation capability on competitive advantage"?
RQ2: "Does marketing agility mediate the link among data-driven innovation capability and competitive advantage"?
RQ3: "Does market turbulence moderate the link among marketing agility and competitive advantage"?
RQ4: "How do the data driven innovation capability–marketing agility–competitive advantage hypotheses hold up when tested utilising the cross-lagged panel method (CLPM) of analysis of longitudinal data"?

Our research presents a theoretical contribution to the literature review in various ways. First, our study offers a comprehensive understanding of the influence of data-driven innovation capability (DDICs), namely market orientation capabilities (MOCs), infrastructure capabilities (IFCs), and innovation talent capabilities (INTCs) on marketing agility (MAG). Second, it examines the mediating influence of MAG in the relationships between DDICs and competitive advantage. Third, it examines the critical role of market turbulence in the connection among marketing agility and competitive advantage, which enables organisations to determine how to implement appropriate changes. Finally, this research demonstrates the value of CLPM for analysing the lagging effects of data-driven innovation capabilities and marketing agility on competitive advantage. Studies in this area have generally yielded descriptive results in the past (see, for example, Bhatti et al., 2022; Hajli et al., 2020). Utilising two-wave data of retail companies collected in 2022 (T) and 2023 (T+1), this study employs CLPM to quantify and analyse the temporal causal effects within the data driven innovation capability - marketing agility - competitive advantage linkages.

2. Literature review

2.1. Underlying theories

This investigation draws on the "dynamic capabilities" (DC; Teece et al., 1997) and "resource-based view" (RBV; Barney, 1986) theories to comprehend the main reasons why retail companies utilise data driven innovation capabilities to attain competitive advantage. When it comes to explaining resource characterization, which is crucial for achieving a sustained competitive advantage (Barney et al., 2001), RBV is one of the most prominent and commonly used theory. RBV postulates that businesses can acquire an edge in the marketplace by creating and utilising resources that are highly sought after, rare, distinctive, and hard to replicate. For examples of how RBV has been used in the past to shed light on the significance of digital capabilities for achieving competitive advantage (e.g., Chaudhuri et al., 2022; Khalil and Belitski, 2020). Because of this, RBV represents the significance of resource heterogeneity in developing flexible skills that give an organisation an edge in the marketplace (Bhatti et al., 2022).

Dynamic capabilities view considers as an expansion of the RBV (Teece, 2007), which analyse the business capacity to develop new skills and reconfigure current ones. According to Mikalef et al. (2019), dynamic capabilities are highly prized since they allow companies to stand out from the crowd. These dynamic skills, as outlined by Teece (2012), stand out as distinct from static ones. Typical capabilities, which are part of a company's regular resource base (Bhatti et al., 2022), are deeply ingrained in daily operations to optimise productivity (Teece, 2012; Truong, 2013). These may include carrying out the steps that are (technically) required to carry out a wide range of operations and managerial processes in order to fulfil one's assigned tasks and obligations (Teece, 2012). To that end, the dynamic capabilities perspective (Teece, 2012) validates a business's ability to seek out, consolidate, and transform knowledge from its surroundings in order to create a flexible and adaptable competitive advantage. The DC viewpoint considers a business's resource renewal capabilities in light of external developments (Agag and Eid, 2019; Tarn and Wang, 2023). Therefore, dynamic capabilities can shed light on how businesses adapt their capacities in light of technological developments (Wamba et al., 2020). Recombining resources can provide a competitive edge, and doing so with rare or unusual components can improve results even further. This is why a number of investigations have combined RBV with the theory of dynamic capabilities to explain the potential for data-driven innovation capabilities (Bhatti et al., 2022; Sultana et al., 2022). Strong dynamic skills, according to researchers (e.g., Agag and Eid, 2020; Kalubanga and Gudergan, 2022), are essential for businesses to achieve sustained innovation outcomes and respond rapidly to shifts in their environments. Consequently, this paper utilises the RBV and DC to posit that data driven innovation capabilities can achieve a competitive advantage through marketing agility.

2.2. Data-driven innovation capability

Viewed through the lens of DCs, innovation management is perceived as an example of enterprise-level capabilities. To generate new products and services, refine existing ones, and boost productivity, organisations should significantly invest in and develop their innovation capabilities (Bhatti et al., 2022). Dynamic capabilities were defined as the abilities that merge, generate, and reorganise resources and skills to enhance a performance of business in shifting contexts (Teece et al., 1997a,b). Scholars have discovered that dynamic capabilities are a central notion in numerous areas, including business strategy development (Morabito and Morabito, 2015), organisational performance (Albors-Garrigos, 2020; Bresciani et al., 2021; Kwon et al., 2021), competitive advantage (Dubey et al., 2018), and new product innovations and developments (Agag and El-Masry, 2016; Babu et al., 2021; Saura et al., 2021). According to the RBV, a company gains an edge over the competition when its personnel, facilities, and other assets come together in ways that are hard for rivals to duplicate. Due to their path dependency, embeddedness, and causal ambiguity, inequitable distribution of these resources among businesses might lead to a competitive advantage (Agag et al., 2019; Barney, 1991).

The term “innovation” refers to the “generation, acceptance, and implementation of new ideas, processes, products, or services” (Ferreira et al., 2020, p. 4). Innovation is critical to a company’s success and growth in today’s highly competitive and unstable marketplaces (Alsuwaidi et al., 2022; Saunila, 2016). Also based on a thorough literature review of the relevant examinations on innovation capability published among 2000 and 2018, innovation capability was identified as “ability to continuously transform knowledge and ideas into new products, processes, and systems for the benefit of the firm and its stakeholders” (Lawson and Samson, 2001, p. 384). Weber and Heidenreich (2018), using data from 154 German high-tech B2B enterprises, also find that collaboration at any step of the innovation process and with any sort of partner can create several benefits for a firm.

Data-driven innovation capabilities in this research align well with the elements of dynamic capabilities theory, as they utilise the infrastructure (e.g., technology) and talent capabilitiy necessary to enhance marketing agility (Alyahya et al., 2023a; Akter et al., 2020; Farah and Ramadan, 2020). For instance, advanced analytics skills (i.e., predictive analytics) are essential for data-centric innovation, as they support or verify the intuitive judgments of innovation talents (Alyahya et al., 2023b; Sultana et al., 2021). Instances of big data initiatives’ success in generating business-related knowledge, providing value to business ecosystems, enhancing performance, and thereby maintaining competitive advantage in the constantly changing market are evident in existing literature (e.g., Alyahya et al., 2023c; Chatterjee et al., 2022; Mikalef et al., 2019). This paper proposes that data driven innovation capability is positively related to marketing agility and competitive advantage in the environment of big data. Companies that put a premium on data analysis are more likely to cultivate skills that enable them to respond to changing market conditions by synthesising information and coming up with novel solutions.

2.3. Marketing agility as a dynamic capability

The concept of marketing agility is still in its infancy. Based on Zahoor et al. (2022), a firm’s marketing efforts may be more agile if management is willing to adapt in response to changing market conditions, consumer preferences, and strategic growth objectives. Agility in marketing is a hallmark of highly adaptable businesses (Eid et al., 2019; Zahoor et al., 2022). Their marketing members collaborate to cater for both consumers and the firm (Alzaidi and Agag, 2022; Perrigot et al., 2021; Zahoor et al., 2022). Marketing agility implies proactivity. Companies attempt to predict their customers’ desires in order to fulfil that demand and retain them as clients. Marketing agility also requires the ability to anticipate and respond to shifting consumer demands (Eid et al., 2020; Elbaz et al., 2018; Gyemang and Emeagwali, 2020). Marketing agility is defined as to a firm’s ability to quickly make and implement marketing decisions in response to shifting market conditions (Alyahya et al., 2022; Kalaignanam et al., 2021). Expanding on this idea, "marketing agility" was defined as firm’s capacity to detect, predict, and comprehend shifts in the marketplace, as well as to rapidly revise its marketing strategy and implement adaptive, timely responses.

Several marketing and non-marketing concepts are conceptually related to marketing agility (Kalaignanam, et al., 2021). The emphasis on marketing decisions is what sets marketing agility apart from agility in other fields (such as software development and supply chain). “Adaptive marketing abilities, market-focused strategy flexibility, market orientation, and market-based organisational learning” are the four fundamental marketing concepts we propose are related to marketing agility. The unique combination of these four conceptual pillars is what sets marketing agility apart from these other frameworks. In contrast to marketing agility, which places a premium on making quick decisions, adaptive marketing capabilities place a premium on learning quickly but not on making decisions quickly. As an addendum, marketing agility is not defined by the fact that adaptive marketing capabilities place an emphasis on mobilising scattered and adaptable partner resources. Moreover, marketing agility differs from market-focused strategic flexibility because the latter does not emphasise the former’s emphasis on rapid market understanding and iterative marketing decision making (Kalaignanam, et al., 2021). Another distinction between marketing agility and market orientation is the former’s priority on rapid decision making and iterative improvement. In conclusion, marketing agility places a greater emphasis on iterative and rapid sensemaking and speedy execution of marketing choices than market-based organisational learning.

