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Market-Driving Capability: An Empirical Study on Antecedents and Consequences

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What enables market-driving behaviour, and is it a worthwhile business strategy? This fundamental question intrigues both managers in firms and researchers in marketing and strategic management, yet surprisingly, it remains underexplored. To this end, we assess the antecedents and consequences of market-driving capability. Using the resource-based view as our theoretical underpinning, we develop a conceptual model and empirically test the hypotheses with a sample of 416 managers via partial least squares structural equation modelling. We find that learning capability and big data analytics capability significantly influence market-driving capability in contemporary, data-intensive contexts, resulting in firms not only having a competitive advantage but also achieving improved financial and market performance. A follow-up study, conducted 4 years after the original study, provides exploratory evidence that market-driving capability can contribute to changes in market structure over time. Overall, this paper enhances our understanding of capabilities that enable firms to drive markets and highlights the implications for individual firm performance and overall market structure.

Introduction

In its boldest form, 'strategy is revolution' (Hamel, 1996, p. 70). The most effective strategies not only fulfil existing market demands but also create entirely new markets, address latent customer needs and redefine industry structures. Iconic firms like Apple, Red Bull and Tesla have demonstrated such transformative strategies, altering competitive landscapes and achieving remarkable success (Humphreys and Carpenter, 2018). Despite the apparent success of these market-driving firms, a comprehensive understanding of the underlying mechanisms that enable such strategies remains underexplored. Although past research has laid the conceptual groundwork for market-driving strategies (Jaworski, Kohli and Sahay, 2000; N. Kumar, Scheer and Kotler, 2000), empirical studies examining the specific capabilities that facilitate market-driving behaviour are scarce. At the same time, recent work reflects growing scholarly interest in market driving, with much of this literature relying on qualitative and conceptual approaches that offer rich process-level insights, while leaving open questions regarding generalizability across firms and contexts (Dion, Carpenter and Humphreys, 2025; Humphreys and Carpenter, 2018; Nenonen, Storbacka and Windahl, 2019).

Recent literature highlights the need to delve deeper into the capabilities that enable firms to influence market structures and behaviours (Helfat *et al.*, 2023). While some studies have begun to explore the antecedents and performance outcomes of market-driving strategies (Stathakopoulos *et al.*, 2022), the role of emerging capabilities, such as big data analytics, warrants further investigation (Karaboga *et al.*, 2023; Mikalef *et al.*, 2018; Xia *et al.*, 2024). Big data analytics capability (BDAC), defined as the firm's ability to leverage large datasets to derive actionable insights, is increasingly seen as a strategic asset (Gupta and George, 2016). However, its direct linkage to firm-level market-driving capability remains contentious and underexplored in the literature.

The rationale for including BDAC as an antecedent of market-driving capability stems from its potential to enable firms to navigate and influence complex market dynamics (Suoniemi *et al.*, 2020). BDAC facilitates the analysis of vast and diverse datasets, helping firms identify emerging trends, anticipate market shifts and tailor firm-level strategies to capitalize on these insights (Mikalef *et al.*, 2019). For instance, Amazon's use of

BDAC has been pivotal in understanding customer preferences, optimizing inventory and personalizing marketing efforts, which in turn has reshaped the retail industry (Bouakel and Zerbout, 2021).

Moreover, BDAC provides firms with the agility to respond to competitive pressures and rapidly changing market conditions. By leveraging predictive analytics and real-time data, firms can anticipate disruptions and innovate proactively, positioning themselves as market leaders (Wamba *et al.*, 2017). This capability is particularly crucial in industries characterized by high volatility and rapid technological advancements, where traditional market-driving strategies may fall short. While BDAC represents a powerful and contemporary capability in this regard, we also recognize that market-driving behaviour often arises from the interplay of multiple organizational capabilities.

Among the various capabilities examined in this study, BDAC is positioned as the most novel and timely enabler in the context of market-driving strategies, and we present it as the primary theoretical contribution of this paper. While we include learning capability and alliance orientation as complementary capabilities, their inclusion provides a more comprehensive capability-based framework that reflects the multifactorial nature of market-driving capability. The inclusion of additional antecedents reflects our belief, grounded in the resource-based view (RBV), that firms develop market-driving capabilities through the interplay of diverse internal and relational assets—not solely technological ones. This broader approach aligns with prior work in strategic marketing and capability theory that emphasizes the synergetic effects of learning, technology and network-based resources in shaping competitive behaviour (Helfat *et al.*, 2007).

The objective of this paper is twofold: (a) to identify the capabilities that enable firms to drive markets and (b) to examine the performance consequences of these capabilities. Grounded in RBV, our study investigates how specific capabilities, including BDAC and learning capability, contribute to a firm's ability to shape markets. By doing so, we respond to recent calls to extend the predominantly qualitative market-driving literature with quantitative, capability-based evidence that enhances generalizability while preserving theoretical depth. We aim to clarify the distinct roles these capabilities play in enabling firms to proactively influence market structures and behaviours.

The concept of market-driving capability extends beyond merely responding to customer needs—it involves actively shaping market dynamics and influencing industry standards (Jaworski, Kohli and Sahay, 2000; Stathakopoulos *et al.*, 2022). Unlike a proactive market orientation, which focuses on anticipating and fulfilling latent customer needs (Narver, Slater and MacLachlan, 2004), market-driving capability seeks to redefine market boundaries and alter competitive landscapes. This strategic posture entails significant effects on competitors and industry structures, often leading to long-term changes in market dynamics (Nenonen, Storbacka and Frethey-Bentham, 2019). In this study, we conceptualize market-driving capability as a firm-level strategic capability that manifests in observable market-driving behaviours, such as customer education, preference shaping and the introduction of disruptive value propositions.

While traditional examples of market-driving firms, such as Apple with its iPhone, illustrate the profound impact of such strategies, the role of BDAC in facilitating market-driving capability requires further scrutiny. Some firms, including IKEA and Ford, achieved market-driving success without the extensive use of big data analytics, suggesting that BDAC may not be a necessary antecedent for all market-driving strategies. We acknowledge these historical examples; however, the contemporary business environment is increasingly shaped by digitalization, algorithmic decision-making and real-time data flows—conditions under which BDAC becomes especially consequential (Vesterinen, Mero and Skippari, 2025). In today's data-rich environment, the potential of BDAC to enhance a firm's ability to predict and shape market trends cannot be overlooked (Mikalef *et al.*, 2019; Olabode *et al.*, 2022).

In addressing this research gap, our study builds on both conceptual and empirical foundations to offer a nuanced understanding of the capabilities that drive market innovation. By employing a robust methodological framework—specifically, partial least squares structural equation modelling (PLS-SEM)—we provide empirical insights into the interplay between BDAC, learning capability and market-driving capability. Importantly, this quantitative analysis is complemented by a follow-up empirical study, allowing us to triangulate findings and strengthen the robustness of our conclusions. Our findings contribute to the ongoing discourse on market-driving strategies, highlighting both the potential and limitations of BDAC in contemporary strategic management.

In summary, this paper advances the understanding of market-driving capability by integrating insights from RBV and recent empirical research. We aim to provide a comprehensive analysis of how specific capabilities enable firms to shape markets and achieve superior performance outcomes, thereby addressing critical gaps in the existing literature. From a methodological standpoint, this paper also contributes by introducing a reflective first-order scale for market-driving capability and by demonstrating how second-order and third-order constructs can be effectively operationalized within a PLS-SEM framework.

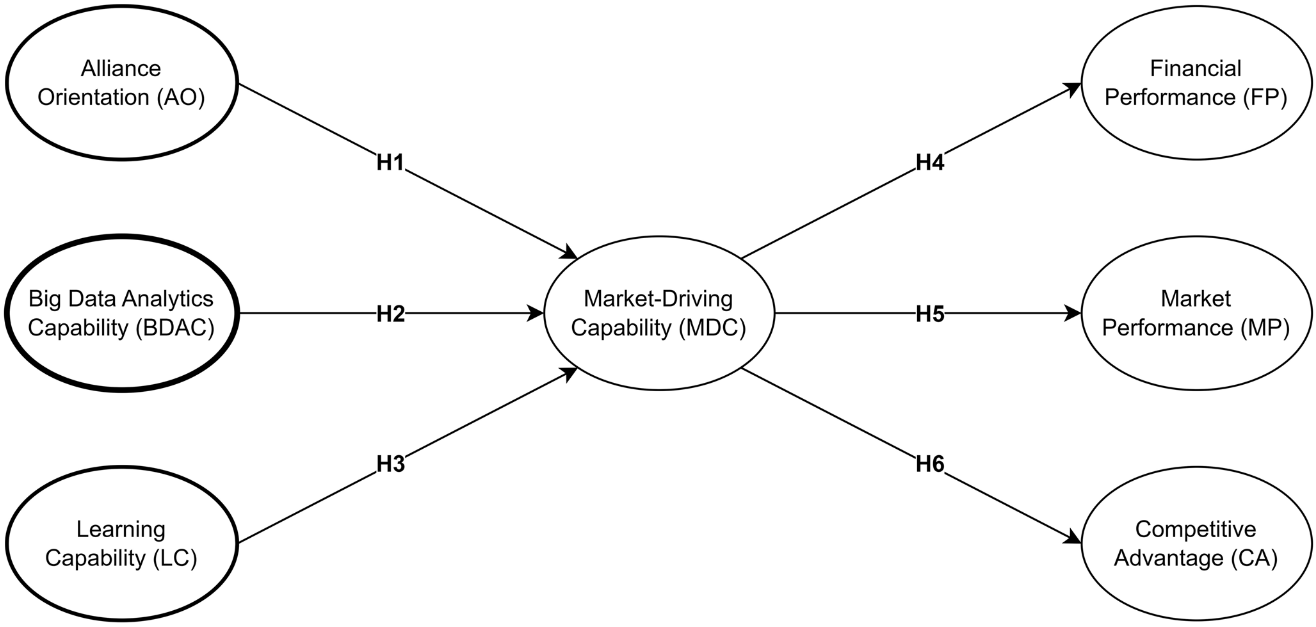

Figure 1. Research model

Theoretical framework and hypotheses

The RBV theorizes linkages between capabilities and performance. The RBV emphasizes not only the prominence of actions over environmental conditions for sustained profitability but suggests that these actions can both respond to and 'even create market change' (Eisenhardt and Martin, 2000, p. 1107). As such, the RBV serves as the primary theoretical foundation for this study. The creation of market change is the focus of this study; hence, the RBV is an appropriate theoretical anchor for the research model: we expect that firms that drive markets exhibit distinct capabilities enabling them to (a) assemble resources and learn from a large set of partner companies, (b) predict and understand market dynamics and (c) deliver a compelling value proposition via joint exploration and exploitation (see Figure 1).

While we draw primarily on the RBV to conceptualize market-driving capability as an outcome of valuable, rare and inimitable resources, we note that BDAC possesses properties that align with the logic of dynamic capabilities—particularly in enabling firms to sense trends, seize data-driven opportunities and reconfigure offerings accordingly. We reference the dynamic capabilities framework to emphasize this alignment, but do not adopt it as our core theoretical framework, in order to preserve coherence with the RBV-driven design of this study.

