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Developing customer analytics capability in firms of different ages: Examining the complementarity of outside-in and inside-out resources

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A B S T R A C T

Customer analytics capability remains underdeveloped among firms despite its potential for enhancing competitiveness. Previous research has predominantly focused on inside-out organizational factors as drivers of customer analytics capability. This paper examines the role of outside-in resource, the complementarity between outside-in and inside-out resources, and their boundary conditions. Specifically, we study how customer orientation culture (an outside-in resource) complements data-driven culture (an inside-out resource) in firms of different ages to drive customer analytics capability and subsequently, firm performance. Using survey data obtained from Canadian firms, we find that customer orientation is not only positively related to customer analytics capability but also reinforces the effect of data-driven culture. We further find that the conditional effect of customer orientation becomes stronger as firm age increases. In particular, among older firms, the impact of data-driven culture is greatest when customer orientation is high, but it becomes nonsignificant when customer orientation is low. We also link these relationships to firm performance using mediation and moderated mediation analyses. Overall, the results suggest that achieving customer analytics excellence and resultant competitive performance requires marketing to continuously act as customer champions and advocate data analytics efforts to ensure the firm embraces an outside-in orientation.

1. Introduction

During the last decade, firms have become increasingly interested in developing their capacity for customer analytics (Hallikainen, Savimäki, & Laukkanen, 2020; Hossain, Akter, & Yanamandram, 2021). Defined as a "technology-enabled and model-supported approach to harness customer and market data to enhance marketing decision-making" (Germann, Lilien, Moorman, & Fiedler, 2020), customer analytics is believed to be a contemporary capability that can contribute to firms' competitive advantage[1] (Bokman, Fiedler, Perrey, & Pickersgill, 2014; Gregg, Maes, & Pickersgill, 2014). There is growing evidence that supports this hypothesis. For example, recent studies have linked customer analytics to a variety of outcomes including customer management (Hallikainen et al., 2020; Hossain, Akter, Yanamandram, & Wamba, 2023), innovation (Cao, Duan, & El Banna, 2019), and performance (Germann, Lilien, Fiedler, & Kraus, 2014; Hossain et al., 2021; Liang, Li, Zhang, Nolan, & Chen, 2022). Table 1 provides a summary of studies linking customer analytics to various performance outcomes.

However, despite its potential for enhancing competitiveness, customer analytics capability remains underdeveloped among firms as managers struggle to transform their decision-making process in marketing (Bokman et al., 2014; Carey, 2017; De Luca, Herhausen, Troilo, & Rossi, 2021; Germann et al., 2020). A recent Gartner study of CMOs highlighted that marketing analytics is the top marketing capability gap

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[1] While traditional streams of marketing literature, such as CRM and behavioral market orientation (Kohli and Jaworski, 1990; Mithas, Krishnan, and Fornell, 2005), have provided valuable insights into using customer data for competitive advantage, the marketing landscape has significantly evolved. The surge in data volume, coupled with the emergence of sophisticated analytics tools, has surpassed the capabilities of these traditional approaches. This shift has led to increasing calls for the development of customer analytics capability (Germann et al., 2014; Griva et al., 2021; Moorman & Day, 2016). Importantly, as our research will demonstrate, the evolution toward advanced customer analytics does not imply that we should abandon traditional approaches; instead, it suggests that we can build upon them.

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that demands attention (Costello & LoDolce, 2022). This resonates with the general concern that many organizations have failed to meaningfully advance their business analytics capabilities (Liang et al., 2022; Ransbotham, Kiron, & Prentice, 2016; Smith, Stiller, Guszcza, & Davenport, 2019). Therefore, understanding how firms can effectively develop customer analytics capability is a crucial research question for both marketing theory and practice (Bokman et al., 2014; Hossain, Akter, & Yanamandram, 2020).

Our review of the emerging customer analytics literature (Table 2) reveals that despite some early steps toward understanding how firms can organize for customer analytics excellence, two important research gaps remain. First, extant studies predominately focus on the investigation of inside-out drivers of customer analytics such as data culture, information technology infrastructure, and top management support (Cao et al., 2019; Germann, Lilien, & Rangaswamy, 2013; Rahman, Hossain, Fattah, & Akter, 2020). However, relying solely on an inside-out perspective may hinder a firm's ability to adapt to changing customer behaviour and develop new marketing capabilities to their full potential (Du, Netzer, Schweidel, & Mitra, 2021; Mu, 2015). Instead, recent literature has underscored the renewed importance of outside-in factors in developing new marketing capabilities in today's data-rich, technology-empowered markets (Day, 2011; Musarra & Morgan, 2020; Quach, Thaichon, Lee, Weaven, & Palmatier, 2020; also see the 2020 special issue on outside-in marketing in Industrial Marketing Management). In particular, Quach et al. (2020) theorize that developing advantageous capabilities that enable firms to extract market information from data is a significant path of influence in the outside-in perspective. Varadarajan (2020) additionally proposes that the synergy between outside-in and inside-out perspectives is key to developing new and valuable marketing capabilities such as customer analytics. While these recent conceptualizations point to the vital roles of 1) outside-in factors and 2) complementarity between outside-in and inside-out factors in developing customer analytics capability, systematic and empirical investigations into these relationships remain scarce.

Second, a deeper understanding of the drivers of customer analytics capability necessitates knowledge about boundary conditions. Specifically, some scholars have posited that established firms might face potential threats from younger firms in the race for analytics capability development (Brynjolfsson, Hitt, & Kim, 2011; Davenport & Bean, 2018; Sebastian et al., 2020). Presumably, this relates to the distinct challenges (and advantages) of older and younger firms during the process of capability expansion (Kopalle, Kumar, & Subramaniam, 2020; Kotha, Zheng, & George, 2011). However, as we discern through our literature review (Table 2), no empirical research has examined how the development of customer analytics capability varies among firms of different ages. Generating such insight will be instrumental for younger and older firms to strategize their efforts accordingly in order to develop this essential marketing technology capability.

Our study is motivated by these research opportunities. We capture them by conceptualizing the development of customer analytics as a process of building a marketing capability and by theorizing that outside-in and inside-out resources collectively drive this process. In particular, we focus on intangible resources (i.e., culture and orientation) because they are considered central to building organizational capabilities and obtaining competitive advantage (Grant, 1991; Teece, 2015). Such a focus is also supported by anecdotal evidence indicating

Table 1
Summary of studies linking customer analytics capability to performance impact.

Studies	Outcome variable(s)	Moderators	Method	Key findings
Hossain et al. (2023, TFSC)	• Customer relationship performance • Market effectiveness	n/a	Survey	• Customer analytics capability positively impacts both market effectiveness and customer relationship performance. • Customer relationship performance mediates the relationship between customer analytics capability and market effectiveness.
Hossain, Agnihotri, Rushan, Rahman, and Sumi (2022, IMM)	• Market sensing, seizing, and reconfiguring • Sustained competitive advantage	• Adoption of artificial intelligence	Survey	• Market sensing, seizing and reconfiguring mediate the relationship between marketing analytics capability and sustained competitive advantage. • Adoption of artificial intelligence enhances the relationships between marketing analytics capability and market sensing, seizing and reconfiguring.
Liang et al. (2022, JBR)	• Market agility • Firm performance	• Success traps • Coordination • Market turbulence	Survey	• Market agility acts as a mediator between marketing analytics and firm performance. • The relationship between marketing analytics and market agility is enhanced by inter-departmental coordination and market turbulence and weakened by success traps.
Hossain et al. (2021, JBR)	• Customer linking • Sustained competitive advantage	n/a	Survey	• Customer analytics capability is positively related to both customer linking and sustained competitive advantage. • Customer linking mediates the effect of customer analytics capability on sustained competitive advantage.
Rahman, Hossain, and Fattah (2021, JEIM)	• Holistic marketing decision-making • Competitive marketing performance	• Adoption of artificial intelligence	Survey	• Marketing analytics capability is positively related to holistic marketing decision-making and competitive marketing performance; these relationships are stronger in firms that adopt artificial intelligence. • Holistic marketing decision-making mediates the relationships between marketing analytics capability and competitive marketing performance.
Hallikainen et al. (2020, IMM)	• Customer relationship performance • Sales growth	• Analytics culture	Survey	• Customer big data analytics is positively related to customer relationship performance and sales growth; analytics culture positively moderates the former but not the latter effect.
Cao et al. (2019, IMM)	• Marketing decision-making • Product development management • Sustained competitive advantage	n/a	Survey	• Use of marketing analytics positively affects both marketing decision-making and product development management. • Marketing decision-making positively affects sustained competitive advantage through product development management.
Germann et al. (2014, JOR)	• Financial performance	• Retail industry	Survey	• Firm performance increases with the deployment of customer analytics. • Firms in the retail industry benefit more from the deployment of customer analytics compared to firms in other industries.
Germann et al. (2013, IJRM)	• Firm performance	• Competition • Needs and wants change • Analytics prevalence	Survey	• Deployment of marketing analytics increases firm performance. • This effect is amplified by environmental competitiveness and frequent changes in customer needs and wants; however, the results do not support the expected negative moderating effect of analytics prevalence on the relationship between marketing analytics and firm performance.