A key dynamic capability is agility (Ajgaonkar et al., 2022; Asseraf et al., 2019; Elhoushy et al., 2020; Selim et al., 2022). Teece et al. (1997a,b) argue that to overcome organisational inertia, businesses must constantly reorganise their capabilities. Therefore, companies need to be vigilant and responsive to opportunities and threats while also safeguarding their competitive edge through ongoing investment in resource development. The dynamic capabilities perspective has been employed in several fields (e.g., Blome et al., 2013; Shehawy et al., 2018; Sultana et al., 2022; Ye et al., 2022). Resource integration, reconfiguration and resource acquisition and deployment are examples of dynamic capabilities (Jafari-Sadeghi et al., 2022). Dynamic capabilities are built on sensing and seizing, leveraging, reconfiguring, integrating, learning and creating new knowledge, and leveraging. For instance, sensing and acting quickly are both components of agility (Li et al., 2022). According to the research presented in our study, marketing agility allows retailers to respond rapidly to changes in customer demand and increased competition by reorienting their organisational structure and allocating resources accordingly.

Performance can be boosted, hindered or even negatively impacted by dynamic capabilities (Raj et al., 2023; Shaalan et al., 2022). This exemplifies the different nature of dynamic capabilities as opposed to ordinary ones and are not merely a by-product of business success. Thus, the most suitable context for marketing agility is the dynamic capabilities framework. According to research on marketing agility, marketing agility is an organisation’s ability to monitor changes in the dynamic marketplace and swiftly allocate resources necessary for a creative response (Wang and Hsu, 2018). Marketing agility entails observing situations and acting swiftly (Mandal, 2018; Wood et al., 2021). A company’s responsiveness refers to its ability to capitalise on new opportunities by implementing a series of actions in response to identified promising changes in its environment (Mandal, 2018; Youssef et al., 2022). Utilising a dynamic capabilities viewpoint and in line with Zhou et l. (2019), this research takes a marketing-centric view of agility, defining it as an organization’s capacity to proactively detect marketing opportunities, as well as its capacity to respond swiftly and flexibly to these chances in order to better meet the requirements of its consumers.

3. Conceptual framework and hypotheses development

Our proposed mode (Fig. 1) was developed based on DC and RBV perspectives. The extent to which an organisation can adapt to, and even shape, its swiftly changing business environment relies on its capacity to involves, produce, and reconfigure its internal and external capabilities and resources (Teece et al., 1997a,b; Zahoor et al., 2022). The resource base comprises both “tangible and intangible assets” as well as everyday skills (Gyemang and Emeagwali, 2020). Ability to recognise and evaluate possibilities, act on those opportunities, and adapt to changing circumstances are all essential components of dynamic capacities (Teece et al., 1997a,b). Consequently, this paper investigates the links among data-driven innovation capabilities, marketing agility, and competitive advantage. In addition, it examines the moderating role of market turbulence on the association among marketing agility and competitive

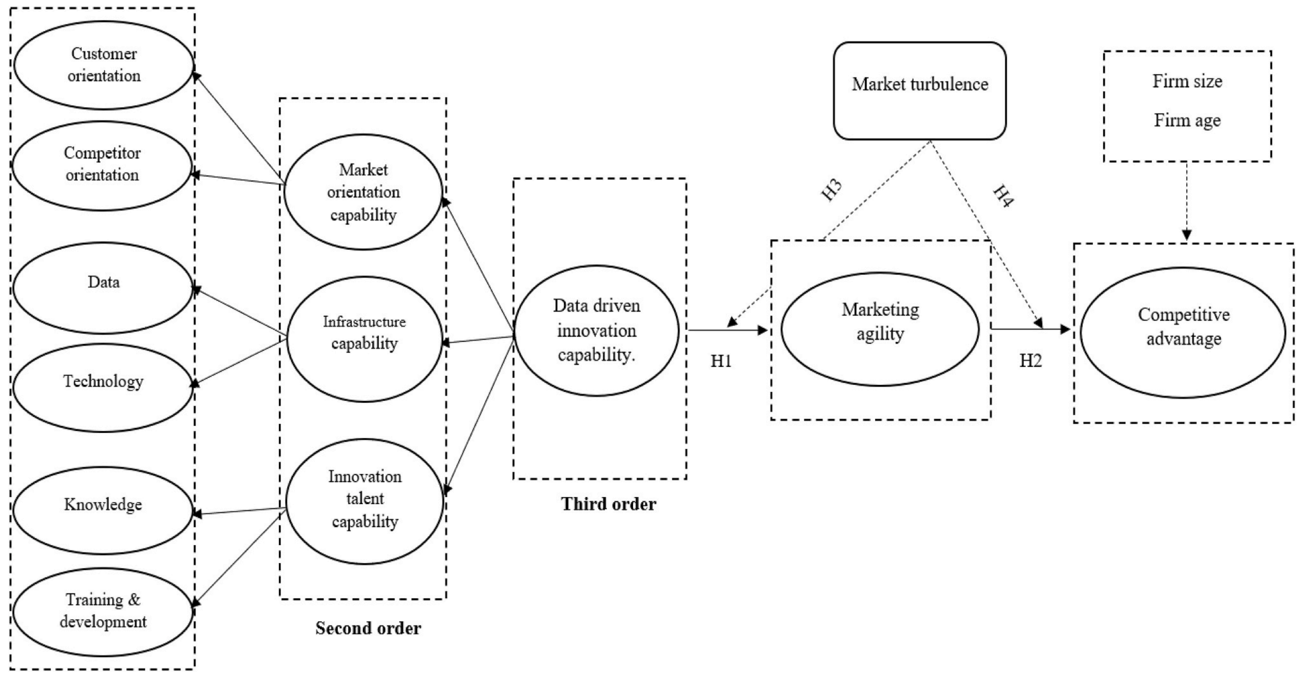

Fig. 1. Research model.

advantage.

3.1. Data driven-innovation capabilities and marketing agility

The firm's nimbleness in recognising opportunities and promptly capitalising on them has been repeatedly praised as a crucial factor in its success in today's fast-paced business context (Sultana et al., 2022). For instance, Bhatti et al. (2022) explored numerous situations and concluded that to succeed with big data analytics for launching new products, businesses needed an in-depth comprehension of consumer adaptability. Wong and Ngai (2022) argued that agile teams might employ strategic management abilities and techniques to foresee market demands and develop innovative value propositions. The innovation cycle of products, services, and business models can be sped up with the help of agility (Bresciani et al., 2021). Agility also helps improve product personalization, delivery performance, and development time (Chatterjee et al., 2022). Market agility has been shown to be a significant indicator of company success (Akter et al., 2020; Del Vecchio et al., 2018). Marketing agility strengthens a company's ability to adapt creatively and nimbly to shifting market conditions and consumer demands (Moktadir et al., 2019).

The present study posits that "marketing agility" is a dynamic capability (Hossain et al., 2022) that can mediate the association among data-driven innovation capabilities (i.e., "market orientation capability, innovation talent capabilities, and infrastructure capabilities") and competitive advantage. Previous examinations on innovation capabilities (Pietronudo et al., 2022), along with earlier research (Iddris et al., 2016), has investigated the links among innovation capabilities and company performance. Several examinations have explored the significance of innovative talents in ensuring continuous growth, profitability, and competitiveness (Behl et al., 2023). Iddris et al. (2016) examined the impact of data-driven innovation capabilities on supply chain integration and financial performance. The effects of data-driven innovation capabilities and the competitive advantage derived from them have yet to be tested. The capacity to innovate is widely accepted as a crucial resource for achieving success in today's rapid, uncertain business landscape (Behl et al., 2023). A company's success improves as its internal capabilities increase (Mikalef et al., 2019). When firms possess the skills and resources to introduce market-oriented innovations, they can maintain a competitive edge and enhance their innovation capacity, both of which contribute to their performance (Zheng et al., 2022). We argue that DDICs are key driver of marketing agility and competitive advantage. Consequently, we suggest the following hypotheses:

H1. "Data driven innovation capability has a significant influence on competitive advantage".

H2. "Data driven innovation capability has a significant influence on marketing agility".