Alliance orientation and market-driving capability

Alliances 'purposefully create, extend, or modify the firm's resource base, augmented to include the resources of its alliance partners' (Helfat *et al.*, 2007, p. 66). In parallel to research in the marketing domain on market-driving strategies (Jaworski, Kohli and Sahay, 2000; N. Kumar, Scheer and Kotler, 2000), scholars in the strategy domain have also explored, at about the same time, the mechanisms underlying strategies aimed at creating fundamentally new markets. Finding that alliances play a fundamental role in the process of new market creation, these scholars used the term 'virtual value chain orchestration', seeing it 'as a way of creating and capturing value by structuring, coordinating and integrating the activities of previously separate markets, and by relating these activities effectively to in-house operations with the aim of developing a network of activities that create fundamentally new markets' (Hinterhuber, 2002, p. 615). Alliance orientation, the ability to identify, coordinate and learn from alliances, mirrors a company's market orientation (Kandemir, 2006) and captures the ability to learn from other parties with whom the focal firm has entered into collaborative relationships.

The literature is very clear that market driving does not require technological change (Sozuer *et al.*, 2020). However, qualitative research suggests that market driving is the result of a firm's ability to forge relationships with and learn from a large variety of other companies (Humphreys and Carpenter, 2018). Several marketing thought leaders agree on this notion (Schweitzer, Malek and Sarin, 2023). Moreover, a recent review of studies highlights the interrelationship between strategic alliances and BDAC (Xia *et al.*, 2024). Nonetheless, while alliance orientation has been identified as a means of expanding resource bases and fostering learning, it is also conceivable that in certain contexts—particularly those involving radical innovation or disruptive change—collaborative approaches may introduce strategic constraints or inertia. In such cases, market-driving behaviour may be better facilitated by internal capabilities that allow greater control, speed and vision-led action, rather than by shared or negotiated strategies. This line of reasoning is consistent with studies suggesting that market-driving initiatives are often led by firms acting independently to break with conventional industry logic (Reid and de Brentani, 2010; Taeuscher, Bouncken and Pesch, 2021). We, therefore, posit the following:

H 1. *Alliance orientation positively influences market-driving capability.*

BDAC and market-driving capability

The RBV posits that competitive advantage stems from resources and capabilities that are valuable, rare, inimitable and non-substitutable (VRIN) (Barney, 1991). Among the capabilities examined in this study, BDAC represents the most novel and timely in relation to market-driving strategies. BDAC, defined as the firm's ability to assemble, integrate and deploy big data-based resources via (a) tangible resources, (b) intangible resources and (c) human resources (Gupta and George, 2016), aligns with these attributes, making it a strategic asset.

While BDAC has not traditionally been examined within the market-driving literature, this absence reflects the relative novelty of analytics-based capabilities as strategic resources rather than a theoretical incompatibility. Market-driving research emerged largely before the widespread diffusion of large-scale analytics infrastructures, algorithmic decision-making and real-time data integration. As such, the lack of direct prior empirical tests linking BDAC to market-driving capability should be interpreted as an opportunity for theoretical extension rather than as evidence of weak theoretical grounding.

We also draw conceptual support from the Dynamic Capabilities Framework (Teece, 2007), which views dynamic capabilities as the firm's ability to sense, seize and reconfigure resources to address environmental change. Importantly, market-driving capability is inherently forward-looking: it involves shaping customer preferences, influencing competitive behaviour and redefining market structures before they fully materialize. BDAC reflects this logic in that it enables firms to systematically sense weak signals in markets, shape strategic interpretations of emerging trends and influence market outcomes through data-driven foresight, rather than merely reacting to existing demand.

BDAC's tangible resources—data, technology and funding—form the foundation for leveraging big data to achieve market leadership. Integrating large, diverse datasets enables firms to uncover latent customer needs and emerging patterns, supporting strategic initiatives that precede observable market change (Mikalef *et al.*, 2019). Advanced technologies such as machine learning, parallel computing and data visualization tools enhance firms' abilities to model future scenarios, anticipate competitor moves and proactively influence customer preferences (Johnson, Friend and Lee, 2017).

BDAC's intangible resources, including a data-driven culture and managerial acumen, provide the cognitive and organizational infrastructure required for market-driving behaviour. A data-driven culture prioritizes systematic experimentation, hypothesis testing and evidence-based decision-making (Gupta and George, 2016). Such a culture supports market-driving initiatives by legitimizing strategic moves that challenge existing market logics and by reducing reliance on backward-looking heuristics. Managerial capabilities—such as cross-functional integration and strategic sensemaking—ensure that analytics-derived insights are translated into coordinated market-shaping actions rather than isolated operational improvements (Sheng, Amankwah-Amoah and Wang, 2017).

The human resource dimension of BDAC—comprising analytical, technical and managerial expertise—is pivotal in transforming data into strategic action. Skilled analytics teams translate complex datasets into forward-looking insights, while managerial leaders embed these insights into organizational routines and strategic narratives that guide market-driving initiatives (Mikalef *et al.*, 2020). In this way, BDAC operates as a micro-foundational capability that enables firms to influence how markets evolve, not merely how firms compete within existing market structures (Erevelles, Fukawa and Swayne, 2016).

BDAC thus functions as a dynamic, higher-order capability that supports market-driving behaviour by enabling firms to continuously reconfigure resources in anticipation of market change (Eisenhardt and Martin, 2000). Firms leveraging BDAC can introduce novel value propositions, disrupt established pricing or channel conventions, and legitimize new market categories—core mechanisms through which markets are actively shaped rather than passively served (Mattila, Yrjölä and Hautamäki, 2021).

Several studies have documented positive relationships between BDAC and firm performance, market performance, manufacturing agility, marketing capability and disruptive business models (Awan *et al.*, 2022; Karaboga *et al.*, 2023; Mikalef *et al.*, 2020; Olabode *et al.*, 2022; Suoniemi *et al.*, 2020; Vesterinen, Mero and Skippari, 2025; Wamba *et al.*, 2017). While these studies do not explicitly examine market-driving capability, they collectively indicate that BDAC equips firms with the anticipatory, integrative and reconfigurational capacities required to shape markets proactively.

We acknowledge that BDAC may not constitute a universal antecedent of market-driving capability across all contexts. Historical examples demonstrate that firms have driven markets without extensive analytics infrastructures. However, in contemporary, data-rich environments characterized by digitalization, algorithmic mediation and rapid feedback cycles, BDAC becomes a particularly salient enabler of forward-looking market-shaping behaviour. Importantly, this hypothesis does not imply that BDAC is a necessary condition for market driving, but rather that it constitutes a salient enabler under contemporary, data-rich market conditions. Accordingly, BDAC should be viewed as a theoretically defensible, context-sensitive antecedent that extends existing explanations of market-driving capability into the digital era. Thus, we hypothesize:

H 2. *Big data analytics capability positively influences market-driving capability.*

Learning orientation and market-driving capability

It is trite to state that customer needs change over time. The implications are not trite; however, changing customer needs implies that new, unmet needs emerge; it also implies that companies differ in their abilities to address these hitherto unmet needs.

We argue that in the process of addressing latent needs and driving markets, learning capabilities assume a prominent role (Bao, Wei and Di Benedetto, 2020). They require operationalization: we follow prior studies operationalizing learning capabilities as a second-order construct composed of measures fitting the particular research question (Lin *et al.*, 2013). For the objective of this study, we define learning capabilities as practices that promote competence exploration, competence exploitation and value proposition development.

It is well established that exploitative processes refer to efficiency and the management of what is known, and that explorative processes refer to effectiveness and the creation of novelty (Gibson and Birkinshaw, 2004). While intuitive reasoning may suggest that market-driving behaviour depends primarily on exploration, literature cautions against such bias. Entrepreneurial orientation studies, for example, show that strategic novelty and risk-taking involve a delicate balance between opportunity-seeking (exploration) and advantage-seeking (exploitation) (Duane Ireland and Webb, 2007; Kollmann and Stöckmann, 2014).

This ambidexterity—simultaneously leveraging existing competencies while exploring new ones—is critical in market-driving strategies. Firms must not only discover latent needs but also deliver them through operational excellence. In this light, learning capability—by enabling both exploration and exploitation—emerges as a critical enabler of market-driving capability.

Learning capability allows firms to accumulate, interpret and apply knowledge in novel ways, which is essential for identifying latent needs and reframing customer preferences—both hallmarks of market-driving firms. This makes learning capability not only complementary to BDAC but a distinct enabler of market-driving innovation (Hurley and Hult, 1998).

A prior study finds that learning facilitates the identification of latent customer needs (Bao, Wei and Di Benedetto, 2020); a study on market-driving strategies in the wine industry points out that virtually all market-driving companies become ‘effective learning organizations’ (Humphreys and Carpenter, 2018, p. 135). We, therefore, posit the following:

H 3. *Learning capability positively influences market-driving capability.*

Consequences of market-driving capability

The RBV clearly argues that some resources and capabilities enable firms to achieve above-average performance and competitive advantages. The literature distinguishes between financial performance and market performance (Slater and Olson, 2000). Financial performance measures performance on quantitative indicators, such as sales and profit growth vis-à-vis competitors (Tippins and Sohi, 2003); market performance measures performance on qualitative indicators such as speed of new product introductions or relationship quality with customers, again relative to competitors (Wang *et al.*, 2012). In sum, firm performance is a multifaceted construct that we operationalize via financial indicators, qualitative indicators and the overall assessment of competitive advantages.

Market-driving capability will be positively related to the firm’s financial and market performance (Blut, Holzmüller and Stolper, 2012; Martín-Consuegra, Molina and Esteban, 2008; Stathakopoulos *et al.*, 2022). Market-driving strategies allow firms to innovate offerings that redefine value, often creating new demand curves or market categories. These actions generate not only customer loyalty and reputation (market performance) but also revenue and profit growth (financial performance).

The firm’s focus may not necessarily be on the satisfaction of latent customer needs, but it will initiate industry structural change, which disrupts the existing competitive landscape. As noted earlier in the Apple example, the iPhone launch satisfied latent customer needs for an all-purpose device, but also significantly changed the structure of several industries (e.g. mobile phones, digital cameras, etc.) and impacted competitors who provided several services (such as access to music and other entertainment, access to email, etc.). Apple successfully drove the market and soon came to dominate it, recording a market share of over 55% in the United States and almost 28% worldwide (Oberlo, 2024a, 2024b); it has been described as a 'longtime leader in smartphone revenue and profits' (Kaur, 2024). Further, Apple's brand equity has been estimated at over $500 billion (Interbrand, 2024), indicative of its strength in the market and its ability to leverage its brand name to increase marketing efficiency.

These real-world examples illustrate that market-driving capability can produce substantial and sustained performance outcomes—both financial and market-based. In RBV terms, market-driving capability serves as a valuable and rare resource that enables firms to proactively generate value, establish revenue leadership and realize superior financial returns. Thus, a firm can reap significant financial and market rewards with the successful deployment of its market-driving capability. We posit the following:

H 4. *Market-driving capability positively influences financial performance.*

H 5. *Market-driving capability positively influences market performance.*

We further hypothesize that market-driving capability will also influence firm performance. In this case, the firm's focus may not be on the satisfaction of latent customer needs, but it will initiate industry structural change with serious consequences for competitors. To continue with the Apple iPhone example, major competitors prior to the iPhone launch, such as Blackberry or Nokia, were immediately affected; neither is currently a significant competitor in the global market (Oberlo, 2024a). As another classic example, manufacturers of inexpensive small office copiers successfully and profitably entered the copier industry. They developed products that matched the needs of an emerging market segment, significantly disrupting the structure of the copier industry and placing pressure on incumbent competitors (Bower and Christensen, 1995).

By altering the rules of competition, firms with strong market-driving capability weaken rival positions and create sustainable differentiation. This capability-driven advantage is hard to imitate, especially when underpinned by data-driven insights, learning routines and unique market-shaping actions—characteristics central to the RBV (Barney, 1991; Peteraf, 1993).