Table 2
Summary of studies on the antecedents of customer analytics capability.

Studies	Outside-in drivers?	Inside-out drivers?	Boundary conditions?	Antecedents	Moderators	Firm age
Germann et al. (2013, IJRM)		✓		TMT advocacy, data and IT, analytics skills, analytics culture		Older (Fortune 1000)
Cao et al. (2019, IMM)		✓		Data availability, managerial perception, managerial support, competitive pressure		n/a
Germann et al. (2020, CNS)		✓		TMT advocacy, firm goals, marketing operational emphases, human capital, IT, external environment		n/a
Rahman, Hossain, Fattah, & Akter (2020)		✓		Information system support for marketing		n/a
Current study	✓	✓	✓	Data-driven culture, customer orientation	Three-way interactions among data-driven culture, customer orientation and firm age	Mixed

that organizational culture is pivotal in the development of new marketing technology capabilities (Brinker & Heller, 2015) as well as analytics capabilities (Díaz, Rowshankish, & Saleh, 2018).

We classify these intangibles into inside-out and outside-in categories following Day's (1994) framework. The inside-out driver is represented by a firm's data-driven culture, which is an essential internal enabler of analytics capacity (Davenport & Bean, 2018; Gupta & George, 2016; Mikalef, Krogstie, Pappas, & Pavlou, 2020; Tabesh, Mousavidin, & Hasani, 2019; Yu, Wong, Chavez, & Jacobs, 2021). Data-driven culture represents an organizational culture that embraces an evidence-based decision-making approach (Gupta & George, 2016). To capture the outside-in driver, we use the concept of customer orientation, the most fundamental aspect of an outside-in, market-oriented culture (Musarra & Morgan, 2020; Varadarajan, 2020). Customer orientation is defined as "the set of beliefs that puts the customer's interest first, while not excluding those of all other stakeholders such as owners, managers, and employees, in order to develop a long-term profitable enterprise" (Deshpandé, Farley, & Webster, 1993, p. 27). Given that customer orientation culture intensifies the firm's focus on customer relationships (Deshpandé et al., 1993; Rapp, Trainor, & Agnihotri, 2010) and that customer analytics capability is considered essential for building long-term relationships with customers in today's information-rich markets (Hallikainen et al., 2020), customer orientation should play a critical role in the development of customer analytics capability.

In this study, we test the complementarity (synergetic impact) of inside-out and outside-in resources by modeling the interactive effect of customer orientation and data-driven culture on the development of customer analytics capability. Furthermore, we investigate the boundary condition of firm age, positing that the advantages (or liabilities) associated with firm age (Autio, Sapienza, & Almeida, 2000) can alter the complementarity of inside-out and outside-in resources in the development of emerging marketing capabilities, such as customer analytics capability. Finally, we link these relationships to firm performance to investigate how customer analytics capability might mediate the performance impact of inside-out and outside-in resources among firms of different ages.

Our study contributes to the marketing literature in several ways. First, we extend the understanding of customer analytics capability development by incorporating an outside-in perspective and exploring the interaction between inside-out and outside-in drivers, as well as the moderating influence of firm age. This serves as an early step in systematically unraveling the boundary conditions of the developmental drivers of customer analytics capability, addressing the pressing need to close the analytics capability gap, identified as the top marketing capability gap (Costello & LoDolce, 2022).

Second, we contribute to the broader literature on marketing capabilities. Moorman and Day (2016) emphasize that while contemporary marketing capabilities are essential to fully leverage advances for improved understanding and experience of customers, we know little about the development and management of these capabilities. In a similar vein, Morgan (2019) asserts that despite the valuable existing research on the impact of marketing capabilities on firm performance, our understanding of how to develop these capabilities remains limited. Our study helps address this gap, offering a theoretical model on how firms can cultivate novel marketing capabilities in the evolving digitalized market environments, thereby influencing their performance.

Finally, our work propels the research on outside-in marketing forward, specifically in the context of contemporary challenges faced by marketing organizations in developing their customer analytics capability. We delve into the key debate surrounding the relationship between outside-in and inside-out perspectives in bolstering firm competitiveness (Mu, Bao, Sekhon, Qi, & Love, 2018; Saeed, Yousafzai, Paladino, & De Luca, 2015), providing new insight into their complementary roles and associated boundary conditions. We explicitly emphasize the mediating influence of customer analytics capability and the moderating role of firm age in shaping the relationships between customer orientation, data-driven culture, and firm performance.[2] Thus, we respond directly to the call for research seeking to understand "how and when" outside-in and inside-out perspectives yield competitive advantage in today's increasingly digital data-rich market environments (Moorman & Day, 2016; Mu et al., 2018; Musarra & Morgan, 2020).

The subsequent section of this paper introduces the theoretical background and formulates the hypotheses. Following that, the research methodology and the findings of the study are elaborated. Finally, the paper concludes with a discussion of the results and their implications.

2. Theory and hypotheses

Organizational capabilities refer to an organization's ability to coordinate and deploy its existing resources in a repeatable manner to achieve a particular goal (Helfat & Peteraf, 2003). Marketing capabilities are a unique set of capabilities that reflect a distinctive outside-in characteristic, which combines skills and knowledge that allow firms

[2] While prior studies have examined the relationships between data-driven culture, customer orientation, and firm performance, the central focus of our research is on elucidating the development of customer analytics capability in a three-way interaction model. Our main goal is to shed light on the dynamics of these relationships and their influence on firm performance. We specifically investigate the mediating impact of customer analytics and the moderating role of firm age, offering a nuanced perspective on how these factors collectively shape organizational outcomes.

to create superior customer value (Day, 1994, 2011). Building on the resource-based view (RBV) and capability theory, marketing scholars argue that these skills and knowledge on creating superior value for customers are valuable, rare and difficult to imitate; therefore, marketing capabilities are a source of competitive advantage (Vorhies & Morgan, 2005). Numerous studies have supported this argument by linking marketing capabilities to a wide array of superior organizational performance outcomes (Krasnikov & Jayachandran, 2008). But how do firms build these marketing capabilities?

The development of organizational capabilities is considered path-dependent (Henderson & Cockburn, 1994). Existing organizational resources (e.g., experience, knowledge, culture) act as the precondition for new capability development (Amit & Schoemaker, 1993; Grant, 1996; Kogut & Zander, 1992). Building marketing capabilities, as a distinctive set of organizational capabilities, also requires these resource precursors, but this process is distinguished by the necessity of outside-in, market-based resources. This is because marketing capabilities "shift the span of all [organizational] processes further toward the external end of the orientation dimensions" to create superior customer value (Day, 1994, p. 41). Such a shift allows organizations to satisfy the ever-changing needs and desires of customers more effectively (Hunt & Madhavaram, 2020). Available market-oriented experience, knowledge and culture (i.e., resources) are crucial in identifying the gap between the needs of customers and a firm's ability to deliver value to customers. Thus, these resources are essential in subsequently filling this gap by building and upgrading marketing capabilities (Atuahene-Gima, 2005; Morgan, 2012).