3.2. Marketing agility and competitive advantage

A firm possesses a competitive advantage if its product or service is perceived favourably by its target market's consumers. A firm's competitive advantage is the aggregate outcome of its actions and the managerial decisions that resulted in those outcomes (Yusuf et al., 2022). One company has a competitive advantage compared to its competitors in the same business if it can do things like reduce costs, create innovative products, or deliver superior customer service (Chen, 2019). When existing or potential rivals cannot imitate it, or when it would be extremely costly to emulate it, the company is deemed to have a competitive advantage. We argue that digital capabilities (i.e., data driven innovation capabilities) to be a significant aspect of the dynamic capabilities' model (Teece, 2012), which is important for business success (Eisenhardt and Martin, 2000; Rashid and Ratten, 2021). A business's ability to adapt to shifting market conditions and fend off aggressive competitors are two other vital success factors that must be considered (Qosasi et al., 2019). A firm's competitive advantage can be assessed not only concerning the items it sells but also regarding its intangible capabilities, efficiency, and customer responses to those offerings. According to Asseraf et al. (2019), competitive advantages may stem from various sources. For example, an organisation's competencies are something it can leverage to outperform competitors (Almahamid et al., 2010).

To adapt swiftly to shifting market conditions, successful companies cultivate a culture of marketing agility. Dubey et al. (2018) argue that adaptability in marketing is valuable as demand and supply constantly change in most markets. Firms such as H&M, Mango and Zara employ marketing agility to differentiate themselves from competitors, as stated by Gomes et al. (2020). Zhou et al. (2019) used a survey of 132 participants to experimentally assess their hypothesis stating that marketing agility, along with other competencies (i.e., adaptability and alignment), positively impacts organisational success. Khan (2020) notes that agility contributes to better corporate performance. Agility in both sensing and responding is distinct, yet complementary (Kalaignanam et al., 2021). They are concrete choices that can help maintain a company's competitive edge (Tse et al., 2016). To maintain a long-term competitive advantage, companies must set themselves apart from competitors by offering superior service to their target market. Prior research revealed that agility mediates the association among big data analytics capabilities and competitive advantage (Dubey et al., 2018). Moreover, prior research revealed that agility could mediate the link among DDICs and performance (Sultana et al., 2022). We argue that the relationship between data driven innovation capabilities (i.e., "market orientation capability, infrastructure capability, and innovation talent capability") and competitive advantage is mediated by marketing agility. Consequently, we propose:

H3. "Marketing agility has a significant influence on competitive advantage".

H4. "Marketing agility mediates the link between data driven innovation capability and competitive advantage".

3.3. The moderating role of market turbulence

In the literature, it is suggested that dynamic capabilities hold increased value in chaotic contexts as they contribute to change (Akter et al., 2022). Agility represents the ability to rapidly adapt to new situations and use them to one's advantage. However, there may be inconsistencies in the literature. In highly uncertain environments where accurately predicting events becomes difficult, it is argued that dynamic capabilities instead become experiential and exhibit a weak relationship to performance (Akter et al., 2022). Earlier studies have demonstrated that organisations possessing greater market expertise are more capable of quickly absorbing new knowledge and integrating it into their practices (Osei et al., 2019). Dynamic capabilities tend to replace and restructure routine capabilities. In extremely turbulent markets, they gain more prominence (Teece et al., 1997a,b). Empirical research conducted by Elazhary et al. (2022) indicates that the positive influences of dynamic abilities on routine capabilities are magnified for firms operating in particularly chaotic contexts. The enhanced opportunities and possibility for capability gains, in other words, make it imperative to engage in frequent sensing and swiftly react to new information in a highly unpredictable market. The benefits of utilising marketing capabilities can outweigh the costs associated with doing so under the given conditions (Liang et al., 2022). To keep their routine capabilities aligned with external environments amidst uncertainty, companies need access to rapid, relevant information (Tarn and Wang, 2023). The ability to swiftly adapt marketing strategies to novel circumstances is essential for maintaining a competitive edge in today's business climate. Consequently, we suggest the following hypothesis:

H5. "Market turbulence plays a moderating role on the relationships among marketing agility and competitive advantage; the greater the market turbulence, the stronger the positive association between marketing agility and competitive advantage".

3.4. Longitudinal perspective

All these examinations investigated cross-firm data obtained at a single point in time ("cross-sectional data"), which may explain why there are contradictory correlations between data driven innovation capability, marketing agility, and competitive advantage. To yet, there has been no analysis of data collected from multiple companies over time ("time-series data"). In the short-term or when looking at cross-sectional data, a positive correlation between data driven innovation capability, marketing agility, and competitive advantage. Time series data may be necessary to see the connection clearly (Bernhardt et al., 2000; Roxas, 2022). Efforts to boost data driven innovation capabilities and marketing agility may not immediately result in more profits, but they usually pay off in the long run (Schneider and Sodian, 1991; Sultana et al., 2022).

Companies may see the effect of data-driven innovation capability and agility on competitive advantage (assuming other variables don't change over time), which is a feature unique to time-series data. However, cross-sectional data can be deceiving because it pits one company against another, both of which may experience shifts in their competitive advantage for reasons unrelated to their own data driven innovation capability and marketing agility.

The fact that short-term expenses are spent when attempting to enhance data-driven innovation capabilities and agility is reflected in the usage of cross-sectional data. The sting of these expenditures is diminished over time. Efforts to boost data-driven innovation capabilities and agility may also need some time to bear fruit. Data-driven innovation capabilities in period t will affect marketing agility in period t, but it is unclear whether or not this will translate to a competitive advantage in period t + n. Thus, it is argued that a cross-sectional analysis conceals the underlying impact of data-driven innovation capabilities on marketing agility and competitive advantage. It appears that a longitudinal perspective is required to investigate the relationships between these factors.

4. Research method

4.1. Sample and data collection

We employed positivist research philosophy to test the proposed model. Our questionnaire was designed consistent with prior research on DDICs and agility. We recruited qualified participants from a reputable Saudi Arabia market list firm. This company has a database of greater than 80,000 registered retail companies. This professional firm provides us with a random list included 1000 retail companies in its database across various retailers (i.e., "Department stores, clothing specialty stores, grocery stores, housing specialty stores, clothing supermarkets, grocery supermarkets, housing supermarkets, home improvement stores, and Others"). Furthermore, respondents were required to be "top executives, business managers, operations managers, or IT managers to participate in our study".

We collected the required data at two two-times intervals form the beginning of August 2022 (T) and ending in February 2023 (T+1). One thousand individuals who fulfilled the sample requirements were contacted through email at time T. We were able to use receive 740 respondents who participated in the study. 63 missing data were omitted, thereby 677 responses were valid for further analysis. At time T+1, we repeated the same steps we took initially in order to boost the response rate, and we contacted the same participants in time T. There was a total of 608 respondents over this time period, however we had to eliminate 39 responses due to missing data. Thus, the suggested model was evaluated using a total of 569 valid responses. The representativeness of our sample is in line with managers' survey statistics big data analytics and innovation adoption in Saudi retail industry, which had recently been announced by the Saudi Government (Aseeri and Kang, 2022). Most companies had been established for at least three years (83%) and employed 500 or more individuals (79.5%). Table 1 shows the sampling profile for T and T+1. This indicates that they have previously encountered challenges related to innovation, agility and market turbulence. Most surveyed individuals held senior management or general management positions and were familiar with the issues under discussion.

We investigated if there are significant variances among the early and late participants to evaluate the possibility of nonresponse bias,

Table 1
Participant demographics.

Demographics	T (n = 677)		T+1 (n = 569)	
	Frequency	Percentage %	Frequency	Percentage %
Gender				
Male	349	52	289	51
Female	328	48	280	49
Age				
<30	88	13	85	15
30–40	104	15	78	14
41–50	219	32	169	30
51–60	166	25	162	28
>61	100	15	75	13
Job Position				
Executive	167	25	124	21
Manager	439	65	386	68
Senior staff	71	10	59	11
Firm size				
<200 employees	105	15	89	16
200-500 employees	169	25	126	22
500-1000 employees	361	53	328	58
>1000 employees	42	7	26	4
Retail format				
Department stores	58	8	41	7
Clothing specialty stores	72	11	66	12
Grocery stores	102	15	99	17
Housing specialty stores	69	10	53	9
Clothing supermarkets	55	8	49	8
Grocery supermarkets	79	12	62	10
Housing supermarkets	101	15	80	15
Home improvement stores	46	7	41	7
Others	60	9	57	10
	35	5	21	4

using an approach recommended by Armstrong and Overton (1977). At the 5% level of significance, the chi-square test did not reveal any variances between early and late participants. Consequently, nonresponse bias is not a concern in this examination.