Thus, over and above the effect of a proactive market orientation, we expect that market-driving capability will positively and sustainably influence competitive advantage, due to the disruptive impact on industry structure and the weakening of the position of incumbent competitors. We posit the following:

H 6. *Market-driving capability positively influences competitive advantage.*

Methodology and findings

Main study

Data collection. Our main study, like prior studies (Ameen *et al.*, 2024; Frank and Otterbring, 2024; Hinterhuber and Khan, 2025), collected data in 2020 from key informants with the help of an online panel provider, Cint. Online panel providers allow very specific targeting of qualified key informants that are difficult to reach otherwise. Furthermore, researchers recommend online panel providers specifically to collect sensitive research data (Porter *et al.*, 2019). We had to ask multiple questions about company performance, a sensitive topic. Finally, a recent meta-analysis has shown the convergence between online panel data and conventionally sourced data, concluding that online panel data are 'suitable' for exploratory research questions (Walter *et al.*, 2019). In sum, these studies all indicate that the use of an online panel provider is appropriate in the context of this research.

We instructed the panel provider to recruit managers employed in sales, marketing, key account management, IT/IS, or general management. Given the prominent role of BDAC in our proposed research model, we specifically instructed the panel provider to recruit respondents with expertise in business intelligence and analytics or big data analytics initiatives. Unqualified respondents were prevented from participating in the online survey through a screening question. As random responses undermine validity, we included four attention-check questions. These questions were formatted exactly like other questions and were embedded randomly in four different blocks of the questionnaire. We asked respondents to give specific answers to verify that they were paying attention. Before data analysis, respondents who did not pass attention checks were excluded. Our sample size consists of 416 respondents (see Table 1).

Non-response bias, stemming from significant disparities between participants and eligible nonparticipants, is a threat to validity (Hulland, Baumgartner and Smith, 2018). We compared early and late responses since the latter served as proxies for nonparticipants (Armstrong and Overton, 1977). We divided the sample into two groups and then randomly selected indicators from each construct. We compared the two groups for selected indicators as well as for all constructs using the Mann–Whitney U-test (Hinterhuber and Khan, 2025; Marini, Khan and Hinterhuber, 2025). This test did not show any significant difference between early and late responses ($p < 0.05$). Our study thus seems free from non-response bias.

Table 1. Sample description

Characteristics	Description	Frequency	Percentage (%)
Company age	<5 years	15	3.61
	5–15 years	74	17.79
	16–50 years	213	51.20
	51–100 years	78	18.75
	>100 years	36	8.65
Company size	<250 employees	10	2.40
	251–500 employees	8	1.92
	501–1000 employees	113	27.16
	1001–10,000 employees	191	45.91
	> 10,000 employees	94	22.60
Company annual revenue	<125 million USD	58	13.94
	125–249 million USD	48	11.54
	250–499 million USD	49	11.78
	500–999 million USD	93	22.36
	1000–1999 million USD	40	9.62
	2000–3999 million USD	43	10.34
	>4000 million USD	85	20.43
Big data budget	<1 million USD	39	9.38
	1–10 million USD	115	27.64
	10–100 million USD	139	33.41
	100–1000 million USD	59	14.18
	>1000 million USD	28	6.73
	Undisclosed	36	8.65
Company focus	B2B	108	25.96
	B2C	110	26.44
	Both	191	45.91
	Undisclosed	7	1.68
Company ownership	Privately owned	250	60.10
	Publicly traded	131	31.49
	Both	35	8.41
Company headquarters	The Americas	216	51.92
	Europe	197	47.36
	Asia/Pacific	3	0.72

Constructs and scales. Our proposed research model is a hierarchical component model (HCM) that contains first-order, second-order and third-order constructs (Sarstedt *et al.*, 2019). That is, some constructs were operationalized with their respective sub-constructs. The first-order constructs are depicted by thinner oval shapes, while the second-order and third-order constructs are depicted by thicker oval shapes (see Figure 1).

Alliance orientation (AO): The construct, developed to parallel the conceptualization of market orientation, measures a firm's orientation to (a) skilfully scan for and identify partnering opportunities in its markets, (b) coordinate its alliance activities capably and (c) learn from its alliance experiences more proficiently than its competitors; second-order formative construct composed of alliance scanning, coordination and learning (Kandemir, 2006).

Big data analytics capability (BDAC): The construct measures the firm's capability to assemble, integrate and deploy its big data-based resources; a third-order formative construct composed of tangible resources, intangible resources and human resources (Gupta and George, 2016).

Learning capability (LC): The construct measures the ability to explore, exploit and translate needs into a resonating value proposition; second-order formative construct composed of competence exploration (Atuahene-Gima, 2005), competence exploitation (Atuahene-Gima, 2005) and value creation competence (Sullivan, Peterson and Krishnan, 2012).

Market-driving capability (MDC): While prior studies have examined market-driving strategies primarily through qualitative approaches (Hills and Sarin, 2003; Humphreys and Carpenter, 2018; N. Kumar, Scheer and Kotler, 2000), only limited efforts have been made to develop quantitative measures of this construct. At the time of our study design and data collection in 2020, no widely established or validated quantitative scale for market-driving capability was available.

More recent work by Stathakopoulos *et al.* (2022) represents an important and valuable advancement in the quantitative operationalization of market-driving strategies. However, this scale was published after our data collection had been completed and therefore could not be incorporated into our research design. In light of this, and consistent with established scale-development practices in strategic and marketing research, we developed a new MDC scale tailored to the objectives and temporal context of our study. Our approach follows prior research that has introduced novel constructs through careful theoretical grounding and empirical validation when standardized measures were not yet available (Hunter, 2014; Zhang and Xiao, 2020).

Importantly, our scale is not intended to replace or compete with existing or emerging measures of market-driving capability. Rather, it provides a complementary firm-level operationalization that focuses on strategic actions through which firms proactively shape markets. This perspective aligns with foundational market-driving literature, which emphasizes customer education, preference shaping, disruptive value propositions and competitive leadership as core mechanisms of market driving (Hills and Sarin, 2003; Humphreys and Carpenter, 2018; N. Kumar, Scheer and Kotler, 2000).

The resulting MDC scale captures key firm-level manifestations of market-driving behaviour, including shaping customer preferences, introducing novel value propositions, influencing market norms, educating customers, engaging in pricing innovation and leading competitors to follow. While broader system-level outcomes—such as regulatory change, societal norm shifts, or ecosystem-wide orchestration—are integral to market evolution, these effects often emerge cumulatively from firm-level strategic actions and unfold over longer time horizons. Our scale is therefore intentionally focused on proximal, firm-driven mechanisms that initiate market change and manifest as observable market-driving behaviours within a cross-sectional survey design.

This design choice reflects both conceptual scope and methodological feasibility. Capturing system-wide or societal-level market shaping would require longitudinal, multi-actor data and alternative research designs, which are beyond the scope of the present study. Accordingly, our MDC scale should be interpreted as measuring a firm's capability to initiate and lead market-driving actions, rather than as an exhaustive representation of all possible dimensions of market transformation.

The scale development process was guided by foundational literature on market-driving strategies (Hills and Sarin, 2003; Humphreys and Carpenter, 2018; N. Kumar, Scheer and Kotler, 2000) and followed established best practices. The resulting MDC scale is a 10-item, first-order reflective construct, designed to balance conceptual rigor with empirical tractability. We pre-tested the scale, along with other elements of the survey instrument, with a sample of 36 managers to ensure clarity, relevance and content validity.

Consistent with the evolution of other complex strategic constructs—such as dynamic capabilities or market orientation—we view the coexistence of multiple operationalizations as beneficial for cumulative theory development. Future research may therefore compare, integrate, or extend different MDC scales across contexts, industries and levels of analysis, thereby further refining the measurement of market-driving capability.

Financial performance (FP): The construct measures firm performance, vis-à-vis competitors, on quantitative indicators, as reported by respondents (Tippins and Sohi, 2003).

Market performance (MP): The construct measures firm performance, vis-à-vis competitors, on qualitative indicators, as reported by respondents (Wang *et al.*, 2012).

Competitive advantage (CA): The construct measures a firm's ability to profit from current or future market opportunities; we adapted existing construct measurements (Barney, 1991; Peteraf and Barney, 2003; Sigalas, Pekka Economou and B. Georgopoulos, 2013; Weerawardena, 2003) to the needs of our study.

The use of these two subjective performance indicators requires clarification: In a review of correlations between objective and subjective firm performance data, researchers note the overall high correlations between the two and state that we 'should not view the choice of subjective measures as a second-best alternative' (Richard *et al.*, 2009, p. 737). A subsequent study finds a correlation of about '0.8' between the two (V. Kumar *et al.*, 2011, p. 25). Furthermore, scholars oppose the utilization of objective performance data, particularly in research conducted within small and medium-sized companies, since such data are prone to bias due to manipulation by managers for both corporate and personal tax purposes (Sapienza, Smith and Gannon, 1988). In addition, given that the firms in our sample encompass diverse industries and geographical locations, employing a multidimensional measure that relies on perceptual assessments of firm performance enables meaningful comparisons across different contexts (Dess and Robinson, 1984). In sum, given the characteristics of our sample (about 60% privately owned; about 40% small and medium-sized companies), our study, like others (O'Sullivan and Abela, 2007), views subjective data as the overall most suitable performance indicator.

Data analysis. We analysed the data through PLS-SEM with SmartPLS 4 software (Ringle, Wende and Becker, 2024). Sarstedt *et al.* (2019) point out that the embedded two-stage approach should be employed instead of the repeated indicators since the latter approach causes issues in HCM. We, therefore, employed the embedded two-stage approach (mode B) for measuring our proposed HCM. A PLS-SEM model is assessed as two conjoint parts: the measurement model and the structural model (Khan, 2025). Accordingly, in the first step, the measurement model was assessed by using the PLS algorithm with the default settings of the software. In the second step, the structural model was examined using the function in the software called bootstrapping with 10,000 subsamples. All given rules and guidelines were followed, not just in performing PLS-SEM but also in presenting the findings of this study (Hair *et al.*, 2019).

Measurement model. We assessed the measurement model as per the guidelines (Hair *et al.*, 2022). The outer loadings of indicators are generally supposed to be above 0.708, but if the AVE of a construct is above 0.50, then in that case, indicators having outer loadings between 0.400 and 0.708 are also considered valid and retained in the measurement model (Hair *et al.*, 2012). The outer loadings of all indicators, excluding four indicators (namely AO-C3, AO-L3, BDAC-HR-M6 and BDAC-HR-T1), were between 0.672 and 0.950 (see Table 2). Moreover, the outer weights of formative indicators, except for one indicator (namely BDAC-TR-T4), were significant (Hair *et al.*, 2022). The Cronbach's alpha values of all constructs were between 0.780 and 0.917, while the CR values were between 0.899 and 0.938 (see Table 2). The AVE values were between 0.553 and 0.883 (see Table 2), passing the criterion comfortably (Hair *et al.*, 2019).

The discriminant validity was tested through the Heterotrait–Monotrait Ratio (HTMT) criterion. This criterion posits that HTMT values must be lower than 0.900 if the involved constructs are conceptually similar (Hair *et al.*, 2019). The HTMT values for all constructs, after deleting the four said indicators, were under the limits, indicating that there was no serious issue of discriminant validity (see Table 3).

The psychometric properties of first-order and second-order constructs (i.e. constructs acting as formative indicators for second-order and third-order constructs in our proposed HCM) must be assessed in terms of the significance and relevance of their weights before proceeding to the assessment of the structural model (Khan, Daddi and Iraldo, 2021). This study satisfies this requirement, since the t-values were greater than 1.96 (see Table 2).