However, outside-in resources not only directly contribute to the development of marketing capabilities but also have the potential to enhance the benefits of inside-out resources (Musarra & Morgan, 2020). We note that the need for outside-in resources does not preclude the support of other resource types in the development of marketing capabilities. For example, in his pioneering work, Day (1994) highlights the importance of leveraging (information) technologies in the creation of marketing capabilities. More recently, Day (2011) reemphasizes the crucial role of leveraging new technologies in building a new generation of marketing capabilities to keep up with today's fast-paced and dynamic markets. Moorman and Day (2016) further observe that "marketing has become one of the most technology dependent functions in business" (p. 17).

In our view, the necessity for technology management (i.e., an inside-out resource) does not conflict with the outside-in nature of marketing capabilities. It is widely recognized that firms recombine various types of resources to develop new capabilities (Danneels, 2002). To cultivate distinctive marketing capabilities, a firm might foster pertinent inside-out resources *and* buttress them with the required outside-in resources to counterbalance the inherent limitations of inside-out resources (Day, 2020; Mu, 2015). We contend that such a complementarity, where outside-in and inside-in resources reinforce each other, underpins the fundamental mechanism of marketing capability development in today's data-rich, technologically advanced environments.

The development of customer analytics capability is a case in point. General business analytics, as a broad *technology* capability, is known to be driven by inside-out resources such as data processing skills, infrastructure, and culture (Gupta & George, 2016; Mikalef et al., 2020). On the other hand, developing customer analytics as a *marketing technology* capability should require outside-in resources to orient the analytics effort to first look for opportunities for customer value creation.

Our conceptual model (Fig. 1) is guided by this overarching theoretical argument. Accordingly, we first examine the separate and interactive impacts of data-driven culture (as an inside-out resource) and customer orientation (as an outside-in resource) on customer analytics capability (as a marketing capability). We then deepen our investigation by modeling these relationships under different conditions of firm age (as a capability developmental environment). Lastly, we delineate the mediation effects of customer analytics capability between resource input and firm performance in younger vs. older firms.

2.1. Effect of data-driven culture

A firm exhibits a data-driven culture when "organizational members, including top-level executives, middle managers, and lower-level employees, make decisions based on the insights extracted from data" (Gupta & George, 2016, p. 1053). This reflects a unified pattern of beliefs, behaviours, and practices among the internal members of the organization (Chatterjee, Chaudhuri, & Vrontis, 2021). The data-driven culture empowers firms to generate and utilize knowledge across diverse aspects of their operations by encouraging the use of analytics (Díaz et al., 2018). As businesses compete to adopt sophisticated analytical tools to extract insights from large volumes of data, the concept of data-driven culture has gained significant importance. However, despite its important role, a recent Deloitte study of over 1000 executives reveals that most companies have yet to become data-driven (Smith et al., 2019). Alarmingly, 67% of the executives in the study expressed a lack of confidence in accessing or utilizing data.

Companies that successfully establish a collective belief in evidence-based decision-making recognize the benefits of available data, thus fostering the development and deployment of organization-wide analytics capabilities (Gupta & George, 2016; Zhang, Wang, Cui, & Han, 2020). We expect the benefit of data-driven culture also extends to the development of customer analytics capability.

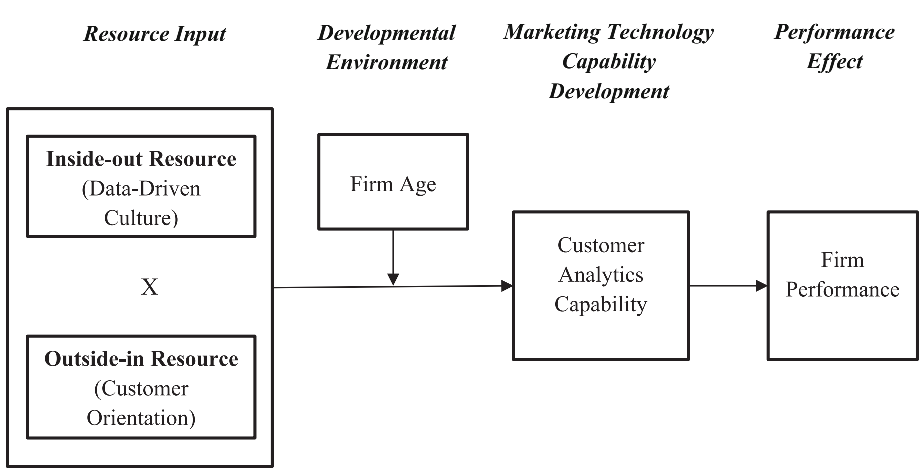

Fig. 1. The conceptual model.

An organization that deeply understands and values data-driven decision-making is more likely to motivate and support functional areas to build domain-specific analytics capabilities (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). Because harnessing customer and market data represents a key analytics domain in organizations (Germann et al., 2020), everything else equal, data-driven firms are more likely to commit to and invest in customer analytics. Moreover, data-driven culture can help create a favourable environment for the dissemination and exchange of data-derived insights within a firm. This, in turn, reinforces the deployment, commitment, and investment in domain-specific analytics capabilities, such as customer analytics (Germann et al., 2013). Accordingly, we hypothesize that:

H_1. Data-driven culture is positively related to the development of customer analytics capability.

2.2. Effect of customer orientation

Customer orientation is an integral element of a firm's market-oriented culture and the cornerstone of the outside-in marketing philosophy (Rust, 2020; Slater & Narver, 1994). Though the positive contribution of customer orientation to various business outcomes has been well supported by academic research for decades, in practice, many firms still lack a robust customer orientation culture. A study by the CMO Council in 2014 startlingly reveals that a mere 14% of senior marketing executives view customer centricity as a defining characteristic of their organizations; even fewer, just 11%, believe their customers would recognize the organization for its customer centricity. Commenting on these alarming results, Yohn (2018) posits that the absence of a pervasive customer-oriented culture is the most common and fundamental barrier to achieving customer centricity in today's digital data-rich market environment.

So how might a culture of customer orientation help overcome such a challenge? We argue that customer orientation leads to an organization-wide focus on the creation of intelligence about customers (Atuahene-Gima, 2005; Deshpandé et al., 1993). This is because a top priority for firms with a strong customer orientation is to find opportunities for creating superior value for customers and building strong relationships with them (Slater & Narver, 1994). This involves the development of capabilities that guide the firm toward these goals (Rapp et al., 2010). Doing so in today's information-rich market entails the ability to handle substantial datasets to understand, follow, and even anticipate the ever-changing needs of customers (Day, 2011). As traditional customer insight systems are becoming less adequate (Griva, Bardaki, Pramatari, & Doukidis, 2021; Hossain et al., 2020), we expect firms with a higher level of customer orientation to be more sensitive to the advantage of harvesting customer analytics in today's market environments and more willing to direct resources to prioritize the development of customer analytics capability. Therefore, we posit the following:

H_2. Customer orientation is positively related to the development of customer analytics capability.

2.3. The interactive effect of data-driven culture and customer orientation

Although data-driven culture might encourage insights that are more objective and reliable (Zhang et al., 2020), it is unlikely to adequately resolve tensions between functions with distinct thought worlds (Germann et al., 2020; Solis, 2021). In fact, because of the finite resources and competing agendas within organizations (LaValle et al., 2011), data-driven culture might even spark competition for resources among different domain-specific analytics development efforts. We reason that customer orientation should strengthen the positive impact of data-driven culture on the development of customer analytics capability.

As we argue above, customer orientation entails a strong outside-in focus, which drives firms to look to their market first and then prioritize customer value creation. This can complement data-driven culture by promoting inter-functional coordination, uniting the functional efforts and orienting them to learning the changing needs and wants of customers (Kennedy, Goolsby, & Arnould, 2003). In other words, customer orientation can strengthen the benefits of data-driven culture by fostering a clear strategic focus on customer value and shifting data analytics efforts, as Day (1994) puts it, toward the external end of the spectrum. Therefore, with data-driven culture, customer orientation might channel greater resources toward the development of customer analytics—a contemporary marketing technology capability for organizations. This leads to the following hypothesis:

H_3. Data-driven culture and customer orientation interact to positively affect customer analytics capability; hence, customer analytics capability is the strongest when both data-driven culture and customer orientation are at high levels.