4.2. Measures

We operationalised all the variables of this research using pre-validated measures adopted from previous studies (see Appendix A). Consistent with previous examinations (e.g., Sultana et al., 2022), "our study operationalised data driven innovation capability as a third-order variable comprises of 22 items (9 + 7 + 6), where 9 items (4 + 5) denote market orientation capability, 7 items (3 + 4) present infrastructure capability and 6 items (2 + 4) represent innovation talent capability". Marketing agility was operationalised with nine items adopted from Zhou et al. (2019), for example, "We can spot the first indicators of new market threats". Competitive advantage was evaluated using seven items derived from prior research (Medeiros and Maçada, 2022), such as "Our organization has gained strategic advantages over competitors". Finally, market turbulence was assessed with three items taken from Zhou et al. (2019), like "In our markets, customer preferences change quickly". All measures were evaluated employing a 5-point Likert scale.

We conducted a pilot test to examine the reliability and validity of our study instrument. The questionnaire was delivered to a group of 20 academic staff members and 5 retail managers. The respondents provided us with some comments that aided us to improve our questionnaire in terms of its readability, length, clarity, and format. We administrated two versions of the questionnaire (i.e., English and Arabic). A bilingual individual who was fluent in both Arabic and English developed the questionnaire in English and then translated it into Arabic. Another bilingual individual who is a native Arabic speaker retranslated these questions into English. After looking at the two versions, we found no linguistic or cultural references in the two English versions.

4.3. Common method bias

In this study, we examined and analysed common method variance using two distinct approaches to address the potential CMB issue that might arise in survey-based research. First, we performed Harman's one-factor test, as advised by Podsakoff et al. (2012). The most dominant component accounts for only 31.6% of the total variation, which is considerably below the 50% threshold set by the one-factor test (Podsakoff et al., 2012). Thus, the influence of common method variance is not a significant concern in our investigation. We incorporated a theoretically irrelevant concept (i.e., 'respondents' leisure/catering choice') in the data analysis by employing the "marker variable technique" to assess common method bias (Lindell and Whitney, 2001). Earlier research (e.g., Liu et al., 2023) has suggested using respondents' catering preferences as a marker variable. The analysis indicated that standardised regression weights of the models with and without the common latent variable were found to be comparable ("differences less than 0.2"). Both models had comparable model fit indices ("model with common latent factor: $\chi2/df = 2.1829$; model without CLF: $\chi2/df = 2.4307$"). Thus, the official survey data does not suffer from a severe common method variance problem. For our post hoc assessment of CMV, we followed Malhotra et al.'s (2006) method and settled on a value of 0.02 for the weakest positive correlation between two manifest constructs. We reconducted the analysis after removing this value from each correlation. The corrected correlation estimates were not significantly different from the original results. This test confirmed that the presence of CMV was not a major issue in our investigation (Bozionelos and Simmering, 2022).

4.4. Higher-order measurement model

Due to the nested structure of the proposed model, this research attempts to assess the psychometric qualities of the third order factor (i.e., "data driven innovation capabilities"), and the second order factor (i.e., "market orientation capability, infrastructure capability and innovation talent capability"). Table 2 demonstrated the properties of these variables. This analysis indicates that the path coefficients among the higher-order DDIC variable are significant at the $p < 0.05$ level, lending credence to the notion that this construct is reflective in nature. Examples include the fact that 93% of the variance in DDIC can be attributed to a company's market orientation capability, 91% to its infrastructure capability, and 95% to its innovation talent capability. All of these findings are significant at the at $p < 0.001$ level.

4.5. Measurement comparison

We compared the shifts in the research variables by assessing the variances among the two-time intervals (T and T+1). To determine whether there were statistically significant shifts between T and T+1 in the means of the two variables, we used a pairwise *t*-test. Table 3 demonstrates that the variances between two times (T and T+1) remained the same. In addition, the consistency of all Cronbach's alphas was maintained.

5. Analysis and results

PLS technique was employed to assess shifts in data driven innovation capability, marketing agility, and competitive advantage. "Partial least squares" (PLS), according to Hulland (1999), is the method of choice when trying to assess highly structured and complex models. Specifically, "PLS is more robust with fewer identification issues, works with much smaller as well as much larger sample, and readily

Table 2
Assessment of the higher-order, reflective model.

Models (T)	Latent constructs	AVE	CR	Dimensions	β	t-statistic
Third order	"Data-driven Innovation Capabilities" (DDIC)	0.6105	0.9670	- "Market orientation capability"	0.6290	23.039
				- "Infrastructure capability"	0.4716	27.120
				- "Innovation talent capability"	0.5883	38.015
Second-order	- "Market orientation capability"	0.5269	0.9520	- "Customer orientation"	0.3789	21.267
	- "Infrastructure capability"	0.6271	0.9721	- "Competitor orientation"	0.4783	18.920
	- "Innovation talent capability"	0.6602	0.9356	- "Data "	0.6372	34.230
				- "Technology"	0.7041	47.029
				- "Knowledge"	0.5680	26.337
				- "Training and development"	0.4219	21.209
Models (T+1)	Latent constructs	AVE	CR	Dimensions	β	t-statistic
Third order	"Data-driven Innovation Capabilities" (DDIC)	0.5849	0.9521	- "Market orientation capability"	0.5926	23.039
				- "Infrastructure capability"	0.4027	27.120
				- "Innovation talent capability"	0.3252	38.015
Second-order	- "Market orientation capability"	0.5730	0.9628	- "Customer orientation"	0.3927	39.028
	- "Infrastructure capability"	0.6629	0.9820	- "Competitor orientation"	0.4023	23.201
	- "Innovation talent capability"	0.5210	0.9421	- "Data"	0.5478	31.267
				- "Technology"	0.6129	26.197
				- "Knowledge"	0.4463	22.385
				- "Training and development"	0.6172	35.992

incorporates formative as well as reflective constructs" (Hair et al., 2021, P.143). Kock (2022) revealed that utilising PLS can maximize the proposed model prediction power through adjusting the principal component weights. Our study utilises the "cross-lagged panel method" (CLPM) to assess the "longitudinal data".

5.1. Measurement model

We checked the model's validity and reliability of each factor utilising "Cronbach's alpha" (CA) and "composite reliability" (CR) for T and T+1. We inferred construct reliability because all CA and CR estimations were greater than 0.70 (Hair et al., 2021). The second thing we did was check the convergent validity with the use of factor loadings. All of the factor loadings in Table 3 are statistically significant and more than 0.70 for T and T+1 (Kline, 2012), demonstrating convergent validity. We also considered the "average variance extracted" (AVE) to check convergent validity at the level of constructs. AVE for all variables were greater than 0.50 (Bagozzi et al., 1991), indicating that the variables accounted for more than 50% of the variation in the items and demonstrating convergent validity (Fornell and Larcker, 1981). We also calculated the square root of the AVE and compared it to the correlation among the latent variables (Fornell and Larcker, 1981). "Discriminant validity" was met because the square root of AVE was higher than the inter-variable correlation (see Table 4).

5.2. CLPM of path analysis

PLS-SEM evaluates how well the hypothesised H1–H4 structural models predict future outcomes. In order to establish reliable cause-and-effect associations, we used a "CLPM of longitudinal data analysis" (Anderson and Kida, 1982; Selig and Preacher, 2009; Tyagi and Singh, 2014). CLPM provides a reliable method of assessing variables repeatedly and then evaluating the strength of temporal precedence by one variable over another (Martens and Haase, 2006), and is therefore often referred to as a quasi-experimental approach (Anderson and Kida, 1982). Using this method, we can find out whether one variable is having a substantial impact on another, or if the association is more circular (i.e., "reverse causality"). Based on the CLPM, an independent construct X1 (i.e., "X measured in t1") that causes a dependent construct Y1 (i.e., "Y measured in t1") should also be a strong temporal driver of a second dependent variable Y2 (i.e., "Y measured in t2"). To disprove the possibility of reverse causation and to develop the temporal precedence ("causal effects") of X over Y, it is necessary to show that the level of the X1-Y2 association is higher than the effects of Y1 on X2 (i.e., "X measured in t2"). CLPM is based on the tenets of "synchronicity, stationarity and stability" (Selig and Preacher, 2009). When the target variables are measured at the same time (i.e., "t1"), this is called synchronous measurement (Kenny et al., 1998; Roxas, 2021). The premise of synchronous data was met in our examination because DDIC, AGT, and CMD (together with the control variables) were all assessed at the same time in both t1 and t2. Stationarity necessitates that the DDIC-AGT-CMD structural model be relatively stable over time. Autocorrelations of DDIC, AGT, and CMD between t1 and t2 that are statistically significant are indicative of stability (Kenny et al., 1998; Roxas, 2022). Table 5 demonstrates the CLPM analysis outcomes.