Structural model. We assessed the structural model as per the guidelines (Hair *et al.*, 2022). Our study contains no serious issue of multicollinearity since the VIF values of constructs involved in the structural model were under the limits (Hair *et al.*, 2019). The predictive power of a model is explained by the R^2 values of endogenous constructs (Khan and Hinterhuber, 2025). The R^2 values for CA, FP, MDC and MP were respectively 0.643, 0.529, 0.720 and 0.607, implying moderate to substantial predictive powers (Hair *et al.*, 2019). This study satisfies the model fit criteria since the SRMR value was 0.059 (Hair *et al.*, 2022).

Our PLS-SEM analysis revealed that AO influences MDC with a correlation value of 0.030 ($p > 0.1$), BDAC influences MDC with a correlation value of 0.338 ($p < 0.001$) and LC influences MDC with a correlation value of 0.370 ($p < 0.001$). Our PLS-SEM analysis further revealed that MDC influences FP, MP and CA with respective correlation values of 0.447 ($p < 0.001$), 0.545 ($p < 0.001$) and 0.580 ($p < 0.001$). Hence, all hypotheses, except hypothesis 1, are empirically supported (see Table 4).

Robustness checks. If the data are collected for both exogenous and endogenous constructs from a single respondent, then common method bias may occur (Podsakoff *et al.*, 2003). To check whether our study is contaminated by this bias, we performed the full collinearity test. This test suggests that if the VIF values of constructs are above 3.3 on the inclusion of a random variable, then common method bias may exist. Otherwise, potential common method bias can be ruled out (Kock, 2015). Our study contains no serious issue of common method bias since the VIF values of constructs were under the limits when a random variable was included.

It is argued that the omission of variables, simultaneous causality and measurement errors may induce endogeneity (Zaefarian *et al.*, 2017). Our research model is HCM and contains four endogenous variables. There are no specific (practical) guidelines in the extant literature on how to check endogeneity in HCM. Yet we followed a systematic procedure to address potential endogeneity (Hult *et al.*, 2018, p. 7). Accordingly, we checked the assumptions of the Gaussian copula approach through the Kolmogorov–Smirnov test with Lilliefors correction. This test showed that all constructs have non-normally distributed data ($p < 0.05$) except LC (see Table A1). Put differently, the assumptions were not fulfilled for LC. Nevertheless, we applied the Gaussian copula approach (Sarstedt *et al.*, 2020). After assessing 10 models in total, we found that all cupolas were insignificant, implying that endogeneity is not a critical issue (see Table A2). However, knowing the fact that the assumptions of the Gaussian copula approach were not fulfilled, we decided to include suitable control variables as per the recommended guidelines (Hult *et al.*, 2018, p. 7).

Supplementary study

Data collection. We conducted an exploratory follow-up study in 2024 to assess the influence of market-driving capability on market structure.[1] We did so by following a recent study that suggests a positive influence of market-driving strategy on market change

[1] We are grateful to an anonymous reviewer for this critically important suggestion.

Table 2. Reliability and validity of measurement model

Third-order construct	Second-order constructs	First-order constructs	Indicator codes	Indicators	Loadings/ weights (*p*-values)	Cronbach alpha	CR	AVE
–	Alliance orientation (AO) VIF = 2.775	Alliance scanning (AO-S)	AO-S1	We actively monitor our environment to identify partnering opportunities.	0.887	0.837	0.902	0.755
		Weights = 0.353 t-value = 20.165 VIF = 2.291	AO-S2	We routinely gather information about prospective partners from various forums (e.g. trade shows, industry conventions, databases, publications, internet, etc.).	0.866			
			AO-S3	We are alert to market developments that create potential alliance opportunities.	0.853			
		Alliance coordination (AO-C)	AO-C1	Our activities across different alliances are well coordinated.	0.940	0.867	0.938	0.883
		Weights = 0.392 t-value = 18.909	AO-C2	We systematically coordinate our strategies across different alliances.	0.939			
		VIF = 2.818	AO-C3	We have processes to systematically transfer knowledge across alliance partners.	-			
		Alliance learning (AO-L) Weights = 0.369 t-value = 19.133 VIF = 2.339	AO-L1	We conduct periodic reviews of our alliances to understand what we are doing right and where we are going wrong.	0.908	0.780	0.901	0.820
			AO-L2	We periodically collect and analyze field experiences from our alliances.	0.903			
			AO-L3	We modify our alliance related procedures as we learn from experience.	-			
Big data analytics capability (BDAC) VIF = 3.958	Tangible resources (BDAC-TR) Weights = 0.406 t-value = 18.427 VIF = 3.351	Data (BDAC-TR-D) Weights = 0.386 t-value = 30.057 VIF = 2.132	BDAC-TR-D1	We have access to very large, unstructured, or fast-moving data for analysis.	0.365 (0.000)	-	-	-
			BDAC-TR-D2	We integrate data from multiple sources into a data warehouse for easy access.	0.444 (0.000)			
			BDAC-TR-D3	We integrate external data with internal data to facilitate high-value analysis of our business environment.	0.376 (0.000)			

Table 2. (*Continued*)

Third-order construct	Second-order constructs	First-order constructs	Indicator codes	Indicators	Loadings/ weights (*p*-values)	Cronbach alpha	CR	AVE
		Technology (BDAC-TR-T) Weights = 0.404 t-value = 27.284 VIF = 2.346	BDAC-TR-T1	We have explored or adopted parallel computing approaches (e.g. Hadoop) to big data processing.	0.490 (0.000)	-	-	-
			BDAC-TR-T2	We have explored or adopted different data visualization tools.	0.281 (0.000)			
			BDAC-TR-T3	We have explored or adopted cloud-based services for processing data and performing analytics.	0.187 (0.002)			
			BDAC-TR-T4	We have explored or adopted open-source software for big data analytics.	0.104 (0.102)			
			BDAC-TR-T5	We have explored or adopted new forms of databases such as Not Only SQL (NoSQL) for storing data.	0.147 (0.014)			
		Basic resources (BDAC-TR-B) Weights = 0.351 t-value = 30.529 VIF = 1.830	BDAC-TR-B1	Our 'big data analytics' projects are adequately funded.	0.589 (0.000)	-	-	-
			BDAC-TR-B2	Our 'big data analytics' projects are given enough time to achieve their objectives.	0.477 (0.000)			
	Human resources (BDAC-HR) Weights = 0.330 t-value = 15.169 VIF = 3.965	Managerial skills (BDAC-HR-M) Weights = 0.535 t-value = 37.102 VIF = 3.005	BDAC-HR-M1	Our big data analytics managers understand and appreciate the business needs of other functional managers, suppliers and customers.	0.871	0.917	0.938	0.751
			BDAC-HR-M2	Our big data analytics managers are able to work with functional managers, suppliers and customers to determine opportunities that big data might bring to our business.	0.862			
			BDAC-HR-M3	Our big data analytics managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers and customers.	0.879			
			BDAC-HR-M4	Our big data analytics managers are able to anticipate the future business needs of functional managers, suppliers and customers.	0.862			
			BDAC-HR-M5	Our big data analytics managers have a good sense of where to apply big data.	0.860			
			BDAC-HR-M6	Our big data analytics managers are able to understand and evaluate the output extracted from big data.	-			

Table 2. *(Continued)*

Third-order construct	Second-order constructs	First-order constructs	Indicator codes	Indicators	Loadings/ weights (*p*-values)	Cronbach alpha	CR	AVE
		Technical skills (BDAC-HR-T) Weights = 0.514 t-value = 33.255 VIF = 3.005	BDAC-HR-T1	We provide big data analytics training to our own employees.	-	0.905	0.930	0.729
			BDAC-HR-T2	We hire new employees that already have big data analytics skills.	0.720			
			BDAC-HR-T3	Our big data analytics staff has the right skills to accomplish their jobs successfully.	0.889			
			BDAC-HR-T4	Our big data analytics staff has suitable education to fulfil their jobs.	0.884			
			BDAC-HR-T5	Our big data analytics staff holds suitable work experience to accomplish their jobs successfully.	0.876			
			BDAC-HR-T6	Our big data analytics staff is well trained.	0.887			
	Intangible resources (BDAC-IR) Weights = 0.332 t-value = 16.287 VIF = 3.672	Data-driven culture (BDAC-IR-D) Weights = 0.504 t-value = 25.863 VIF = 2.462	BDAC-IR-D1	We consider data a tangible asset.	0.742	0.863	0.901	0.647
			BDAC-IR-D2	We base our decisions on data rather than on instinct.	0.806			
			BDAC-IR-D3	We are willing to override our own intuition when data contradict our viewpoints.	0.787			
			BDAC-IR-D4	We continuously assess and improve the business rules in response to insights extracted from data.	0.852			
			BDAC-IR-D5	We continuously coach our employees to make decisions based on data.	0.829			
		Intensity of organizational learning (BDAC-IR-I) Weights = 0.558 t-value = 23.332 VIF = 2.462	BDAC-IR-I1	We are able to search for new and relevant knowledge.	0.816	0.892	0.921	0.700
			BDAC-IR-I2	We are able to acquire new and relevant knowledge.	0.867			
			BDAC-IR-I3	We are able to assimilate relevant knowledge.	0.849			
			BDAC-IR-I4	We are able to apply relevant knowledge.	0.851			
			BDAC-IR-I5	We have made concerted efforts for the exploitation of existing competencies and the exploration of new knowledge.	0.796			
-	Learning capability (LC) VIF = 3.142	Exploration competence (LC-XLOR) Weights = 0.373 t-value = 20.085 VIF = 2.134	LC-XLOR1	Acquired manufacturing technologies and skills entirely new to the firm?	0.789	0.879	0.912	0.674

Table 2. (Continued)

Third-order construct	Second-order constructs	First-order constructs	Indicator codes	Indicators	Loadings/ weights (p-values)	Cronbach alpha	CR	AVE
			LC-XLOR2	Learned product development skills and processes (such as product design, prototyping new products, timing of new product introductions and customizing products for local markets) entirely new to the industry.	0.835			
			LC-XLOR3	Acquired entirely new managerial and organizational skills that are important for innovation (such as forecasting technological and customer trends; identifying emerging markets and technologies; coordinating and integrating R&D; marketing, manufacturing and other functions; managing the product development process).	0.824			
			LC-XLOR4	Learned new skills in areas such as funding new technology, staffing R&D function, training and development of R&D and engineering personnel for the first time.	0.851			
			LC-XLOR5	Strengthened innovation skills in areas where it had no prior experience.	0.803			
		Exploitation competence (LC-XOIT) weights = 0.381 t-value = 20.722 VIF = 2.810	LC-XOIT1	Upgraded current knowledge and skills for familiar products and technologies.	0.821	0.909	0.932	0.734
			LC-XOIT2	Invested in enhancing skills in exploiting mature technologies that improve productivity of current innovation operations.	0.867			
			LC-XOIT3	Enhanced competencies in searching for solutions to customer problems that are near to existing solutions rather than completely new solutions.	0.855			
			LC-XOIT4	Upgraded skills in product development processes in which the firm already possesses significant experience.	0.880			
			LC-XOIT5	Strengthened our knowledge and skills for projects that improve efficiency of existing innovation activities.	0.860			