2.4. The role of firm age on the complementarity between data-driven culture and customer orientation

Younger and older firms represent distinct developmental environments for customer analytics capability. We propose that the positive moderating effect of customer orientation on the relationship between data-driven culture and customer analytics capability is further reinforced as firm age increases.

In developing their customer analytics capability, firms need to transform their resource base and make an uncomfortable but necessary reconciliation of the interests of different functional units (Germann et al., 2020; Kopalle et al., 2020). These organizational dynamics are especially challenging in older firms. This is because as firms mature, they tend to face the constraints of dominant coalitions, rigid mental models, and restricted information channels, all of which impair new capability expansion (Autio et al., 2000; Kotha et al., 2011). This issue is further exacerbated by mature firms' susceptibility to an internally oriented decision-making approach, which often leads to their failure to adjust to changes in their external market (e.g., customer) requirements (Beatty & Ulrich, 1991). In other words, a mature organizational environment presents an even greater need for aligning internal interests and for channeling efforts toward customer value creation to develop market-based (rather than internally oriented) analytics capabilities, such as customer analytics capability.

The marketing literature indicates that customer orientation can play a vital role in addressing these very issues. First, the ability of customer orientation to integrate firm members to prioritize customer needs (Kennedy et al., 2003) is likely to improve alignment within older organizations and help their members rally behind superior customer value creation. In addition, a strong customer orientation makes older firms more sensitive to external environment cues and thus places them in a better position to uncover potential deficiencies in their firm with respect to market-based capabilities (Atuahene-Gima, 2005; Rapp et al., 2010). Therefore, although data-driven culture alone, as an inside-out resource, is unlikely to resolve the stated liabilities of older firm age, it can be guided by customer orientation to promote a data analytics effort to aid the development of customer analytics, as suggested in H_3. Accordingly, these arguments lead us to expect that the positive moderating effect of customer orientation on the relationship between data-driven culture and the development of customer analytics capability is extended and strengthened in older firms.

In contrast, younger firms have the advantage of operational (e.g., cognitive, structural and political) flexibility (Autio et al., 2000; Kotha et al., 2011). With less rigid mental models, routines and coalitions, younger firms enjoy a more favourable internal environment for new capability development and knowledge absorption (Autio et al., 2000; Cohen & Levinthal, 1990). This implies that the positive complementary effect (i.e., greater integration of and sensitivity to external environmental cues and market-based capability gaps) of customer orientation on data-driven culture might be weakened. Therefore, we hypothesize that:

H₄. Firm age reinforces the moderating effect of customer orientation on the relationship between data-driven culture and customer analytics capability, such that the relationship between data-driven culture and customer analytics capability is the strongest when customer orientation is high and firm age is old.

2.5. Mediating effects of customer analytics capability

In today's contemporary business landscape, customer analytics capability has emerged as a source of competitive advantage. By harnessing the growing volume of data, this capability affords firms the unique opportunity to glean valuable insights into their customer base, facilitating not only the fulfillment of extant customer needs but also the prospective shaping of customer preferences (Cao et al., 2019; Hallikainen et al., 2020; Hossain et al., 2023). In concordance with extant literature (refer to Table 1), we posit a positive relationship between customer analytics capability and firm performance. This, together with our preceding arguments that underscore the role of data-driven culture, customer orientation, and firm age in fostering its development, implies that customer analytics capability should mediate the influence of both inside-out and outside-in resources, as well as their synergistic effects, on performance. Such a mediated relationship aligns coherently with the marketing capability theory, which asserts that the evolution and assimilation of marketing capabilities are instrumental in maintaining and propelling firm performance (Moorman & Day, 2016).

Pertinently, our moderation arguments suggest that the mediating effect of customer analytics capability is not uniform. Given that the synergistic effect of data-driven culture and customer orientation on customer analytics capability amplifies with increasing firm age, we reason that their indirect influence on performance becomes more pronounced in older firms by fostering a more robust development of the customer analytics capability. Conversely, in younger firms, the potency of this combined influence may be weakened. Consequently, our culminating hypothesis is formulated as follows:

H₅. Customer analytics capability mediates the effects of a) data-driven culture, b) customer orientation, and c) their complementarity on firm performance.

H₆. The synergetic effect of customer orientation and data-driven culture on firm performance through customer analytics capability is positively moderated by firm age, such that the effect is stronger in older firms.

3. Data and methods

3.1. Data collection

Data were collected from Canadian firms using an online survey administered by a professional business panel provider over a three-week period. We used the survey method because data regarding culture, orientation and customer analytics capability are not available in databases. This method is also consistent with other research of this type (e.g., Cao et al., 2019; Hallikainen et al., 2020; Mikalef et al., 2020; Torres, Sidorova, & Jones, 2018). The panel provider sent study invites to its extensive business panel members. 472 members responded to the request. To qualify for the study, a panel member had to represent an independently owned Canadian firm (i.e., excluding subsidiaries and joint ventures), work in a related operation (e.g., marketing, sales, technology) and be knowledgeable about the firm's data analytics systems. These criteria resulted in 285 qualified respondents. We also implemented several proven quality checks to minimize inattentive responses. Ultimately, we received 154 useable surveys (54% of 285). Of note, this relatively high rate could be attributed to the fact that the 285 qualified participants had already completed our screening questions and were ready to proceed immediately to the survey questions. For comparison, past studies using well-established business panel providers have reported similar completion rates (e.g., Dahlquist & Griffith, 2014; Mehrabi, Coviello, & Ranaweera, 2021). Nonresponse bias cannot be assessed with panel data. However, we compared early and late respondents on key variables (Armstrong & Overton, 1977) and did not find any significant difference ($p > 0.05$).

In validating the adequacy of our sample size, we employed a statistical power analysis guided by a power threshold of 0.8, a significance level of 0.05, and a hypothesized variable count of 15–18 in the regression models. We conservatively estimated a medium effect size (Cohen's $f^2 = 0.15$ or $R^2 = 0.13$) for the overall models, based on prior marketing analytics research (e.g., Germann et al., 2013; Germann et al., 2020) that reported relatively large effect sizes. This cautious approach ensures our analysis remains robust, even under more stringent conditions. Our sample size of 154 exceeds the calculated requirements. The realized models and their R^2 figures (seen in the Results section below) support our estimation and bolster confidence in the robustness of our findings.

The sample represents a variety of industries, including technology (40.3%), financial services (14.3%), retail (7.8%), general manufacturing (6.5%), healthcare (3.9%), construction (3.2%), and other industries (24%). The median firm age is 21 years. In addition, 54% of the sample are either B2B or serve both business and consumer markets. Finally, 48% of the sample firms are publicly traded. Our key informants were knowledgeable managers with an average of 9.1 years of experience at their firm. In addition, we asked the question "How knowledgeable were you about the issues covered in this survey?" The average score was 6.0 (on a seven-point scale ranging from 1 = "not at all knowledgeable" to 7 = "highly knowledgeable").

3.2. Measures

All survey scales (see Appendix A for scale items) were adoptions or adaptations from the relevant literature. We pretested them with three academic experts. No changes were made to the scale items following the pretest. We employed seven-point Likert scales (1 = "Strongly Disagree", 7 = "Strongly Agree") for the measures.

Customer analytics capability was measured using seven items adapted from Hallikainen et al. (2020) and Jayachandran, Sharma, Kaufman, and Raman (2005). These items specifically focus on capturing organizational processes (a common definition of capability, see Day (2011, p.185)) related to the usage of business intelligence and analytics in customer value creation. The scale for data-driven culture included four items adopted from Gupta and George (2016), which measure values, norms and behaviours (a common definition of culture, see Moorman and Day (2016, p. 6)) that reflect a culture promoting decision-making based on data. Customer orientation was measured using five items from Conduit and Mavondo (2001) and Luo, Hsu, and Liu (2008), capturing a culture of prioritizing customer needs and desires. Firm age was measured as the number of years since founding (Mikalef et al., 2020). Finally, firm performance was measured using four items adapted from Germann et al. (2013).