Model A is the standard stationary model displaying the estimated associations between the three variables at times T1 and T2. All DDIC-AGT-CMD linkages have statistically significant intratime path coefficients. The Fisher's z test of variance (Diedenhofen and Much, 2015) among the path coefficients for DDIC1-AGT1 against DDIC2-AGT2 and AGT1-CMD1 versus DDIC2-CMD2 produced z values of −2.109 ($p = 0.26$) and 2.027 ($p = 0.39$) respectively. The data appear to be adequately and acceptably stationary at $a = 0.05$ level of significance, as indicated by the Fisher z-test.

Statistically significant inferences can be made from the path coefficients due to their large effect size (see column 3). The r 2 values show how much difference in one variable (i.e., AGT1) can be accounted for by changes in a different variable (i.e., DDIC1). All Stone-Geisser Q2 values are greater than zero, demonstrating that the predictive power of the underlying structural model is sufficient (Geisser, 1975). For PLS-SEM applications, the corresponding indices for describing the goodness-of-fit between the suggested model and the data are shown in the final column (Hair et al., 2021; Kock, 2022). Both the "average path coefficient" (APC) and the "average r 2" (ARS) should be statistically significant for a model to be considered reliable (Kock, 2022). According to Kock (2022), the optimal value for the "average variance inflation factor" (AVIF) is less than 3.3, and the minimum value for the "Tenenhaus' Goodness of Fit" (GoF) index for a sufficiently big effect size is 0.36. Kock (2022) explains that the average predictive power, the average a priori explanatory power of the exogenous constructs, and the average level of multicollinearity are all measures of the strength and significance of the associations among the model's factors. The "Sympson's Paradox Ratio" (SPR) quantifies the degree to which a statistical occurrence indicating a causality issues, such as implausible or reverse causality concerns, does not taint a model. The lack of "Sympson's paradox" (i.e., "credible causal associations and no problem with reverse causality") is shown by an SPR equal to 1 or more than 0.70. Finally, a strong indicator of the hypothesised causal linkages between the factors is "the non-linear bivariate causality direction ratio" (NLBCDR). If the value is 1 or greater, then the postulated causal associations are likely,

Table 3
Measurement statistics of construct scale.

Construct/Indicators	Standard Loading		CR		Cronbach's α		AVE		Mean		SD		Δ
	T	T+1	T	T+1	T	T+1	T	T+1	T	T+1	T	T+1	
Competitive advantage (CMD)													
CMD1	0.93	0.90	0.94	0.92	0.91	0.89	0.549	0.607	2.34	2.12	0.89	0.83	0.05 (ns)
CMD2	0.95	0.94							2.90	2.67	0.83	0.86	
CMD3	0.87	0.93							2.37	2.09	0.82	0.80	
CMD4	0.94	0.91							3.02	2.97	0.79	0.75	
CMD5	0.89	0.88							2.78	2.36	0.85	0.78	
CMD6	0.90	0.94							2.30	2.03	0.83	0.89	
CMD7	0.93	0.92							2.78	2.18	0.80	0.86	
Marketing agility (MAG)													
MAG1	0.94	0.89	0.97	0.94	0.95	0.93	0.610	0.592	3.08	2.19	0.85	0.89	0.09 (ns)
MAG2	0.89	0.90							2.09	2.45	0.83	0.90	
MAG3	0.95	0.94							2.48	2.78	0.82	0.82	
MAG4	0.89	0.84							2.12	2.35	0.85	0.85	
MAG5	0.93	0.89							2.89	2.10	0.89	0.81	
MAG6	0.95	0.90							2.38	2.06	0.79	0.84	
MAG7	0.93	0.95							2.36	2.37	0.84	0.85	
MAG8	0.91	0.94							3.04	2.08	0.80	0.79	
MAG9	0.90	0.90							2.38	3.19	0.91	0.91	
Competition Orientation (COM)													
COM1	0.94	0.89	0.94	0.96	0.93	0.95	0.519	0.583	2.10	3.29	0.90	0.89	0.01 (ns)
COM2	0.87	0.94							2.39	2.34	0.84	0.85	
COM3	0.94	0.93							2.07	2.18	0.80	0.83	
COM4	0.92	0.90							2.19	2.45	0.82	0.80	
COM5	0.90	0.91							2.18	2.36	0.79	0.86	
Customer Orientation (CUS)													
CUS1	0.96	0.90	0.93	0.90	0.92	0.88	0.581	0.627	2.10	2.12	0.89	0.84	0.07 (ns)
CUS2	0.93	0.95							3.28	2.36	0.90	0.80	
CUS3	0.91	0.89							3.10	3.09	0.79	0.86	
CUS4	0.95	0.93							2.73	2.18	0.83	0.81	
Data (DAT)													
DAT1	0.93	0.89	0.94	0.91	0.93	0.89	0.590	0.609	2.38	2.12	0.90	0.79	0.03 (ns)
DAT2	0.96	0.94							2.57	2.30	0.84	0.82	
DAT3	0.90	0.86							2.39	2.41	0.78	0.85	
Technology (TEC)													
TEC1	0.94	0.89	0.96	0.94	0.95	0.92	0.528	0.589	2.78	2.36	0.85	0.81	0.01 (ns)
TEC2	0.91	0.93							2.35	2.30	0.83	0.85	
TEC3	0.97	0.95							3.20	2.56	0.89	0.72	
TEC4	0.93	0.92							2.31	2.14	0.73	0.79	
Knowledge (KNW)													
KNW1	0.94	0.95	0.93	0.95	0.92	0.93	0.521	0.506	2.37	3.12	0.84	0.79	0.06 (ns)
KNW2	0.91	0.93							2.93	3.09	0.81	0.83	
Training and Development (TRD)													
TRD1	0.89	0.92	0.95	0.96	0.93	0.94	0.650	0.627	3.10	2.38	0.90	0.83	0.08 (ns)
TRD2	0.94	0.95							3.09	2.35	0.85	0.81	
TRD3	0.93	0.89							2.37	2.10	0.79	0.90	
TRD4	0.90	0.93							2.63	2.37	0.83	0.77	
Market turbulence (MAT)													
MAT1	0.93	0.92	0.94	0.92	0.93	0.90	0.679	0.521	2.39	3.12	0.83	0.85	0.02 (ns)
MAT2	0.86	0.90							2.28	2.87	0.81	0.83	
MAT3	0.90	0.93							2.70	2.09	0.79	0.89	

and the possibility of reverse causality is eliminated from the model (Kock, 2022).

In Model B, the values of the variables at T1 are connected with those at T 2. The autoregressive trajectories displayed by this model provide evidence for the consistency of the research's conceptual frameworks (Kenny et al., 1998; Martens and Haase, 2006). The next three models are cross-lagged examples of stability models demonstrating the sequential incorporation of components in driving dependent constructs at time point T2. Which structure is a better temporal driver or cause of another is revealed by cross-lagged structural models (Martens and Haase, 2006). "The baseline models and cross-lagged effects" of relevant T1 variables on T2 variables are displayed in Model E, the final model in CLPM examination. The model has considerable predictive validity for hypothesis testing, as evidenced by good goodness of fit indices.

5.2.1. Hypothesis 1: DDIC→CMD

Our analysis revealed a significant and positive impact of DDIC1 on AGT1($\beta = 0.54^{**}$), with a large effect size of this relationship (*F2* = 0.51). It also indicated that AGT1has no significant influence on DDIC2 ($\beta = 0.10$), with a small effect size. This confirms "the temporal precedence causal effects" of DDIC on AGT, as indicated by the Fisher's z value of 2.801 ($p = 0.001$), demonstrating support for H1.

5.2.2. Hypothesis 2: DDIC→AGT

The analysis revealed that DDIC1was found to have a positive and significant impact on CMD2 ($\beta = 0.60^{**}$), with a large effect size (*F2* = 0.56), while CMD1 has no significant influence on DDIC2 ($\beta = 0.12$), with a small effect size. The analysis also revealed that the Fisher's z value is 2.08 ($p = 0.001$). This confirms the "temporal precedence causal effects" of DDIC on CMD, demonstrating support for H2.

5.2.3. Hypothesis 3: AGT→CMD

With a large effect size (*F2* = 0.52), AGT1 was found have a significant impact on CMD2 ($\beta = 0.54^{**}$). In contrast, CMD1 has no effect on AGT1 ($\beta = 0.14$). Fisher's z = 1.829 ($p > 0.05$), proving the "temporal precedence" of AGT over CMD, demonstrating support for H3.

Table 4
Correlation table.