Table 2. *(Continued)*

Third-order construct	Second-order constructs	First-order constructs	Indicator codes	Indicators	Loadings/ weights (*p*-values)	Cronbach alpha	CR	AVE
		Value creation competence (LC-VCC)	LC-VCC1	We have a formalized value proposition that is very compelling to our prospects.	0.765	0.871	0.902	0.607
		Weights = 0.386 t-value = 23.518 VIF = 1.895	LC-VCC2	Our salespeople have a solid understanding of our customer's business needs.	0.807			
			LC-VCC3	We clearly understand our customers' issues before we propose a solution.	0.787			
			LC-VCC4	We consistently follow a standard process to qualify opportunities.	0.810			
			LC-VCC5	Our salespeople are experts in our products and services.	0.742			
			LC-VCC6	We have an established procedure to know when to stop investment in large deals.	0.761			
-	-	Market-driving capability (MDC)	MDC1	We are recognized as the thought leader in our industry.	0.761	0.910	0.925	0.553
			MDC2	We use technology to disrupt existing markets.	0.708			
			MDC3	We build alliances with influential ecosystem actors to influence industry structure.	0.771			
			MDC4	We create markets that did not exist before.	0.720			
			MDC5	We introduce products with dramatic improvements in benefits or price.	0.811			
			MDC6	We are innovative in our pricing models (e.g. new metrics, subscriptions, as-a-service pricing, etc.).	0.747			
			MDC7	We invest heavily in educating our customers about the benefits of our new products.	0.722			
			MDC8	We influence and shape customer preferences.	0.735			
			MDC9	We lead our competitors: where we go, others follow.	0.776			
			MDC10	We aggressively cannibalize our current products with our new products.	0.672			

Table 2. (Continued)

Third-order construct	Second-order constructs	First-order constructs	Indicator codes	Indicators	Loadings/ weights (*p*-values)	Cronbach alpha	CR	AVE
-	-	Financial performance (FP)	FP1	Sales growth	0.830	0.888	0.918	0.692
			FP2	Profitability	0.868			
			FP3	Return on investment	0.845			
			FP4	Overall financial performance	0.858			
			FP5	Customer retention	0.755			
-	-	Market performance (MP)	MP1	Speed of new market entry.	0.865	0.885	0.921	0.744
			MP2	Speed of new product introductions.	0.885			
			MP3	New product or service success rate.	0.859			
			MP4	Market share vis-à-vis competitors.	0.840			
-	-	Competitive advantage (CA)	CA1	We are in a better position to profit from future market opportunities than competitors.	0.831	0.860	0.899	0.642
			CA2	We are able to exploit current market opportunities better than competitors.	0.837			
			CA3	It is difficult for competitors to imitate key elements of our value proposition.	0.717			
			CA4	Vis-à-vis competitors, we have more valuable relationships, resources or capabilities.	0.816			
			CA5	We are able to attract or retain more qualified personnel than our competitors.	0.800			

Note: AO-C3, AO-L3, BDAC-HR-M6 and BDAC-HR-T1 were deleted to achieve the HTMT value <0.900. Before deletion, the loadings of AO-C3, AO-L3, BDAC-HR-M6 and BDAC-HR-T1 were respectively 0.890, 0.785, 0.836 and 0.802, while the AVE values of their constructs were respectively 0.819, 0.700, 0.733 and 0.703. The constructs BDAC-TR-D, BDAC-TR-T and BDAC-TR-B were measured with formative indicators. Hence, their weights and significance (*p*-values) are reported. The loadings of all formative indicators were >0.500 and so no formative indicator was deleted (Hair *et al.*, 2022).

Table 3. HTMT criterion

	AO-C	AO-L	AO-S	BDAC-HR-M	BDAC-HR-T	BDAC-IR-D	BDAC-IR-I	CA	FP	LC-VCC	LC-XLOR	LC-XOIT	MDC	MP
AO-C														
AO-L	0.893													
AO-S	0.855	0.814												
BDAC-HR-M	0.763	0.771	0.641											
BDAC-HR-T	0.671	0.708	0.574	0.893										
BDAC-IR-D	0.726	0.753	0.642	0.798	0.799									
BDAC-IR-I	0.738	0.759	0.690	0.868	0.819	0.872								
CA	0.612	0.590	0.526	0.671	0.651	0.622	0.698							
FP	0.586	0.574	0.533	0.617	0.566	0.540	0.609	0.851						
LC-VCC	0.754	0.732	0.692	0.831	0.784	0.805	0.848	0.724	0.654					
LC-XLOR	0.574	0.626	0.539	0.593	0.640	0.597	0.621	0.598	0.550	0.611				
LC-XOIT	0.672	0.679	0.619	0.723	0.697	0.686	0.784	0.678	0.627	0.759	0.810			
MDC	0.698	0.705	0.656	0.734	0.750	0.730	0.740	0.852	0.737	0.769	0.759	0.786		
MP	0.607	0.582	0.550	0.663	0.618	0.592	0.637	0.884	0.852	0.664	0.677	0.680	0.825	

Note: HTMT < 0.90 is a threshold limit for conceptually similar constructs (Hair *et al.*, 2022).

Table 4. Hypotheses testing

No.	Path	Std beta	Std error	t-values	*p*-values	Effect size (f^2)	95% CI LL	95% CI UL
H1	AO → MDC	0.030	0.061	0.494	0.621	0.001	−0.062	0.142
H2	BDAC → MDC	0.338	0.068	4.957***	0.000	0.100	0.223	0.446
H3	LC → MDC	0.370	0.054	6.798***	0.000	0.143	0.280	0.460
H4	MDC → FP	0.447	0.052	8.564***	0.000	0.238	0.359	0.533
H5	MDC → MP	0.545	0.043	12.581***	0.000	0.424	0.473	0.615
H6	MDC → CA	0.580	0.041	14.103***	0.000	0.529	0.511	0.646

Note: Control variables: company age, company size, company annual revenue, big data budget, market dynamism and relative product advantage.
***$p < 0.001$

(Stathakopoulos *et al.*, 2022). We requested the panel provider to re-recruit the key informants of the main study. This task was challenging because many of the key informants could have progressed to senior positions or moved to other workplaces in the intervening time period. Nonetheless, the panel provider was able to re-recruit 70 key informants of the 416 respondents; given the average annual voluntary job turnover rate of about 20% in the United States, the expected number of respondents still in the same function in 2024 is about 170. Thus, the recruitment in 2024 of 70 key informants is satisfactory. We deleted unqualified and incomplete responses and thus retained 41 responses for the analysis. Considering the exploratory nature of the follow-up study, the nature of the respondents (key informants) and the need to gather data from the same key informant respondents after a 4-year interval (many of whom will not be in the same position, or not easily reached due to resource availability), we argue that the sample size is sufficient.

Constructs and scales. This supplementary study involved two constructs, namely, market-driving capability (MDC) and market change index.

Market change index (MCI): the construct measures the changes to any of the elements, such as products/prices, customers/use, channels, suppliers, representations and norms, that can change the market; second-order formative construct (Nenonen, Storbacka and Frethey-Bentham, 2019; Stathakopoulos *et al.*, 2022).

Data analysis. As MCI is a second-order construct (Nenonen, Storbacka and Frethey-Bentham, 2019), we again analysed the data through PLS-SEM with SmartPLS 4 software following the embedded two-stage approach (Sarstedt *et al.*, 2019). The measurement model was assessed by using the PLS algorithm with the default settings of the software, while the structural model was examined using the bootstrapping function with 10,000 subsamples (Hair *et al.*, 2019). Overall, our PLS-SEM analysis revealed that MDC influences MCI with a correlation value of 0.785 ($p < 0.001$). Hence, MDC significantly impacts market change.

Discussion and implications

As we noted earlier, despite several conceptual studies on the topic of market-driving strategies early in the millennium (Hills and Sarin, 2003; Jaworski, Kohli and Sahay, 2000; N. Kumar, Scheer and Kotler, 2000), few quantitative empirical studies have examined the effect of a market-driving capability, and few studies have identified the factors driving a proactive market orientation (Bodlaj and Čater, 2022, p. 262). Indeed, it has been observed that 'the discussion about capabilities behind … market-driving or proactive market orientation strategies …. has remained embryonic' (Nenonen, Storbacka and Windahl, 2019, pp. 631–632). Therefore, we need research 'to ascertain …. the antecedents to firm shaping of markets, including with respect to dynamic capabilities' (Helfat, 2021, p. 368).

Theoretical contributions

In order to provide insights into these under-researched topics, we make two theoretical contributions. Firstly, we contribute to the literature on capabilities that enable market-driving capability. Previous qualitative studies have empirically identified market-driving capabilities (Nenonen, Storbacka and Windahl, 2019); our quantitative methodology provides empirical support for these studies. We find that a market-driving capability is the result of BDAC and learning capability—two distinct but complementary enablers—while alliance orientation does not exhibit a significant effect (see Figure 2).

The non-significant result for alliance orientation invites deeper theoretical reflection. One possible explanation is that market-driving strategies are often guided by strong internal vision and executed unilaterally, particularly in early or disruptive stages of market creation. Partnerships in such contexts may hinder swift decision-making due to coordination challenges or divergent priorities (Humphreys and Carpenter, 2018; Reid and de Brentani, 2010; Taeuscher, Bouncken and Pesch, 2021). Moreover, BDAC and learning capability may absorb much of the explanatory variance in our model, as both involve internalized mechanisms for sensing and acting on emerging trends. Finally, the multidimensionality of AO may attenuate its explanatory power in this context—its impact may be more pronounced in later phases of market shaping, in regulated industries, or in highly interdependent value chains (Baker and Nenonen, 2020).

In the literature, there is a clear tension between market driving as an individualistic endeavour (Reid and de Brentani, 2010; Taeuscher, Bouncken and Pesch, 2021) and market driving as a collective effort requiring alliances (Baker and Nenonen, 2020; Maciel and Fischer, 2020). The literature therefore supports both views, allowing for the interpretation that market driving efforts in market niches could benefit from alliance capabilities (Baker and Nenonen, 2020; Maciel and Fischer, 2020). Our broad, cross-sectional study, however, lends more support to the idea of market driving strategies as an individualistic effort guided, as extant qualitative research suggests, by individual actions: 'You have your own vision, your own interpretation', is the comment from one market-driving company in the wine industry (Humphreys and Carpenter, 2018, p. 156).

BDAC facilitates the development and deployment of market-driving capability. BDAC entails a set of

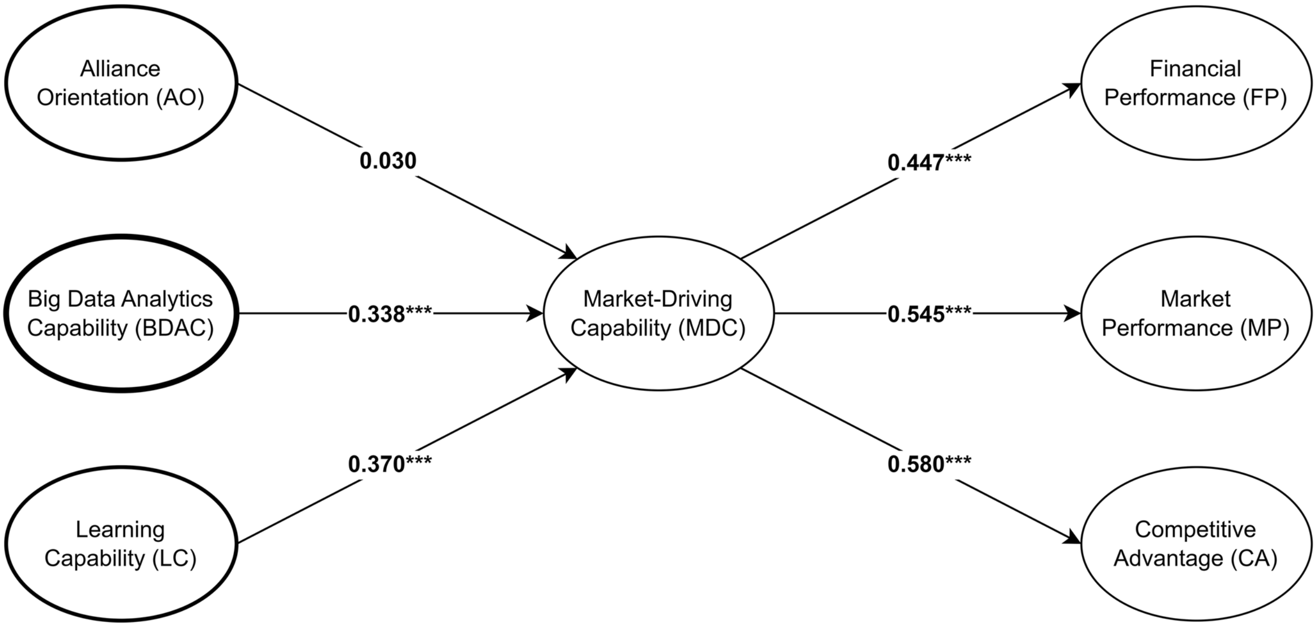

Figure 2. Summary of findings

complex skills, implying that companies prioritize adequate funding for big data analytics projects, that they have access to a diverse range of data sources, that they integrate this data into a centralized data warehouse for comprehensive analysis, and that they make use of advanced analytical tools (parallel computing approaches, data visualization, cloud-based services, open-source software, new database technologies like NoSQL); BDAC moreover implies that these companies focus on nurturing human skills by providing training to employees in big data analytics, that they collaborate effectively within their own companies and with customers to identify opportunities and future business needs; finally, BDAC implies that these companies exhibit a strong data-driven culture, view data as a tangible asset and prioritize data-based decision-making over instinct and improve their operations based on insights derived from data (Gupta and George, 2016). Our study shows that BDAC serves as a high-leverage capability that enables firms to anticipate market trends, identify unmet needs and execute market-shaping strategies with precision.