We included several control variables in our analysis. We accounted for firm size because firms may possess different levels of resources which influence the development of new capabilities and competitive performance. We also controlled for firms' primary market because the nature of customer relationships in B2B and B2C markets are different (Hallikainen et al., 2020); therefore, these firms might have different motivations and outcomes for developing their customer analytics capability. Likewise, public and private firms have different stakeholders, which might impose various expectations on the development and employment of analytics capabilities. Finally, we included industry type to control for the potential differences in customer analytics capability and its performance impact (Cao et al., 2019). This includes six dummy variables representing technology, financial services, retail, general manufacturing, healthcare, and construction, with the 'other industries' category serving as the baseline.

4. Results

4.1. Reliability and validity

We assessed the measures using exploratory and confirmatory factor analysis (CFA). As a result of this process, three items were removed (see Appendix A). We then conducted CFA to examine convergent and discriminant validity. The results of the measurement model indicate a good fit: chi-square = 159.77, degrees of freedom = 102, $p = 0.00$, CFI = 0.95, GFI = 0.90, TLI = 0.93 and RMSEA = 0.06. For evidence of convergent validity, 1) factor loadings are above 0.60 ($p < 0.001$); 2) composite reliabilities are between 0.83 and 0.90; and 3) the average variance extracted measures are above 0.50. To assess discriminant validity, we used the CFA models and compared restricted and unrestricted models for each pair of constructs by performing chi-square difference tests (Anderson & Gerbing, 1988). The unrestricted model was consistently superior in all comparisons ($p < 0.001$).

While adopting the key informant approach, we implemented several procedural and statistical measures to address concerns related to common method variance (CMV), guided by the recommendations of leading scholars (e.g., LaPlaca, Lindgreen, & Vanhamme, 2018; Podsakoff, MacKenzie and Podsakoff, 2012). First, we ensured the anonymity of survey respondents and incorporated a free-response format, allowing participants the freedom to respond without constraints. In addition, we provided clear explanations regarding the purpose of the survey, used knowledgeable respondents, and implemented quality checks to minimize the likelihood of inattentive responses. Second, we conceptualized complex interaction effects as the central contributions of our study. Siemsen, Roth, and Oliveira (2010) show that CMV cannot create interaction effects. They also suggest that in the presence of CMV, "…finding significant interaction effects… should be taken as strong evidence that an interaction effect exists" (p. 470).

Finally, we employed the CFA-based marker variable (MV) technique to assess the potential influence of CMV (Richardson, Simmering, & Sturman, 2009; Williams, Hartman, & Cavazotte, 2010). Following previous studies (e.g., Josiassen, 2011; Verhoef & Leeflang, 2009), we used the following item as an MV in this study: "How much confidence do you have in your national economy today?" The MV meets the three criteria for an ideal MV as it was selected a priori, is theoretically unrelated to the substantive variables, and shares similar context (e.g., business) and response format (e.g., a seven-point Likert scale) (Richardson et al., 2009). We conducted the CFA-based marker variable technique following the steps illustrated in Williams et al. (2010). The CFI values of all the compared models are above 0.96, indicating a satisfactory model fit. The chi-square difference test comparing the baseline model and the Method-C model is not significant ($p > 0.05$).

Table 3
Correlations and descriptive statistics.

	1	2	3	4	5	6	7	8	9
1. Firm size (log)	1.00								
2. B2B	0.08	1.00							
3. B2C	−0.11	−0.48**	1.00						
4. Public	0.16*	−0.09	0.08	1.00					
5. Data-driven culture	0.08	−0.10	0.03	−0.01	1.00				
6. Customer orientation	−0.10	0.01	0.04	−0.04	0.51**	1.00			
7. Firm age (log)	0.50**	−0.05	−0.11	−0.02	0.29**	0.13	1.00		
8. Customer analytics capability	0.03	−0.07	−0.04	0.10	0.44**	0.52**	0.00	1.00	
9. Firm performance	−0.15	0.01	0.07	0.05	0.15	0.30**	−0.12	0.29**	1.00
Mean	2.95	0.17	0.46	0.48	5.62	5.84	1.31	5.61	5.29
Standard deviation	0.79	0.38	0.50	0.50	0.79	0.77	0.37	0.80	1.01

*$p < 0.05$; **$p < 0.01$; all significance tests are two-tailed.
Note that due to space constraints, we have excluded the industry variables from the correlation table. The results indicate that only the technology industry variable shows a significant correlation with the key variables: it is negatively correlated with customer orientation ($r = -0.21$, $p < 0.01$) and positively correlated with firm performance ($r = 0.19$, $p < 0.05$).

Table 4
Impact of data-driven culture, customer orientation, and firm age on customer analytics capability.

	Dependent variable: Customer analytics capability				
	Model 1	Model 2	Model 3	Model 4a	Model 4b
Control variables					
Firm size	0.00	0.14	0.07	0.08	0.05
B2B	−0.10	−0.10	−0.11	−0.14	−0.09
B2C	−0.09	−0.11	−0.08	−0.08	−0.06
Public	0.10	0.10	0.12	0.11	0.11
Industry (six dummy variables)	Included	Included	Included	Included	Included
Main and interaction effects					
Data-driven culture (DDC)		0.28***	0.31***	0.30***	0.33***
Customer orientation (CO)		0.44***	0.54***	0.52***	0.42***
Firm age		−0.23**	−0.20*	−0.21*	−0.24**
DDC × CO			0.31***	0.27***	0.29***
DDC × firm age				−0.03	0.02
CO × firm age				0.12	0.22**
DDC × CO × firm age					0.28***
R^2	0.03	0.38	0.45	0.46	0.50
Adjusted R^2	0.00	0.32	0.40	0.40	0.44
ΔR^2	–	0.35***	0.07***	0.01	0.04***

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; Standardized coefficients are reported; All significance tests are based on bias-corrected 95% percentile method (number of bootstraps = 5000); The six industry type dummy variables show no significant effects in any of the models.

This analysis suggests that there is no evidence of CMV present in the dataset. Table 3 exhibits the correlations and descriptive statistics.

4.2. Hypothesis testing

We tested our hypotheses using ordinary least squares (OLS) regression and path analysis in AMOS. Because of the complex moderation and moderated mediation analyses, we utilized the bootstrapping method and reported the test results based on the bias-corrected percentile in all tests to ensure consistency (Aguinis, Edwards, & Bradley, 2017; Preacher, Rucker, & Hayes, 2007). We used the logarithm of firm age and size to normalize their distribution. The maximum variance inflation factor (VIF) was 1.34, indicating that multicollinearity is not an issue in this study. Customer orientation, data-driven culture, and firm age were mean-centered before creating the interaction terms.

Model 1 in Table 4 shows the results for the control variables. The main variables were entered in Model 2. This increased R^2 by 35% ($p <$ 0.001). Consistent with H_1, we find that data-driven culture is positively associated with customer analytics capability ($\beta = 0.28$, $p < 0.001$). Also, customer orientation positively affects the development of customer analytics capability ($\beta = 0.44$, $p < 0.001$), supporting H_2. Firm age shows a negative effect on customer analytics capability ($\beta = -0.23$, $p < 0.01$). However, we note that the correlation between these two variables is zero (see Table 3). Therefore, this effect might be due to the presence of the two main variables. We therefore repeated the analysis by removing data-driven culture and customer orientation. The results show that adding firm age alone to Model 1 does not lead to an increase in R^2 and that the effect of firm age on customer analytics capability is not significant. These findings thus affirm our focus on the interactive effect of firm age.

Model 3 added the interaction of data-driven culture and customer orientation. This increased R^2 by 7% ($p < 0.001$). Customer orientation positively moderates the effect of data-driven culture on customer analytics capability ($\beta = 0.31$, $p < 0.001$), supporting H_3. We conducted additional analysis using the Hayes Process Model (Model 1). Fig. 2 illustrates our findings. The relationship between data-driven culture and customer analytics capability is greater ($b = 0.52$, $p < 0.001$) when customer orientation is high and becomes nonsignificant when customer orientation is low ($b = 0.01$, n.s.). These results suggest that customer orientation and data-driven culture are complementary, and that data-driven culture requires a specific threshold of customer orientation to drive the development of customer analytics capability.