Variables	CMD(T)	MAG(T)	COM(T)	CUS(T)	DAT(T)	TEC(T)	KNW(T)	TRD(T)	MAT(T)
CMD (T)	0.741								
MAG (T)	0.398	0.781							
COM (T)	0.271	0.430	0.720						
CUS (T)	0.429	0.293	0.276	0.761					
DAT (T)	0.447	0.280	0.522	0.590	0.768				
TEC (T)	0.236	0.336	0.290	0.263	0.287	0.727			
KNW (T)	0.390	0.291	0.353	0.273	0.321	0.290	0.721		
TRD (T)	0.463	0.317	0.225	0.601	0.399	0.562	0.437	0.806	
MAT (T)	0.251	0.526	0.518	0.447	0.287	0.619	0.260	0.318	0.824
Variables	CMD (T+1)	MAG (T+1)	COM (T+1)	CUS (T+1)	DAT (T+1)	TEC (T+1)	KNW (T+1)	TRD (T+1)	MAT (T+1)
CMD (T+1)	0.779								
MAG (T+1)	0.337	0.769							
COM (T+1)	0.325	0.446	0.764						
CUS (T+1)	0.437	0.293	0.459	0.792					
DAT (T+1)	0.278	0.297	0.238	0.437	0.780				
TEC (T+1)	0.476	0.276	0.410	0.392	0.328	0.767			
KNW (T+1)	0.562	0.520	0.423	0.417	0.209	0.412	0.711		
TRD (T+1)	0.309	0.129	0.489	0.225	0.512	0.290	0.227	0.791	
MAT (T+1)	0.321	0.265	0.217	0.461	0.327	0.237	0.418	0.410	0.722

5.2.4. *Hypothesis 4: DDIC→CMD: the mediating influence of AGT*

The direct and indirect impact of DDIC on CMD via the mediating influence of AGT in T1 and T2 are shown in Table 6 in the mediated Models A and B. The findings from T1 and T2 indicate that AGT has a significant mediating impact on the DDIC-CMD correlations. Cross-lagged T1 and T2 data, as in Model C, were also found to have mediating influence when using the methods of Selig and Preacher (2009) and Cole and Maxwell (2003). Positive and statistically significant impact of DDCI1 on AGT2 and CMD2 are found in model C. Additionally a significant mediated effects of DDCI1 on CMD2 via AGT2 was found in Table 6. According to the goodness-of-fit indexes, mediated models are sufficiently predictive. Therefore, H4 is supported.

A moderating effect test was conducted using the PROCESS macro method (Hayes, 2012). Table 7 presents the PROCESS macro results, which reveal a positive and statistically significant interaction influence of marketing agility and market turbulence on competitive advantage for T+1 and T+2 ($\beta = 0.43$, 35, $t = 8$ 0.12, 6.56, $p < 0.001$), demonstrating support for H5.

6. Discussion and conclusion

6.1. *Key findings*

This paper addresses four research questions: (1) What is the effect of data-driven innovation capabilities on competitive advantage? (2) Does marketing agility mediate the link among data-driven innovation capabilities and competitive advantage? (3) Does market turbulence moderate the link among marketing agility and competitive advantage? and (4) How do the data driven innovation capability–marketing agility–competitive advantage hypotheses hold up when assessed employing CLPM of analysis of longitudinal data"?

In line with the resource-based view and the dynamic capabilities, an integrated conceptual framework was developed and tested to understand the links among data-driven innovation capabilities, marketing agility, and competitive advantage. It also explores the role of market turbulence on these relationships. This research emphasizes the overall implications of data-driven innovation capabilities on marketing agility and competitive advantage. Our analysis revealed that data-driven innovation capability proved to be the strongest driver of marketing agility. Previous studies have shown that market orientation capabilities are essential drivers of data-driven innovation capabilities and business performance, consequently improving competitive advantage (Babu et al., 2021; Bhatti et al., 2022; Dubey et al., 2018; Sultana et al., 2022). For instance, Dubey et al. (2018) highlighted that businesses must be able to recognise and synthesise highly competitive market conditions and adapt to consumers' changing wants and needs to create and maintain a competitive advantage in the data-driven innovation process. These findings extend the previous research debates on competitive advantage, which concentrated on organisational and technological factors as its main predictors (Riikkinen et al., 2018). Focusing on DDICs and marketing agility as dynamic capabilities and how these two constructs sequentially explain competitive advantage, this study's findings provide a distilled argument on the roles played by each in achieving competitive advantage.

The significant and positive causal impact of DDIC on AGT propose the crucial impact of data driven innovation capabilities in influencing how companies design and create their strategic reply to technological and innovation changes. Enhancing marketing agility through data-driven innovation relies heavily on innovative talent capabilities, indicating that the contribution of such talents is significant. A recent study's results show that talent skills are crucial in creating effective capacity for dynamic business analytics (Del Vecchio et al., 2018). Thirdly, infrastructure capability emerges as an essential contributing element for marketing agility, stressing the importance of a long-term technical infrastructure according to artificial intelligence and machine learning. This enables the collection and utilisation of valuable insights hidden within data for fostering data-centric innovation. Akter et al.'s (2021) claim that "a wide variety of cutting-edge technologies needed to be developed, acquired, and mastered … New "agile" analytic methodologies and machine learning techniques are being utilised to augment them to create insights at a far faster rate" (p. 523), supports this. Although the findings underline the value of all three data-driven innovation capability components, it appears that they are all necessary for achieving marketing agility.

The validated mediating role of AGT in the DDIC-CMD association show the strategic adaptation and choice that companies can easily exercise in regard to the "market orientation capability, the infrastructure capability, and the innovation talent capability". Firms' management of the link between technology and innovation and the structure of their organisations is illuminated by AGT's crucial role in explaining how DDIC can lead to CMD (Sultana et al., 2022). Moreover, our hypothesis that high market turbulence would strengthen the link among marketing agility and competitive advantage was confirmed. These findings are aligned with previous research demonstrating that market turbulence plays a moderating influence in the links among agility and competitive advantage (Bresciani et al., 2021; Dubey et al., 2018).

Employing longitudinal data and CLPM in our examination provides meaningful insights into the robustness, stability, predictive power, and

Table 5
The baseline stationary, stability and cross-lagged models.

Models	β	Effect size	r 2	Q2	Goodness-of-fit indices
A: Baseline stationary model					
Direct paths:					APC = 0.736*
DDIC1→AGT1	0.38**	0.26	0.25	0.25	ARS = 0.531*
AGT1→CMD1	0.63**	0.58	0.58	0.58	AVIF = 2.085
DDCI2→AGT2	0.49**	0.41	0.41	0.41	GoF = 0.741
AGT2→CMD2	0.67**	0.52	0.52	0.51	SPR = 1.00
					NLBCDR = 1.00
B: Baseline stability model					
Direct paths:					APC = 0.709*
DDIC1→DDIC2	0.43**	0.29	0.28	0.28	ARS = 0.472*
AGT1→AGT2	0.56**	0.52	0.52	0.52	AVIF = 2.568
CMD1→CMD2	0.48**	0.45	0.45	0.44	GoF = 0.651
					SPR = 1.00
					NLBCDR = 1.00
C: Cross-lagged DDCI					
DDIC1→DDIC2	0.31**	0.21	0.21	0.21	APC = 0.629*
AGT1→AGT2	0.69**	0.62	0.62	0.62	ARS = 0.340*
CMD1→CMD2	0.45**	0.40	0.40	0.40	AVIF = 2.789
DDIC1→AGT2	0.47**	0.42	0.41	0.41	GoF = 0.621
DDIC1→CMD2	0.62**	0.57	0.56	0.56	SPR = 1.00
					NLBCDR = 1.00
D: Cross-lagged DDCI and AGT					
DDIC1→DDIC2	0.56**	0.48	0.48	0.48	
AGT1→AGT2	0.32**	0.27	0.27	0.27	APC = 0.528*
CMD1→CMD2	0.41**	0.36	0.36	0.36	ARS = 0.303*
DDIC1→AGT2	0.38**	0.32	0.32	0.32	AVIF = 2.792
DDIC1→CMD2	0.64**	0.61	0.61	0.61	GoF = 0.605
AGT1→DDIC2	0.11	0.08	0.07	0.07	SPR = 1.00
AGT1→CMD2	0.22**	0.19	0.18	0.18	NLBCDR = 1.00
E: Cross-lagged DDCI and AGT					
DDIC1→DDIC2	0.38**	0.25	0.24	0.24	
AGT1→AGT2	0.31**	0.29	0.29	0.29	
CMD1→CMD2	0.29**	0.18	0.18	0.18	
DDIC1→AGT2	0.54**	0.51	0.51	0.51	APC = 0.407*
DDIC1→CMD2	0.60**	0.56	0.56	0.56	ARS = 0.237*
AGT1→DDIC2	0.10	0.02	0.02	0.02	AVIF = 2.820
AGT1→CMD2	0.54**	0.52	0.52	0.52	GoF = 0.526
CMD1→DDIC2	0.12	0.11	0.11	0.11	SPR = 1.00
CMD1→AGT2	0.14	0.14	0.13	0.13	NLBCDR = 1.00

Note.
APC, average path coefficients (should be significant); ARS, average r-squared (should be significant); AVIF, average variance inflation factor (ideal if > 3.3); NLBCDR, non-linear bivariate causality direction ratio (acceptable if ≥ 0.70; Q2, Stone–Geisser q-squared (should be greater than zero); r 2, r-squared; SPR, Sympson's Paradox Ratio (ideal if 1.00); Tenenhaus' GoF, goodness-of-fit (large effect if ≥ 0.36.
Cohen's *f2* (Cohen, 1992): small = 0.20, medium = 0.50, large = 0.80.
**p < 0.01. *p < 0.0.