Finally, learning capability is a market-driving capability. The role of learning capabilities—resulting from competence exploitation, competence exploration and value proposition development—clarifies the important role of customers in market-driving strategies. Findings from prior studies suggest that market-driving strategy goes beyond merely responding to customers' needs. For example, in their study of market-driving strategies in the wine industry, Humphrey and Carpenter quote a wine producer: 'When asked about how he considers the consumer when making wine, Moueix simply replies, "I don't. I make what pleases me"' (Humphreys and Carpenter, 2018, p. 149). But this does not imply that a market-driving capability is compatible with, or indeed requires, low customer orientation. Rather, our quantitative study indicates that learning capabilities—higher-order capabilities resulting from the ability to develop a compelling value proposition for customers, from joint exploration and exploitation—facilitate market driving and proactive market strategies. Stated differently, the joint pursuit of customer centricity (i.e. a nuanced ability to obtain the voice of the customer to fulfil customer needs), continuous optimization (i.e. competence exploitation) and acquisition of new competencies (i.e. competence exploration) defines learning capabilities that enable market-driving strategies. Market-driving strategies are thus associated with high customer centricity, in addition to the ability to successfully manage the tension of joint exploration and exploitation.

Secondly, we provide empirical evidence of the consequences of a market-driving capability. Specifically, we show that a market-driving capability contributes positively to firm performance and competitive advantage (see Figure 2). The effect of market-driving capability or strategies on firm performance is direct and strong, in line with prior studies (Blut, Holzmüller and Stolper, 2012; Martín-Consuegra, Molina and Esteban, 2008; Stathakopoulos *et al.*, 2022). This finding thus complements the prior literature that takes a macro-perspective and analyses how the actions of multiple players influence the process of new market creation in the wine, craft beer, or coffee industry (Dolbec, Arsel and Aboelenien, 2022; Humphreys and Carpenter, 2018; Maciel and Fischer, 2020; Nenonen, Storbacka and Windahl, 2019). Our follow-up study also offers preliminary yet novel support for the idea that market-driving capability can lead to structural market change. Firms reporting high MDC scores also reported changes in customer behaviours, value propositions and competitive interactions—signs consistent with systemic market transformation.

Managerial implications

The world around us is full of firms attempting to drive markets: Google Glass, Meta's investments into the metaverse, as opposed to Monsanto, Starbucks or Tesla (LaPlaca and da Silva, 2016). We find success, alongside failed attempts. Practicing managers rightly demand empirical research that sheds light on factors that increase the likelihood of successful market-driving strategies (Schweitzer, Malek and Sarin, 2023). This study is among the first quantitative studies that attempt to illuminate antecedents. Our model, parsimonious as it may be, sheds light on two levers that are highly correlated with market driving capabilities and firm performance.

First, insights resulting from BDAC are the foundation of market-driving capabilities. Companies should invest to build, develop and defend their BDAC (Gupta and George, 2016). Specifically, executives should invest in resources and infrastructure to ensure funding for big data projects; they should cultivate a skilled workforce to continually enhance big data analytics skills. Executives can promote a data-driven culture that views data as a critical asset and encourages decision-making based on data insights rather than intuition. Executives should work to integrate data to build a 'single source of truth' (Sebastian *et al.*, 2017, p. 201) and then make this data broadly accessible. Executives can then align big data projects with business goals, collaborating with customers and suppliers to determine opportunities to extract value from big data.

Second, executives should encourage their employees to master the difficult tension between exploration, exploitation and customer centricity. Senior executives can foster a culture of continuous learning, innovation and experimentation while, at the same time, leveraging and enhancing existing capabilities and strengthening customer-centric value creation. This study also highlights that while alliances can expand a firm's network reach, they may not be necessary—or even desirable—for early-stage market-driving efforts. Managers must assess the strategic trade-offs between collaboration and autonomy depending on industry, timing and regulatory environment.

At an annual Big Data and Business Analytics Symposium, Constantin Gonzalez, an executive at Amazon, arguably a market driving company, highlights how Amazon uses machine learning and points out that machine learning may 'not be a good idea' for companies that have 'no data, no labels, not a lot of time, no tolerance for mistakes' (Gonzalez, 2018, p. 74). This statement—originating from a single, highly successful case—underscores the critical role of BDAC and organizational learning in market-driving strategies. Our findings provide empirical support for this perspective, demonstrating that firms that invest in BDAC—while fostering a culture of exploration, exploitation and customer-centric learning—are not only better equipped to drive markets but also achieve sustained competitive advantage and superior performance.

In sum, BDAC, combined with continuous exploration, exploitation and the pursuit of customer centricity, enables market driving strategies—with no need to enlist alliance partners in the quest. Our data furthermore indicate that market driving strategies are equally likely in B2B as they are in B2C markets, thus alleviating concerns that this type of strategic posture could be more widespread (or easier to implement) in consumer markets than in industrial markets (LaPlaca and da Silva, 2016).

Limitations and directions for future research

This research has limitations. First, since we collected data via an online panel provider, responses were obtained from a single informant per firm. Our choice to use a panel provider was driven by the nature of our research question and the need to obtain answers on sensitive topics from senior decision-makers in organizations (Porter *et al.*, 2019). While we applied the recommended procedural and statistical remedies to mitigate common method bias, future studies could improve upon this by collecting data from multiple respondents within each firm.

Second, market driving is inherently a process that unfolds over time and involves multiple actors (Dolbec, Arsel and Aboelenien, 2022; Maciel and Fischer, 2020). Our study adopts a firm-level, cross-sectional perspective that focuses on the strategic actions through which individual firms initiate and lead market-driving behaviour. While such actions can accumulate into broader system-level change, capturing industry-wide orchestration, regulatory shifts, or societal norm change would require longitudinal, multi-actor research designs that extend beyond the scope of the present study. Future research could therefore employ longitudinal or process-based methods to examine how firm-level market-driving actions aggregate into systemic market transformation over time.

Third, prior research has emphasized the role of organizational vision and leadership framing in enabling market-driving strategies (Kohli and Jaworski, 2023). Future studies could examine how visionary leadership, managerial cognition, or strategic narratives interact with data-driven and learning-based capabilities to shape markets more effectively.

Fourth, we acknowledge limitations in our follow-up study due to the relatively small sample size ($n = 41$). While the results are promising and provide exploratory support for the relationship between market-driving capability and market change, the limited sample size constrains statistical generalizability. Future research should test this relationship using larger, longitudinal datasets across industries and geographies to enhance external validity.

With respect to measurement, we acknowledge that the scale proposed by Stathakopoulos *et al.* (2022) represents a valuable and timely contribution to the operationalization of market-driving strategies. However, our study was designed and data were collected in 2020, prior to the publication of that scale, making its adoption infeasible without redesigning the study and collecting new data. Our MDC scale focuses deliberately on proximal, firm-level strategic actions—such as customer education, preference shaping, pricing innovation and competitive leadership—that initiate market-driving processes and are observable within a cross-sectional survey design.

Rather than viewing alternative operationalizations as competing, we see them as complementary. As observed in other research domains (e.g. dynamic capabilities, circular economy), conceptual pluralism has facilitated cumulative theory development (Khan, 2025). Future research may therefore compare, integrate, or extend different MDC scales to capture additional dimensions of market driving, including ecosystem orchestration, regulatory influence, or societal-level change.

We also acknowledge that BDAC may not constitute a universal antecedent of market-driving capability. Its influence is likely contingent on contextual factors such as industry turbulence, data intensity, technological maturity and competitive dynamics. Our sampling frame—focused on managers with analytics-related expertise—was appropriate for examining BDAC as a theoretically relevant capability, but future research could investigate boundary conditions under which BDAC is more or less central to market-driving behaviour. Such work would further clarify when data-driven insight generation most strongly contributes to proactive market shaping.

Finally, future research may explore under what conditions alliance orientation becomes a more relevant enabler—such as in mature markets, highly regulated sectors, or ecosystems that require joint infrastructure investments. Identifying these boundary conditions would help reconcile perspectives that emphasize market driving as either an individualistic, vision-led effort or a collaborative, system-level process.

In closing, we view this study as establishing a focused and theoretically grounded foundation for quantitative research on market-driving capability. We encourage future work to refine measurement approaches, examine contextual contingencies and extend analysis across levels of market change.

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Conflict of interest

The authors declare that they have no conflict of interest.

References

Ameen, N., S. Tarba, J. Cheah, S. Xia and G. D. Sharma (2024). 'Coupling artificial intelligence capability and strategic agility for enhanced product and service creativity', *British Journal of Management*, **35**, pp. 1916–1934. https://doi.org/10.1111/1467-8551.12797

Armstrong, J. S. and T. S. Overton (1977). 'Estimating nonresponse bias in mail surveys', *Journal of Marketing Research*, **14**, pp. 396–402. https://doi.org/10.1177/002224377701400320

Atuahene-Gima, K. (2005). 'Resolving the capability–rigidity paradox in new product innovation', *Journal of Marketing*, **69**, pp. 61–83. https://doi.org/10.1509/jmkg.2005.69.4.61

Awan, U., S. H. Bhatti, S. Shamim, Z. Khan, P. Akhtar and M. E. Balta (2022). 'The role of big data analytics in manufacturing agility and performance: moderation–mediation analysis of organizational creativity and of the involvement of customers as data analysts', *British Journal of Management*, **33**, pp. 1200–1220. https://doi.org/10.1111/1467-8551.12549

Baker, J. J. and S. Nenonen (2020). 'Collaborating to shape markets: emergent collective market work', *Industrial Marketing Management*, **85**, pp. 240–253. https://doi.org/10.1016/j.indmarman.2019.11.011

Bao, Y., Z. Wei and A. Di Benedetto (2020). 'Identifying the tacit entrepreneurial opportunity of latent customer needs in an emerging economy: the effects of experiential market learning versus vicarious market learning', *Strategic Entrepreneurship Journal*, **14**, pp. 444–469. https://doi.org/10.1002/sej.1350

Barney, J. (1991). 'Firm resources and sustained competitive advantage', *Journal of Management*, **17**, pp. 99–120. https://doi.org/10.1177/014920639101700108

Blut, M., H. H. Holzmüller and M. Stolper (2012). 'Market shaping orientation and firm performance'. In A. Diamantopoulos, W. Fritz and L. Hildebrandt (eds.), *Quantitative Marketing and Marketing Management*, pp. 447–466. Wiesbaden: Gabler Verlag. https://doi.org/10.1007/978-3-8349-3722-3_21

Bodlaj, M. and B. Čater (2022). 'Responsive and proactive market orientation in relation to SMEs' export venture performance: the mediating role of marketing capabilities', *Journal of Business Research*, **138**, pp. 256–265. https://doi.org/10.1016/j.jbusres.2021.09.034

Bouakel, M. and A. Zerbout (2021). 'Perspectives of big data analytics' integration in the business strategy of Amazon, Inc.' In S. Sedkaoui, M. Khelfaoui and N. Kadi (eds.), *Big Data Analytics*, pp.