Next, we investigate the moderating effect of firm age on this complementarity. First, we used Model 4a to show the two-way interactions between customer orientation and age and between data-driven culture and age. We found that the age-related interaction terms and the change in R^2 are not significant, suggesting that firm age does not moderate the main effects of customer orientation and data-driven culture. Model 4b formally added the three-way interaction, increasing R^2 by 4% ($p < 0.001$). These results show that firm age strengthens the moderating effect of customer orientation on the relationship between data-driven culture and customer analytics capability ($\beta = 0.28$, $p < 0.001$). In particular, in older firms, the moderating effect of customer orientation is positive and significant ($b = 0.58$, $p < 0.001$); however, among younger firms, the moderating effect of customer orientation is not significant ($b = 0.02$, n.s.). We performed the Hayes Process Model (Model 3) by splitting the two moderators (customer orientation and firm age) into high and low groups. The results show that in older firms, when a high level of customer orientation is present, there is a significant positive effect of data-driven culture on customer analytics capability ($b = 0.80$, $p < 0.001$); however, when customer orientation is low, the impact of data-driven culture on customer analytics capability is not significant ($b = -0.09$, n.s.). On the other hand, in younger firms, the effects of data-driven culture, although significant and positive, are not significantly different when customer orientation is low ($b = 0.29$, $p < 0.05$) vs. high ($b = 0.32$, $p < 0.05$).

Collectively, these findings suggest that in terms of developing customer analytics capability, the effect of customer orientation weakens among younger firms. In addition, older firms benefit the most from having a strong data-driven culture and high customer orientation, although the impact of data-driven culture is limited when older firms lack customer orientation. These findings are also illustrated in Fig. 3. For older firms, the slopes indicating the relationship between data-driven culture and customer analytics capability are significantly different from each other under high vs. low customer orientation. For younger firms, there is no difference between the two slopes. Therefore, these results support H_4.

To test H_5 and H_6, we used simple path analysis in AMOS over Hayes' PROCESS because a) none of the pre-configured models in PROCESS suit our structure; and b) AMOS is an established alternative to PROCESS for testing complex mediation models using the recommended bootstrapping method and the bias-corrected confidence intervals (Hayes, 2017; Hayes, Montoya, & Rockwood, 2017). Of note, we also reran our analysis above (where customer analytics capability is the dependent variable) using AMOS and found congruent results. In all path models tested, we consistently found a satisfactory model fit, supported by the Chi-Square test, CFI, and RMSEA metrics. The results of the mediation and moderated mediation analyses are shown in Tables 5 and 6.

As Table 5 shows, the significant direct effect of data-driven ($\beta =$ 0.19, $p < 0.05$) on firm performance disappears when customer orientation is entered into the model. While customer orientation has a significant positive direct effect, its influence diminishes (from $\beta = 0.35$, $p < 0.001$ to $\beta = 0.26$, $p < 0.05$) upon introducing customer analytics capability ($\beta = 0.19$, $p < 0.05$) into the model.

The indirect effect analysis confirms customer analytics capability as a positive mediator for data-driven culture ($\beta = 0.05$, $p < 0.05$) and customer orientation ($\beta = 0.08$, $p < 0.05$). The indirect effects of the hypothesized two-way (i.e., data-driven culture x customer orientation) and three-way (i.e., data-driven culture x customer orientation x firm age) interactions are also significant. These results support H_5 and H_6, indicating the presence of moderated mediation relationships. Further analysis (see Table 6) reveals that for younger firms, the indirect effect of data-driven culture is statistically significant and similar, irrespective of whether customer orientation is high ($b = 0.08$, CI = 0.01–0.24) or low ($b = 0.07$, CI = 0.01–0.21). However, among older firms with high customer orientation, the indirect effect of data-driven culture is most pronounced ($b = 0.19$, CI = 0.03–0.43). In contrast, this effect becomes nonsignificant for older firms with low customer orientation ($b = -0.02$, n.s.).

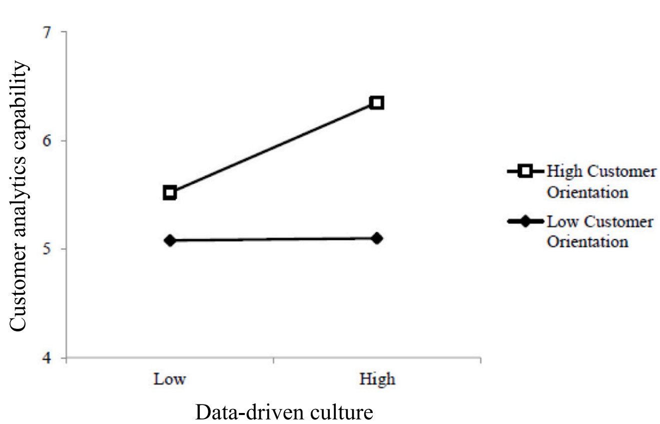

Fig. 2. Interaction effect of data-driven culture and customer orientation on customer analytics capability.

4.3. Further analysis and robustness check

Our moderation analysis, which is based on means and standard

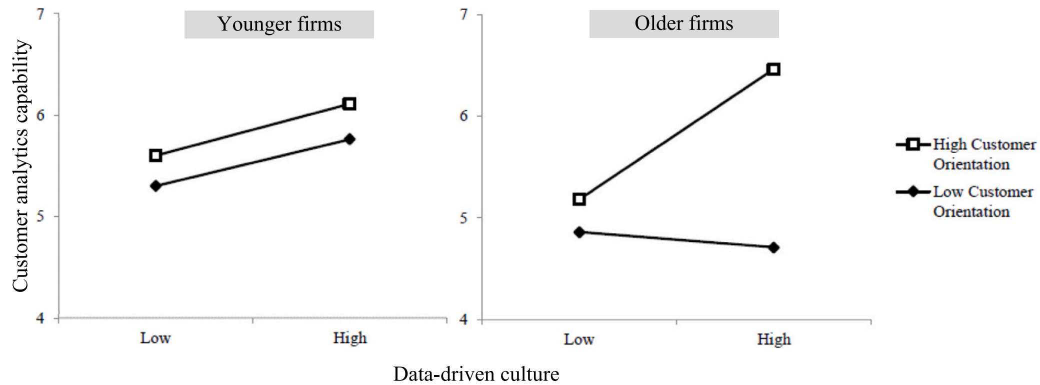

Fig. 3. Interaction effect of data-driven culture, customer orientation, and firm age on customer analytics capability.

Table 5
Impact of data-driven culture, customer orientation, firm age, and customer analytics capability on firm performance.

	Dependent variable: Firm performance						
	Direct effects			Indirect effects			
Independent and interaction variables							
Data-driven culture	0.19*	0.01	−0.04	0.05*	0.05*	0.06*	0.06*
Customer orientation		0.35***	0.26*	0.08*	0.10*	0.10*	0.08*
Firm age	−0.05	−0.07	−0.03	−0.04*	−0.04*	−0.04*	−0.05*
DDC × CO					0.06*	0.05*	0.05*
DDC × firm age						−0.01	0.01
CO × firm age						0.02	0.04*
DDC × CO × firm age							0.05*
Mediator							
Customer analytics capability			0.19*				

*p < 0.05; **p < 0.01; ***p < 0.001; Standardized coefficients are reported. The number of bootstrap samples = 5000. R-squared (firm performance) of the full moderated mediation model is 0.25; Control variables: firm size, B2B, B2C, public, and six industry dummy variables. All significance tests are based on the bias-corrected 95% percentile method; Among the industry-type dummy variables, only the effect of "technology' is significant at $p < 0.05$.

Table 6
Results of moderated mediation analysis.