Table 6
Testing for mediating effect.

Models	β	Effect size	r 2	Q2	Goodness-of-fit
A: Time 1 model					
Direct effects					
DDIC1→AGT1	0.49**	0.42	0.40	0.40	
DDIC1→CMD1	0.33**	0.31	0.29	0.29	APC = 0.492*
AGT1→CMD1	0.56**	0.52	0.50	0.49	ARS = 0.420*
Indirect effects					AVIF = 2.321
DDIC1→AGT1→CMD1	0.17*	0.13	0.11	0.11	GoF = 0.573
Total effects					SPR = 1.00
DDIC1→AGT1→CMD1	0.58**	0.56	0.54	0.54	NLBCDR = 1.00
B: Time 2 model					
Direct effects					
DDIC2→AGT2	0.54**	0.51	0.51	0.51	
DDIC2→CMD2	0.31**	0.26	0.23	0.23	APC = 0.521*
AGT2→CMD2	0.59**	0.50	0.47	0.47	ARS = 0.508*
Indirect effects					AVIF = 2.410
DDIC2→AGT2→CMD2	0.23**	0.21	0.18	0.18	GoF = 0.593
Total effects					SPR = 1.00
DDIC2→AGT2→CMD2	0.62**	0.58	0.55	0.55	NLBCDR = 1.00
C: Time 1 and 2 models					
Direct effects					
DDIC1→CMD2	0.44**	0.43	0.42	0.42	
DDIC1→AGT2	0.39**	0.36	0.36	0.36	APC = 0.427*
AGT2→CMD2	0.27**	0.25	0.24	0.24	ARS = 0.418*
Indirect effects					AVIF = 2.730
DDIC1→AGT2→CMD2	0.26**	0.24	0.23	0.23	GoF = 0.631
Total effects					SPR = 1.00
DDIC1→AGT2→CMD2	0.63**	0.61	0.57	0.57	NLBCDR = 1.00

Table 7
Model coefficients for the conditional process models.

Predictor	β	SE	t	CI
Market turbulence (Time 1)				
Constant	1.302	0.03	−0.26	−0.04, 0.03
Firm size	−0.04	0.17	−0.44	−0.05, 0.18
Firm age	0.08	0.14	−0.17	−0.35, 0.02
Marketing agility (AGT)	1.09**	0.01	6.12	0.12, 1.30
Competitive advantage (CMD)	1.13**	0.08	4.23	0.16, 1.05
Market turbulence (MAT)	0.56**	0.08	3.29	0.13, 1.23
MAG X MAT	0.43**	0.05	8.12	0.13, 1.50
CMD X MAT	0.37**	0.02	2.20	0.12, 0.20
Market turbulence (Time 2)				
Constant	1.46	0.14	−0.28	−0.05, 0.02
Firm size	−0.08	0.17	−0.15	−0.03, 0.05
Firm age	0.03	0.13	−0.26	−0.05, 0.09
Marketing agility (MAG)	1.47***	0.05	5.40	0.47, 1.54
Competitive advantage (CMD)	0.37**	0.06	7.46	0.32, 1.64
Market turbulence (MAT)	0.24*	0.03	2.34	0.19, 1.34
MAG X MAT	0.35*	0.05	5.56	0.16, 1.56
CMD X MAT	0.41**	0.07	9.30	0.04, 0.76

Note: CI = 95% confidence interval. Unstandardized regression coefficients were reported. Bootstrap samples = 5000. One tail *t*-test was used for interaction terms. *** p < 0.001. ** p < 0.01. * p < 0.05.

reliability of the DDIC-AGT-CMD links as shown in the validated structural models. By using CLPM, this study emphasizes "the positive and causal lagged influences" of DDIC on AGT and on CMD and that of AGT on CMD while statistically discounting the possibility of reversed causal associations, in contrast to prior research on the same subject that utilised "single-wave cross-sectional data" (e.g., Chaudhry and Amir, 2020). There is empirical evidence for the arguments regarding technological and innovation determinism on the one hand and strategic adaptation on the other, which, when combined, provide a more "nuanced and robust" justification on how and why retailers develop innovations capabilities to accommodate the changes and challenges in the external markets.

6.2. Theoretical implications

Limited research has been conducted about "big data-centric innovation capabilities" and marketing agility, despite their continued prominence as a significant issue for innovation management (Bhatti et al., 2022; Sultana et al., 2022). This paper makes numerous theoretical advances. We combine findings from the resource-based approach, dynamic capabilities theory, and emerging big data literature to deliver concrete theoretical insights.

First, this research is the initial attempt to conceptualise data-driven innovation capabilities and marketing agility from a dynamic capability's perspective; it is also the first to empirically analyse and offer evidence for the link over time. The second original contribution of this paper is its exploration and validation of marketing agility's mediating influence in the link among data-driven innovation capabilities and competitive advantage. This paper provides theoretical contribution the literature review by demonstrating how marketing agility serves as a catalyst between data-oriented innovation capabilities and a company's competitive edge (Akter et al., 2021). Therefore, this implication stresses the importance of companies' capacities (i.e., "innovation capabilities") to monitor and adapt to shifting external conditions, seize emerging market opportunities, and influence customer preferences (Bresciani et al., 2021; Del Vecchio et al., 2018; Sultana et al., 2022), subsequently investing in agile strategies to capitalise on these abilities. Through this research, significant progress is made in the concept of dynamic capacities. Applying the research on data-centric innovation capacity to the field of new products innovations is aided by the results on "market orientation, infrastructure, and innovation talent capabilities". For instance, our study demonstrates that "market orientation capability and innovation talent capabilities" are the two most crucial components of data-driven innovation capabilities, and consequently, marketing agility and competitive advantage.

Furthermore, this study proposes that incorporating market-sensing mechanisms and market intelligence capacities into business models is crucial for the time-to-market of data products, as contributed by market orientation for data-driven innovation capabilities (Babu et al., 2021). In summary, the study's findings offer empirical evidence that both big data-centric innovation and marketing agility are widely acknowledged as vital to success in today's rapidly evolving business environment. The results also illustrate how a firm can maintain its agility and achieve its competitive performance objectives by continually balancing its innovation and other competencies (Saura et al., 2021).

In addition, this study suggests that incorporating market-sensing mechanisms and market intelligence capabilities into the business model is essential for the time-to-market of data goods, all thanks to the contribution of market orientation for data driven innovation capabilities (Sultana et al., 2022). This theoretical work, then, broadens the scope of market orientation theory in the study of innovation. Overall, the study's findings provide factual proof that big data-centric innovation and marketing agility are seen as essential contributing factors for competitive advantage in today's disruptive climate. The results also show that the dynamic balance of innovation and other competencies is crucial to achieving the desired strategic competitive performance for maintaining agility (Bhatti et al., 2022).

Additionally, our research is the first to empirically investigate how market turbulence affect the relationships among marketing agility and competitive advantage. Thus, this paper enhances the literature by improving our understanding of the various connections between a set of potential outcomes, such as marketing agility and competitive advantage, a set of potential responses, such as market turbulence, and a set of potential antecedent conditions, such as innovation capabilities. This enables us to gain more insight into the circumstances under which data-driven innovation capabilities can enhance marketing agility. As it cannot fully comprehend the complexities involved in combining resources and talents, we provide a robust theoretical foundation for our empirical examination of data-driven innovation capabilities as a driver of marketing agility by merging the perspectives of data-driven innovation and marketing agility (Chatterjee et al., 2021).

6.3. Practical implications

The choices managers make regarding the amount of time and money to allocate towards developing data-driven products and services might be influenced by the positive correlation between data-driven innovation capabilities (i.e., "market orientation capability, infrastructure capability, and innovation talent capability") and competitive advantages discovered in this study. Considering marketing agility's mediating effect on the relationship, it is logical for businesses to invest substantial resources in developing this capability to flourish in an environment characterised by uncertainty, volatility, and rapid change. Moreover, within the big data economy context, managers should consider the three components of data-driven innovation capabilities (i.e., "market orientation capability, infrastructure capability, and innovation talent capability") emphasised by this research. To achieve optimal system performance, it is essential that managers comprehend the time and resources necessary at each stage of the innovation process.