201–220. Apple Academic Press, New York. https://doi.org/10.1201/9781003129660-20

Bower, J. L. and C. M. Christensen (1995). 'Disruptive technologies: catching the wave', *Harvard Business Review*, **73**, pp. 43–53.

Dess, G. G. and R. B. Robinson (1984). 'Measuring organizational performance in the absence of objective measures: the case of the privately-held firm and conglomerate business unit', *Strategic Management Journal*, **5**, pp. 265–273. https://doi.org/10.1002/smj.4250050306

Dion, D., G. Carpenter and A. Humphreys (2025). 'EXPRESS: avant-garde market driving', *Journal of Marketing*, https://doi.org/10.1177/00222429251377752

Dolbec, P.-Y., Z. Arsel and A. Aboelenien (2022). 'A practice perspective on market evolution: how craft and commercial coffee firms expand practices and develop markets', *Journal of Marketing*, **86**, pp. 50–69. https://doi.org/10.1177/00222429221093624

Eisenhardt, K. M. and J. A. Martin (2000). 'Dynamic capabilities: what are they?', *Strategic Management Journal*, **21**, pp. 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11⟨1105::AID-SMJ133⟩3.0.CO;2-E

Erevelles, S., N. Fukawa and L. Swayne (2016). 'Big data consumer analytics and the transformation of marketing', *Journal of Business Research*, **69**, pp. 897–904. https://doi.org/10.1016/j.jbusres.2015.07.001

Frank, D. and T. Otterbring (2024). 'Autonomy, power and the special case of scarcity: consumer adoption of highly autonomous artificial intelligence', *British Journal of Management*, **35**, pp. 1700–1723. https://doi.org/10.1111/1467-8551.12780

Gibson, C. B. and J. Birkinshaw (2004). 'The antecedents, consequences, and mediating role of organizational ambidexterity', *Academy of Management Journal*, **47**, pp. 209–226. https://doi.org/10.5465/20159573

Gonzalez, C. (2018). 'The machine learning process: from business model to machine learning in production'. In *5th Big Data and Business Analytics Symposium*. Wayne State University.

Gupta, M. and J. F. George (2016). 'Toward the development of a big data analytics capability', *Information & Management*, **53**, pp. 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

Hair, J. F., G. T. M. Hult, C. M. Ringle and M. Sarstedt (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd edn. Sage, Thousand Oaks.

Hair, J. F., J. J. Risher, M. Sarstedt and C. M. Ringle (2019). 'When to use and how to report the results of PLS-SEM', *European Business Review*, **31**, pp. 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., M. Sarstedt, C. M. Ringle and J. A. Mena (2012). 'An assessment of the use of partial least squares structural equation modeling in marketing research', *Journal of the Academy of Marketing Science*, **40**, pp. 414–433. https://doi.org/10.1007/s11747-011-0261-6

Hamel, G. (1996). 'Strategy as revolution', *Harvard Business Review*, **74**, pp. 69–82.

Helfat, C. E. (2021). 'What does firm shaping of markets really mean?', *Strategy Science*, **6**, pp. 360–370. https://doi.org/10.1287/stsc.2021.0144

Helfat, C. E., S. Finkelstein, W. Mitchell, M. Peteraf, H. Singh, D. Teece and S. G. Winter (2007). *Dynamic Capabilities: Understanding Strategic Change in Organizations*. Malden, MA: Blackwell Publishing.

Helfat, C. E., A. Kaul, D. J. Ketchen, J. B. Barney, O. Chatain and H. Singh (2023). 'Renewing the resource-based view: new contexts, new concepts, and new methods', *Strategic Management Journal*, **44**, pp. 1357–1390. https://doi.org/10.1002/smj.3500

Hills, S. B. and S. Sarin (2003). 'From market driven to market driving: an alternate paradigm for marketing in high technology industries', *Journal of Marketing Theory and Practice*, **11**, pp. 13–24. https://doi.org/10.1080/10696679.2003.11658498

Hinterhuber, A. (2002). 'Value chain orchestration in action and the case of the global agrochemical industry', *Long Range Planning*, **35**, pp. 615–635. https://doi.org/10.1016/S0024-6301(02)00160-7

Hinterhuber, A. and O. Khan (2025). 'What drives sustainable procurement? Insights from the theory of planned behavior', *International Journal of Operations & Production Management*, **45**, pp. 28–52. https://doi.org/10.1108/IJOPM-02-2024-0164

Hulland, J., H. Baumgartner and K. M. Smith (2018). 'Marketing survey research best practices: evidence and recommendations from a review of JAMS articles', *Journal of the Academy of Marketing Science*, **46**, pp. 92–108. https://doi.org/10.1007/s11747-017-0532-y

Hult, G. T. M., J. F. Hair, D. Proksch, M. Sarstedt, A. Pinkwart and C. M. Ringle (2018). 'Addressing endogeneity in international marketing applications of partial least squares structural equation modeling', *Journal of International Marketing*, **26**, pp. 1–21. https://doi.org/10.1509/jim.17.0151

Humphreys, A. and G. S. Carpenter (2018). 'Status games: market driving through social influence in the U.S. wine industry', *Journal of Marketing*, **82**, pp. 141–159. https://doi.org/10.1509/jm.16.0179

Hunter, G. K. (2014). 'Customer business development: identifying and responding to buyer-implied information preferences', *Industrial Marketing Management*, **43**, pp. 1204–1215. https://doi.org/10.1016/j.indmarman.2014.06.008

Hurley, R. F. and G. T. M. Hult (1998). 'Innovation, market orientation, and organizational learning: an integration and empirical examination', *Journal of Marketing*, **62**, pp. 42–54. https://doi.org/10.2307/1251742

Interbrand. (2024). 'Best global brands 2023', https://interbrand.com/best-brands/

Duane Ireland, R. and J. W. Webb (2007). 'Strategic entrepreneurship: creating competitive advantage through streams of innovation', *Business Horizons*, **50**, pp. 49–59. https://doi.org/10.1016/j.bushor.2006.06.002

Jaworski, B. J., A. K. Kohli and A. Sahay (2000). 'Market-driven versus driving markets', *Journal of the Academy of Marketing Science*, **28**, pp. 45–54. https://doi.org/10.1177/0092070300281005

Johnson, J. S., S. B. Friend and H. S. Lee (2017). 'Big data facilitation, utilization, and monetization: exploring the 3Vs in a new product development process', *Journal of Product Innovation Management*, **34**, pp. 640–658. https://doi.org/10.1111/jpim.12397

Kandemir, D. (2006). 'Alliance orientation: conceptualization, measurement, and impact on market performance', *Journal of the Academy of Marketing Science*, **34**, pp. 324–340. https://doi.org/10.1177/0092070305285953

Karaboga, T., C. Zehir, E. Tatoglu, H. A. Karaboga and A. Bouguerra (2023). 'Big data analytics management capability and firm performance: the mediating role of data-driven culture', *Review of Managerial Science*, **17**, pp. 2655–2684. https://doi.org/10.1007/s11846-022-00596-8

Kaur, D. (2024). 'Apple claims top spot, outshining Samsung in 2023 smartphone sales', https://techhq.com/2024/01/apple-claims-top-spot-outshining-samsung-in-2023-smartphone-sales/

Khan, O. (2025). 'Catalysts of circular transformation: unveiling behavioural intention and absorptive capacity in European hotels', *Current Issues in Tourism*, pp. 1–16. https://doi.org/10.1080/13683500.2025.2454274

Khan, O., T. Daddi and F. Iraldo (2021). 'Sensing, seizing, and reconfiguring: key capabilities and organizational routines for circular economy implementation', *Journal of Cleaner Production*, **287**, art. 125565. https://doi.org/10.1016/j.jclepro.2020.125565

Khan, O. and A. Hinterhuber (2025). 'Personality traits and willingness to pay for sustainability in supply chains', *Journal of Revenue and Pricing Management*, **24**, pp. 3–11. https://doi.org/10.1057/s41272-024-00518-1

Kock, N. (2015). 'Common method bias in PLS-SEM', *International Journal of E-Collaboration*, **11**, pp. 1–10. https://doi.org/10.4018/ijec.2015100101

Kohli, A. K. and B. J. Jaworski (2023). 'Market driving: some directions for future research', *Industrial Marketing Management*, **113**, pp. 348–351. https://doi.org/10.1016/j.indmarman.2023.06.012

Kollmann, T. and C. Stöckmann (2014). 'Filling the entrepreneurial orientation–performance gap: the mediating effects of exploratory and exploitative innovations', *Entrepreneurship Theory and Practice*, **38**, pp. 1001–1026. https://doi.org/10.1111/j.1540-6520.2012.00530.x

Kumar, N., L. Scheer and P. Kotler (2000). 'From market driven to market driving', *European Management Journal*, **18**, pp. 129–142. https://doi.org/10.1016/S0263-2373(99)00084-5

Kumar, V., E. Jones, R. Venkatesan and R. P. Leone (2011). 'Is market orientation a source of sustainable competitive advantage or simply the cost of competing?', *Journal of Marketing*, **75**, pp. 16–30. https://doi.org/10.1509/jmkg.75.1.16

LaPlaca, P. and R. V. da Silva (2016). 'B2B: a paradigm shift from economic exchange to behavioral theory: a quest for better explanations and predictions', *Psychology & Marketing*, **33**, pp. 232–249. https://doi.org/10.1002/mar.20872

Lin, H., E. F. McDonough, S. Lin and C. Y. Lin (2013). 'Managing the exploitation/exploration paradox: the role of a learning capability and innovation ambidexterity', *Journal of Product Innovation Management*, **30**, pp. 262–278. https://doi.org/10.1111/j.1540-5885.2012.00998.x

Maciel, A. F. and E. Fischer (2020). 'Collaborative market driving: how peer firms can develop markets through collective action', *Journal of Marketing*, **84**, pp. 41–59. https://doi.org/10.1177/0022242920917982

Marini, B., O. Khan and A. Hinterhuber (2025). 'Impact of online influencer marketing on consumers' willingness to pay more', *Journal of Marketing Communications*, pp. 1–24. https://doi.org/10.1080/13527266.2025.2544276

Martín-Consuegra, D., A. Molina and Á. Esteban (2008). 'Market driving in retail banking', *International Journal of Bank Marketing*, **26**, pp. 260–274. https://doi.org/10.1108/02652320810884795

Mattila, M., M. Yrjölä and P. Hautamäki (2021). 'Digital transformation of business-to-business sales: what needs to be unlearned?', *Journal of Personal Selling & Sales Management*, **41**, pp. 113–129. https://doi.org/10.1080/08853134.2021.1916396