Mediator	Moderators		Conditional indirect effects		
	Customer orientation	Firm age	Effect	LLCI95	ULCI95
Customer analytics capability	0.77 (+1SD)	0.37 (+1SD)	0.19* (0.10)	0.03	0.43
	−0.77 (-1SD)	0.37 (+1SD)	−0.02 (0.07)	−0.17	0.10
	0.77 (+1SD)	−0.37 (-1SD)	0.08* (0.06)	0.01	0.24
	−0.77 (-1SD)	−0.37 (-1SD)	0.07* (0.05)	0.01	0.21

*p < 0.05; **p < 0.01; ***p < 0.001; Unstandardized estimates and bootstrapping standard errors (in parentheses) are reported. The number of bootstrap samples = 5000. Control variables: firm size, B2B, B2C, public, and six industry dummy variables. LLCI (ULCI) refers to the lower level (upper level) bias-corrected 95% confidence intervals.

deviations, does not specify at what point the moderation effect of customer orientation on the relationship between data-driven culture and customer analytics capability becomes significant. Therefore, we used the Johnson-Neyman procedure, embedded in the Hayes Process Moderation model, to provide additional insights. These results show that the moderation effect of customer orientation becomes significant at age 14 ($p < 0.05$) and that its strength (coefficient) and significance level continue to increase as firm age increases. We also note that firms <11 years old are generally considered young (Coad, Segarra, & Teruel, 2016; Fernhaber & Patel, 2012). Therefore, our determination of this 14-year threshold supports both our initial analysis and our discussion of younger vs. older firms.

Next, we assessed the potential for omitted variable bias using the method developed by Cinelli and Hazlett (2020). We performed this test for 1) the effect of customer orientation, data-driven culture, and firm age on customer analytics capability, and 2) the effect of customer orientation, data-driven culture, firm age, and customer analytics capability on firm performance. The sensitivity analysis suggested that any unobserved confounder must account for 26–38% of the residual variance of both predictors and outcome variables to nullify the effect of predictors (i.e., bring the point estimate of predictor to zero). To make the effect of predictors statistically nonsignificant at $p < 0.05$, the unobserved confounder must account for 12–27% of the residual variance of both predictors and outcome variables. We note that the robustness values (RVs) are substantially larger than the partial R^2 (%) values of the corresponding theoretical predictors (e.g., customer orientation, data-driven culture). This implies that any unobserved confounding variable would have to be substantially stronger than our theoretical (observed) predictors to invalidate our findings. It is hard to think of any potential omitted variable that meets this scenario. We also followed up with additional recommended sensitivity tests to assess the potential impact of unobserved confounders on our findings. Here, we assume the presence of unobserved confounders with the same strength as our strongest control variables: firm size, public (vs. private firm) dummy variable, and technology industry dummy variable. The results show that unobserved factors must account for four to ten times as much variation as these control variables to invalidate the effects of our predictors. Overall, the sensitivity analyses suggest that omitted variable bias is unlikely to affect our results.

Moreover, given the cross-sectional nature of our design, we tested for potential endogeneity bias. First, we used two-stage least-squares regression (2SLS) (cf., Luo, Rindfleisch, & Tse, 2007; Menguc, Auh, & Yannopoulos, 2014). We argue that firm age might impact data-driven culture, biasing the model estimations. For example, older firms might have more accumulated experience (e.g., data), compelling them to lean toward evidence-based decision-making. To perform our robustness test, we thus first regressed data-driven culture on firm age to generate residuals without the influence of firm age. We then repeated all models by substituting the residual values for data-driven culture. These findings are consistent with those of the original models. These results—coupled with the fact that our model is derived from theories (e.g., Atuahene-Gima, 2005; Germann et al., 2013; Gupta & George, 2016) and that our independent variables are organizational-wide constructs that precede the development of domain-specific analytics capabilities—affirm the validity of our findings.

We further addressed the potential endogeneity between customer analytics capability and firm performance utilizing the instrumental variable approach. We relied on a four-item scale measuring industry-level pressure on developing business analytics capacity as our instrumental variable. The instrument is theoretically grounded (Podsakoff, MacKenzie, & Podsakoff, 2012): while industry pressure might spur a firm's push for customer analytics capability, it should not directly impact its competitive performance given uniform pressures across sector players. Our data supports this, showing customer analytics capability (the predictor) fully mediates the effect of instrumental variable on firm performance (the dependent variable), ensuring the instrument's exogeneity. The instrument also aligns with the strength criteria outlined by Staiger and Stock (1997), as reflected by a first-stage regression F-statistic above 10. We employed a 2SLS analysis by first regressing customer analytics capability against the instrumental variable and then using the resultant predicted values as predictors for firm performance. The results indicate a significant ($p < 0.01$) effect of customer analytics capability. The Hausman test comparing the OLS and 2SLS estimates was nonsignificant ($p = 0.53$), further diminishing endogeneity and unobserved bias concerns.

Finally, our theoretical argument posits that culture and orientation drive capability development in marketing, a perspective aligned with those of Gliga and Evers (2023), Huhtala, Sihvonen, Frösén, Jaakkola, and Tikkanen (2014), McGrath and O'Toole (2014), and Zhou and Li (2010). However, culture and orientation may interact with capabilities to influence performance (e.g., Cacciolatti & Lee, 2016; Mu, Thomas, Peng, & Di Benedetto, 2017). To address this, we thoroughly explored all possible two-way and three-way moderation effects of customer orientation, data-driven culture, and firm age on the relationship between customer analytics capability and firm performance. No significant moderations were observed, which further supports our theorization that customer analytics capability acts as the mediator between culture and orientation and firm performance.

5. Discussion and conclusion

In the landscape of today's digitally connected markets, the cultivation of customer analytics capability emerges as a paramount undertaking for firms keen on securing a competitive advantage. Our research explores the interplay between inside-out (data-driven culture) and outside-in (customer orientation) resources, assessing their role in addressing this imperative across firms at disparate life stages.

Our results underscore that both data-driven culture and customer orientation generally bolster the development of customer analytics capability. However, customer orientation stands out, exhibiting a more pronounced influence. Furthermore, we find clear evidence of a synergy between these two orientations – a synergy that is particularly pronounced in more mature firms. Specifically, older firms that embrace a high level of customer orientation reap the greatest benefit from a data-driven culture. In contrast, for those older firms where customer orientation is low, the efficacy of data-driven culture becomes nonsignificant. Younger firms, on the other hand, seem to derive benefits from these two orientations only in a more cumulative (vs. complementary) fashion.

Lastly, we elaborate on how data-driven culture and customer orientation drive competitive advantage through the advancement of customer analytics capability. Our analysis shows that mature firms, with a robust data-driven culture and strong customer orientation, stand in a favourable position to achieve enhanced performance by more effectively harnessing these resources to enhance their customer analytics capability.

5.1. Theoretical implications

Our study contributes several key theoretical advancements to the marketing literature. First, addressing the customer analytics field, our study significantly extends existing research on the precursors and determinants that shape customer analytics capability. Specifically, we move beyond the traditional focus on inside-out resource drivers by highlighting their potential constraints and emphasizing the significant role of outside-in drivers in mitigating these limitations (Day, 2020; Mu, 2015; Varadarajan, 2020). Moreover, our study unveils novel insights into the development of customer analytics capability among firms of varying ages — a topic that has attracted considerable interest (Brynjolfsson et al., 2011; Davenport & Bean, 2018; Sebastian et al., 2020) yet remained largely unexplored until now. Through this analysis, we underscore the vital need for a deeper understanding of the boundary conditions affecting these capability developmental precursors — an area of theoretical inquiry that is critically lacking, as identified in our comprehensive literature review.

Second, prior research has highlighted a significant gap in our understanding of how firms develop distinctive marketing capabilities (Morgan, 2019). While the strategic management literature has explored resource configuration as an underlying mechanism for developing new capabilities (Schilke, Hu, & Helfat, 2018), the question of whether and how it applies to marketing capability development warrants deeper exploration (Moorman & Day, 2016). In this study, we address this research gap by incorporating marketing (outside-in) theory to delineate and validate a marketing resource configuration process through which new marketing capabilities can be developed. Our insight regarding the changing complementarity between two fundamental categories of marketing resources in younger vs. older firms pinpoints the issue of 'fit' between resource input and contextual environment in the development of marketing capabilities. While the contextual (e.g., contingency) perspective is well-established in research on marketing capabilities' impact, its relevance in the development of marketing capabilities remains unclear (Jaworski & Lurie, 2019; Morgan, 2019). That is, whether and how companies adopt different means to win the race for developing new marketing capabilities are questions that have not been systematically investigated.