A lack of skills to produce data outcomes and convert them into novel value-added services for consumers renders investments in a project's technology infrastructure futile. Additionally, data-driven businesses might employ the suggested methodology to identify any existing strategic gaps in their data-driven innovation capabilities. In terms of product innovation, for instance, managers may evaluate whether a particular capability ("i.e., innovation talent") is underperforming or generating poor output compared with others (e.g., "market orientation capability or infrastructure capability"). Our study posits that retail managers must prioritize and invest in data driven innovation capabilities. Based on the results of our study, retail managers should invest in complementary assets such as marketing agility which enables retailers to improve their viability in a volatile, unpredictable, and rapidly changing environment. Retailers should invest in the three constructs (i.e., "market orientation capabilities, infrastructure capability, and innovation talent capability") to check the effectiveness of the entire system. Managers, for instance, may look to data-driven service improvements that provide a competitive advantage over rivals in order to expand into new product and market categories. In addition, they could routinely and frequently compare the level of satisfaction their service innovation receives from customers.

In addition, the proposed approach can be used by data-driven companies to identify the existence of any strategic gaps in their data-driven innovation capabilities. Understanding the many parts necessary to deploy data driven innovation capabilities efficiently is useful for companies who are just starting out on the big data adoption path as well as those that are well down the way. This study's findings have important practical ramifications; thus, it will help managers and policymakers craft effective plans for fostering data-driven innovation capacities.

Another important result of this study is the dissemination of detailed information about the potentials of creating a data-centric product in terms of measuring improved performance on new data products. Managers of new data products can benefit from gaining a deeper understanding of the implications of integrating diverse components, such as "management skills, internal talent, and physical and technical infrastructure", in order to ensure optimal performance, as measured by increased consumers satisfaction and profit margins. Examples of use cases for which firms may want to investigate and implement AI solutions include data-driven service innovation. For data-driven service innovation, they need also have analytics professionals with the proper abilities to do their duties.

Our findings also support the notion that companies led by individuals who utilise cutting-edge technology to enhance employee skills might anticipate gaining a competitive advantage in the marketplace (Babu et al., 2021; Mikalef et al., 2019). However, a thorough understanding of organisational flexibility is imperative before building data-driven innovation capabilities. The ability to adjust organisational structures and resource allocations epitomises organisational flexibility swiftly and efficiently. Our findings suggest that organisational flexibility, combined with data-driven innovation abilities, considerably enhances marketing agility in inherently uncertain environments. Managers require an in-depth comprehension of fostering this essential dynamic talent, even as research indicates that data-driven innovation capabilities yield benefits. Given the substantial time and money required for developing data-driven innovation abilities, this issue is of utmost importance. Consequently, practitioners might fail to achieve the desired outcome through data-driven innovation capabilities if they lack an appropriate understanding of the resources and competencies needed for their construction. Managers should offer analytics training to their employees for service innovations.

Incorporating marketing agility into retailers' system should be approached with a long-term strategic management perspective, as evidenced by the relevance of AGT and its lagging impacts on CMD, which should encourage retailers to do so. Successfully devising and implementing effective AGT fit for retailers' capabilities and resource constraints depends on the development of their innovation and technological competences and capabilities. Furthermore, as part of the system-wide incorporation of innovations sustain capability in businesses, retailers are urged to persistently pursue AGT.

7. Limitations and directions for future studies

Our examination presents some limitations, offering potential directions for further investigations. First, our exploration was carried out in a developing society like Saudi Arabia. Data from a developed country could be employed to challenge the proposed conceptual framework in terms of geography and language. Second, our research concentrates on the influence of data-driven innovation capabilities and marketing agility on competitive advantage. Future investigations could incorporate additional dependent variables like financial performance and firm value. Third, this study has only included marketing agility as the single mediator of the link between data driven innovation capabilities and competitive advantage. Therefore, more capability-related characteristics, such as customer agility, may be the focus of future studies. Hassna and Lowry (2016) suggest that the ability to collect and analyse large amounts of data has a positive effect on businesses by allowing them to better gauge client sentiment. Prior research revealed that data governance capabilities and data driven culture are key drivers of competitive advantage (Abella et al., 2017; Akter et al., 2021). Thus, these variables could be integrated in our model to improve its predictive power. Fourth, our examination focused on one culture (i.e., developing society) and didn't consider cross-cultural examinations. The lack of a global perspective in this study highlights the need for a comparative analysis of developed and developing nations. Fifth, the future examinations could go a step further by exploring the main obstacles of data driven innovation capabilities in the retail industry. Finally, this study relies solely on perceptual measurements, a limitation that needs addressing in subsequent research by using objective metrics to gain deeper insights into the genuine influence of data-driven innovation capabilities and marketing agility on competitive advantage.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. The measurement scales and their sources

Reflective constructs	Measurement scales/item	Factor loading	Source
Competition Orientation	"We consistently collect and disseminate competitor's service innovations related information within the business silos".	0.942	Sultana et al. (2022)
	"We regularly share information within our business concerning competitors' service innovations strategies".	0.907	
	"We rapidly respond to competitive actions that threaten our service innovations.	0.957	
	Our top managers frequently discuss competitors' strategies and actions for service innovations".	0.971	
	"We target new markets and new products for data driven service innovations when they bring competitive advantage over competitors".	0.894	
Customer Orientation	"We constantly monitor our level of commitment and orientation to serving customers' needs".	0.973	Sultana et al. (2022)
	"We comprehend customers' needs and wants".	0.940	
	"We shape business strategies in order to create superior customer value".	0.899	
	"We measure customer satisfaction systematically and frequently against our service innovations".	0.918	
Data	"We have access to very large, unstructured, or fast-moving data for service innovation".	0.905	Sultana et al. (2022)
	"We integrate data from multiple sources into a data warehouse for new service developments".	0.883	
	"We integrate external data with internal to facilitate service innovation".	0.914	
Technology	"For service innovation, we have explored or adopted cutting edge technologies to big data processing".	0.945	Sultana et al. (2022)
	"For service innovation, we have explored or adopted cloud-based services for processing data and performing analytics".	0.914	
	"We have explored and adopted AI solutions for data-driven service innovation".	0.982	
	"Overall, we employ sophisticated technology extensively to share data and information within organization".	0.961	
Knowledge	"We are able to acquire new and relevant knowledge".	0.976	Sultana et al. (2022)
	"We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge".	0.948	
Training and Development	"Our analytics staff has the right skills to accomplish their jobs successfully for data driven service innovation".	0.902	Sultana et al. (2022)
	"Our analytics staff is well trained for service innovation".	0.947	
	"We provide analytics training to our own employees for service innovation".	0.899	
	"Our analytics staff has suitable education to fulfil their jobs for service innovation".	0.975	
Competitive advantage	"Data driven innovation capability has improved the profitability of our organization".	0.915	Medeiros and Maçada (2022).
	"Data driven innovation capability has improved our organization's return on investment".	0.927	
	"Data driven innovation capability has improved our organization's sales growth".	0.919	
	"Data driven innovation capability has improved our organization's customer retention".	0.883	
	"Data driven innovation capability has improved the growth in market share of our organization".	0.895	
	"Our organization has gained strategic advantages over competitors".	0.907	
	"Overall, our organization is more successful than its competitors".	0.926	
Marketing agility	"We can spot the first indicators of new market threats".	0.934	Zhou et al. (2019)
	"We are often the first to seize new market opportunities".	0.910	

(continued on next page)

(*continued*)

Reflective constructs	Measurement scales/item	Factor loading	Source
	"We can anticipate new opportunities for market growth".	0.905	
	"We create new preferences by informing customers about new benefits of our products".	0.891	
	"We can respond to changes in demand without overstocking or losing sales".	0.884	
	"We can respond quickly to supply volume fluctuations by having suppliers in many regions of the world".	0.903	
	"When an unexpected threat emerges, we are able to adjust through resource reconfiguration".	0.968	
	"We can react to fundamental changes with respect changing the competitor landscape".	0.904	
	"We can market a wide variety of products within our portfolio".	0.921	
	"We can offer different products through minor modifications to existing ones".	0.953	
	"We can adjust what we offer to match market needs".	0.908	
	"We can meet customer's changing needs faster than our competitors".	0.896	
	"We compress time from product concept to marketing to respond quickly to the changes in customer needs".	0.914	
	"We can quickly change our product mix in response to changing market opportunities".	0.946	
	"We are fast at changing activities that do not lead to the desired effects".	0.927	
Market turbulence	"In our markets, customer preferences change quickly".	0.948	Zhou et al. (2019)
	"New customers we serve are different from our traditional customers".	0.961	
	"It is very difficult to predict demand for our products".	0.922	

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