Mikalef, P., M. Boura, G. Lekakos and J. Krogstie (2019). 'Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment', *British Journal of Management*, **30**, pp. 272–298. https://doi.org/10.1111/1467-8551.12343

Mikalef, P., J. Krogstie, I. O. Pappas and P. Pavlou (2020). 'Exploring the relationship between big data analytics capability and competitive performance: the mediating roles of dynamic and operational capabilities', *Information & Management*, **57**, p. 103169. https://doi.org/10.1016/j.im.2019.05.004

Mikalef, P., I. O. Pappas, J. Krogstie and M. Giannakos (2018). 'Big data analytics capabilities: a systematic literature review and research agenda', *Information Systems and E-Business Management*, **16**, pp. 547–578. https://doi.org/10.1007/s10257-017-0362-y

Narver, J. C., S. F. Slater and D. L. MacLachlan (2004). 'Responsive and proactive market orientation and new-product success', *Journal of Product Innovation Management*, **21**, pp. 334–347. https://doi.org/10.1111/j.0737-6782.2004.00086.x

Nenonen, S., K. Storbacka and C. Frethey-Bentham (2019). 'Is your industrial marketing work working? Developing a composite index of market change', *Industrial Marketing Management*, **80**, pp. 251–265. https://doi.org/10.1016/j.indmarman.2018.06.006

Nenonen, S., K. Storbacka and C. Windahl (2019). 'Capabilities for market-shaping: triggering and facilitating increased value creation', *Journal of the Academy of Marketing Science*, **47**, pp. 617–639. https://doi.org/10.1007/s11747-019-00643-z

O'Sullivan, D. and A. V. Abela (2007). 'Marketing performance measurement ability and firm performance', *Journal of Marketing*, **71**, pp. 79–93. https://doi.org/10.1509/jmkg.71.2.79

Oberlo. (2024a). 'Smartphone market share worldwide', https://www.oberlo.com/statistics/smartphone-market-share

Oberlo. (2024b). 'US smartphone market share', https://www.oberlo.com/statistics/us-smartphone-market-share

Olabode, O. E., N. Boso, M. Hultman and C. N. Leonidou (2022). 'Big data analytics capability and market performance: the roles of disruptive business models and competitive intensity', *Journal of Business Research*, **139**, pp. 1218–1230. https://doi.org/10.1016/j.jbusres.2021.10.042

Peteraf, M. A. (1993). 'The cornerstones of competitive advantage: a resource-based view', *Strategic Management Journal*, **14**, pp. 179–191. https://doi.org/10.1002/smj.4250140303

Peteraf, M. A. and J. B. Barney (2003). 'Unraveling the resource-based tangle', *Managerial and Decision Economics*, **24**, pp. 309–323. https://doi.org/10.1002/mde.1126

Podsakoff, P. M., S. B. MacKenzie, J.-Y. Lee and N. P. Podsakoff (2003). 'Common method biases in behavioral research: a critical review of the literature and recommended remedies', *Journal of Applied Psychology*, **88**, pp. 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Porter, C. O. L. H., R. Outlaw, J. P. Gale and T. S. Cho (2019). 'The use of online panel data in management research: a review and recommendations', *Journal of Management*, **45**, pp. 319–344. https://doi.org/10.1177/0149206318811569

Reid, S. E. and U. de Brentani (2010). 'Market vision and market visioning competence: impact on early performance for radically new, high-tech products', *Journal of Product Innovation Management*, **27**, pp. 500–518. https://doi.org/10.1111/j.1540-5885.2010.00732.x

Richard, P. J., T. M. Devinney, G. S. Yip and G. Johnson (2009). 'Measuring organizational performance: towards methodological best practice', *Journal of Management*, **35**, pp. 718–804. https://doi.org/10.1177/0149206308330560

Ringle, C. M., S. Wende and J.-M. Becker (2024). 'SmartPLS 4', https://www.smartpls.com/

Sapienza, H. J., K. G. Smith and M. J. Gannon (1988). 'Using subjective evaluations of organizational performance in small business research', *American Journal of Small Business*, **12**, pp. 45–54. https://doi.org/10.1177/104225878801200304

Sarstedt, M., J. F. Hair, J.-H. Cheah, J.-M. Becker and C. M. Ringle (2019). 'How to specify, estimate, and validate higher-order constructs in PLS-SEM', *Australasian Marketing Journal*, **27**, pp. 197–211. https://doi.org/10.1016/j.ausmj.2019.05.003

Sarstedt, M., C. M. Ringle, J.-H. Cheah, H. Ting, O. I. Moisescu and L. Radomir (2020). 'Structural model robustness checks in PLS-SEM', *Tourism Economics*, **26**, pp. 531–554. https://doi.org/10.1177/1354816618823921

Schweitzer, F., S. L. Malek and S. Sarin (2023). 'Exploring the future of market driving: a dialogue with marketing thought leaders', *Industrial Marketing Management*, **113**, pp. 277–294. https://doi.org/10.1016/j.indmarman.2023.06.010

Sebastian, I., J. Ross, C. Beath, M. Mocker, K. Moloney and N. Fonstad (2017). 'How big old companies navigate digital transformation', *MIS Quarterly Executive*, **16**, pp. 197–213. https://aisel.aisnet.org/misqe/vol16/iss3/6

Sheng, J., J. Amankwah-Amoah and X. Wang (2017). 'A multidisciplinary perspective of big data in management research', *International Journal of Production Economics*, **191**, pp. 97–112. https://doi.org/10.1016/j.ijpe.2017.06.006

Sigalas, C., V. Pekka Economou and N.B. Georgopoulos. (2013). 'Developing a measure of competitive advantage', *Journal of Strategy and Management*, **6**, pp. 320–342. https://doi.org/10.1108/JSMA-03-2013-0015

Slater, S. F. and E. M. Olson (2000). 'Strategy type and performance: the influence of sales force management', *Strategic Management Journal*, **21**, pp. 813–829. https://doi.org/10.1002/1097-0266(200008)21:8⟨813::AID-SMJ122⟩3.0.CO;2-G

Sozuer, S., G. S. Carpenter, P. K. Kopalle, L. M. McAlister and D. R. Lehmann (2020). 'The past, present, and future of marketing strategy', *Marketing Letters*, **31**, pp. 163–174. https://doi.org/10.1007/s11002-020-09529-5

Stathakopoulos, V., K. G. Kottikas, G. Painesis, I. G. Theodorakis and E. Kottika (2022). 'Why shape a market? Empirical evidence on the prominent firm-level and market-level outcomes of market-driving strategy', *Journal of Business Research*, **139**, pp. 1240–1254. https://doi.org/10.1016/j.jbusres.2021.10.057

Sullivan, U. Y., R. M. Peterson and V. Krishnan (2012). 'Value creation and firm sales performance: the mediating roles of strategic account management and relationship perception', *Industrial Marketing Management*, **41**, pp. 166–173. https://doi.org/10.1016/j.indmarman.2011.11.019

Suoniemi, S., L. Meyer-Waarden, A. Munzel, A. R. Zablah and D. Straub (2020). 'Big data and firm performance: the roles of market-directed capabilities and business strategy', *Information & Management*, **57**, art. 103365. https://doi.org/10.1016/j.im.2020.103365

Taeuscher, K., R. Bouncken and R. Pesch (2021). 'Gaining legitimacy by being different: optimal distinctiveness in crowdfunding platforms.' *Academy of Management Journal*, **64**, pp. 149–179. https://doi.org/10.5465/amj.2018.0620

Teece, D. J. (2007). 'Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance.' *Strategic Management Journal*, **28**, pp. 1319–1350. https://doi.org/10.1002/smj.640

Tippins, M. J. and R. S. Sohi (2003). 'IT competency and firm performance: is organizational learning a missing link?', *Strategic Management Journal*, **24**, pp. 745–761. https://doi.org/10.1002/smj.337

Vesterinen, M., J. Mero and M. Skippari (2025). 'Big data analytics capability, marketing agility, and firm performance: a conceptual framework', *Journal of Marketing Theory and Practice*, **33**, pp. 310–330. https://doi.org/10.1080/10696679.2024.2322600

Walter, S. L., S. E. Seibert, D. Goering and E. H. O'Boyle (2019). 'A tale of two sample sources: do results from online panel data and conventional data converge?', *Journal of Business and Psychology*, **34**, pp. 425–452. https://doi.org/10.1007/s10869-018-9552-y

Wamba, S. F., A. Gunasekaran, S. Akter, S. J. Ren, R. Dubey and S. J. Childe (2017). 'Big data analytics and firm performance: effects of dynamic capabilities', *Journal of Business Research*, **70**, pp. 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

Wang, N., H. Liang, W. Zhong, Y. Xue and J. Xiao (2012). 'Resource structuring or capability building? An empirical study of the business value of information technology', *Journal of Management Information Systems*, **29**, pp. 325–367. https://doi.org/10.2753/MIS0742-1222290211

Weerawardena, J. (2003). 'The role of marketing capability in innovation-based competitive strategy', *Journal of Strategic Marketing*, **11**, pp. 15–35. https://doi.org/10.1080/0965254032000096766

Xia, S., J. Song, N. Ameen, D. Vrontis, J. Yan and F. Chen (2024). 'What changes and opportunities does big data analytics capability bring to strategic alliance research? A systematic literature review', *International Journal of Management Reviews*, **26**, pp. 34–53. https://doi.org/10.1111/ijmr.12350

Zaefarian, G., V. Kadile, S. C. Henneberg and A. Leischnig (2017). 'Endogeneity bias in marketing research: problem, causes and remedies', *Industrial Marketing Management*, **65**, pp. 39–46. https://doi.org/10.1016/j.indmarman.2017.05.006

Zhang, H. and Y. Xiao (2020). 'Customer involvement in big data analytics and its impact on B2B innovation', *Industrial Marketing Management*, **86**, pp. 99–108. https://doi.org/10.1016/j.indmarman.2019.02.020

APPENDIX

Table A1. ***Assumptions check***

Construct	p-value	Non-normally distributed?
AO	0.0002	Yes
BDAC	0.0002	Yes
CA	0.0292	Yes
FP	0.0420	Yes
LC	0.1790	No
MDC	0.0004	Yes
MP	0.0004	Yes

Table A2. Gaussian copula

		Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Case	Construct	β	p	β	p	β	p	β	p	β	p	β	p	β	p
MDC	AO	0.071	0.540	0.043	0.525	0.041	0.543	0.187	0.206	0.127	0.376	0.043	0.529	0.187	0.218
	BDAC	0.383	0.000	0.268	0.025	0.385	0.000	0.120	0.493	0.389	0.000	0.236	0.238	0.121	0.583
	LC	0.461	0.000	0.446	0.000	0.337	0.117	0.451	0.000	0.206	0.464	0.517	0.121	0.447	0.193
	^{C}AO	−0.037	0.644					−0.154	0.176	−0.093	0.401			−0.155	0.192
	^{C}BDAC			0.123	0.194			0.285	0.056			0.156	0.377	0.283	0.143
	^{C}LC					0.118	0.540			0.258	0.333	−0.073	0.820	0.005	0.989

		Model 1	
Case	**Construct**	$\boldsymbol{\beta}$	$\boldsymbol{p}$
FP	FP	0.247	0.316
	^{C}FP	0.425	0.067

		Model 1	
Case	**Construct**	$\boldsymbol{\beta}$	$\boldsymbol{p}$
MP	MP	0.387	0.050
	^{C}MP	0.359	0.057

		Model 1	
Case	**Construct**	$\boldsymbol{\beta}$	**Case**
CA	CA	0.619	0.004
	^{C}CA	0.141	0.482

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