We believe the findings reported in this study provide a compelling rationale for adopting a contingency approach to explore this important yet underdeveloped area of research in the marketing capability literature. We confirm the significant role of organizational rigidities in the process of building marketing capabilities (Morgan, 2019). In addition, we demonstrate that an outside-in orientation not only serves as an effective remedy for these rigidities but can also enhance the positive impacts of an inside-out orientation. From a theoretical standpoint, this suggests that resource configuration for marketing capability development should increasingly emphasize an outside-in orientation as the influence of rigidity intensifies.

Third, in response to the recent debate regarding the strategic relevance of outside-in approach in today's dynamic and digitalized markets

(Musarra & Morgan, 2020; Quach et al., 2020; Rust, 2020), our research illuminates the significance of an outside-in approach in fostering emerging marketing technology capabilities which can serve as new sources of competitive advantage. This insight is especially pertinent against the backdrop of diminishing effectiveness of market-oriented culture in affecting competitive performance (Kumar, Jones, Venkatesan, & Leone, 2011). Our findings align with Moorman and Day's (2016) emphasis on “put[ting] a premium on finding new capabilities” (p. 13), supporting the critical role of an outside-in, market-oriented culture in nurturing new marketing capabilities and revitalizing competitive strength to enhance performance indirectly.

In this context, our research tackles another key debate in the outside-in literature concerning the interplay between inside-out and outside-in perspectives in enhancing firm competitiveness. While prior studies have predominantly focused on the distinct and hierarchical impacts of these two orientations on performance (Mu et al., 2018; Saeed et al., 2015), Varadarajan (2020) argues that there is a crucial need to study how these perspectives might be complementary in enhancing *advantageous intermediate positions* for firms. Specifically, he proposes that both perspectives may operate in tandem to promote the development of contemporary marketing capabilities. To the best of our knowledge, our study is among the first to offer empirical support for this proposition, showcasing the mediation role of customer analytics capability in the relationships between orientations and firm performance. Consequently, we add to the broader understanding of the complex interactions among contemporary marketing organization elements (Moorman & Day, 2016; Mu, 2015; Mu et al., 2018; Musarra & Morgan, 2020).

5.2. Managerial implications

Customer-led, data-driven. As organizations seek to expand their data analytics efforts, they may grapple with “data blind spots” that paradoxically induce myopic and inward-looking behaviours (Varadarajan, 2020). These behaviours have been known to hinder the development of new analytics capabilities in marketing (Mikalef, Boura, Lekakos, & Krogstie, 2019). This raises an important question: how can managers mitigate or even reverse such behaviour to foster the development of customer analytics capability? Our findings pinpoint championing an outside-in culture as a solution. Thus, our study underscores the necessity of prioritizing customers and placing them at the front and center when developing winning marketing technologies (Edelman, 2016). Marketing managers, armed with these insights, should advocate for greater participation in technology and operations departments. Such active involvement ensures that customer analytics processes appropriately reflect the perspective of existing and potential customers, and that customer value creation remains the focus during the application of data technologies in marketing decisions. This echoes the need for marketing managers to act as “integrating agents” (Day, 2020, p. 86).

Capitalizing on legacy strengths. Our findings illuminate a unique opportunity for marketing managers in more mature firms to drive competitive performance: Leveraging their traditional market-based, outside-in resources to develop superior customer analytics capability. Addressing the literature around the ramifications of outside-in and inside-out approaches on firm performance, Mu et al. (2018) highlighted the research gap regarding the most efficacious resource allocation, calling for insights into these distinct ‘routes of impact’ on performance (page 37). We concur with this insightful point and extend this line of inquiry. We prompt marketing managers in well-established firms to recognize that their amassed market-based resources—be it knowledge, mindset, or processes—are pivotal not only in honing customer analytics but also in navigating organizational rigidity to foster valuable marketing tech capabilities. Our evidence suggests that while all firms benefit from a robust data-driven culture and high customer orientation in the customer analytics race, older firms hold an edge over younger ones, reaping a significant performance advantage.

Resource synergy for a new competitive edge. Lastly, our study emphasizes the imperative of harnessing the synergy between inside-out and outside-in resources. Rather than strictly adhering to a singular perspective, firms ought to strategize around the complementarity of these resources. Such an integrative approach stands pivotal for fortifying customer analytics and other emerging marketing technology capabilities, positioning them as contemporary sources of competitive advantages in today's data-rich markets.

5.3. Limitations and future research

We recognize several limitations in our study. First, the cross-sectional nature of our research design constrains our ability to definitively establish causal relationships. Nevertheless, we argue that the risk of reverse causality is lessened due to substantial evidence and conceptual frameworks suggesting organizational culture and orientation factors precede capabilities (e.g., Cake, Agrawal, Gresham, Johansen, & Di Benedetto, 2020; Lisboa, Skarmeas, & Lages, 2011; Murray, Gao, & Kotabe, 2011; Ngo & O'Cass, 2012). In addition, we employed techniques such as instrumental variable (customer analytics capability-performance relationship) and 2SLS to further alleviate concerns. Nonetheless, we recommend future longitudinal studies to offer additional validation.

Second, our theory-driven model and employment of the newly developed sensitivity test (Cinelli & Hazlett, 2020) aim to address the issue of omitted variable bias. But this concern cannot be completely ruled out. While a ‘perfect’ solution is improbable (Rutz & Watson, 2019), future research and replication are crucial for testing our framework and findings.

Third, our data collection relied on single informants. To minimize potential CMV, we implemented several proven procedural remedies, including the selection of informants with extensive knowledge of the subject matter (Homburg, Klarmann, Reimann, & Schilke, 2012). However, future research employing a multiple-informant approach could enhance the generalizability of our findings. In addition, while our CFA-based marker variable analysis found no evidence of CMV, to further mitigate this concern, future studies might benefit from employing a broader array of advanced statistical remedies. These could include techniques for directly measuring CMV causes or a ‘hybrid method’ that combines markers with measured CMV causes techniques (Podsakoff, Podsakoff, Williams, Huang, & Yang, 2024; Simmering, Fuller, Richardson, Ocal, & Atinc, 2015; Williams & McGonagle, 2016).

Fourth, while we found a positive relationship between customer analytics capability and firm performance, aligning with the existing literature, we acknowledge that customer analytics which often relies on historical data may not invariably yield positive outcomes. Our study's focus and data limitations precluded an examination of the potential negative impacts of customer analytics on performance. This gap suggests an avenue for further investigation.

Lastly, while customer analytics encompasses a wide range of modern tools and methods, such as AI, machine learning, and big data, the scale used in our study broadly measures the concept of customer analytics capability without detailing specific technologies. Future research could develop more detailed scales to investigate the technological aspects of customer analytics capability. For example, such scales could uncover variations in the utilization of AI and machine learning across companies of different ages to further enhance our contextual understanding of how a firm's age influences the development of modern analytics capabilities.

We offer several additional directions for future research. First, although we focus on the development of customer analytics capability, our theoretical framework can presumably be applied to other emerging marketing technology (MarTech) capabilities. Given the limited knowledge of how firms can organize to develop capabilities associated with digitalized markets and the digital transformation of their marketing organizations (Moorman & Day, 2016), further research in this direction can help provide timely and relevant insights to organizations. Second, future research should explore boundary conditions other than firm age. For example, investigating the moderating effect of institutional pressures and/or network characteristics (e.g., breadth and depth of marketing partners) could advance the understanding of the impact and complementarity of inside-out and outside-in orientation drivers regarding developing customer analytics capability as well as other emerging capabilities in marketing. Finally, our model of intangible resource drivers (e.g., culture) represents a step toward a theoretical framework for developing marketing capabilities. Future research should consider the impact of tangible resources and reveal the potential interplays (e.g., complementarity and substitution) between (in)tangibility and external-internal orientations.

CRediT authorship contribution statement

Hamed Mehrabi: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Writing – original draft, Writing – review & editing, Investigation, Validation. **Yongjian (Ken) Chen:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Abbas Keramati:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – original draft, Writing – review & editing.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT solely to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data availability

Data will be made available on request.

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Appendix A. Key measurement scales

Items	Factor Loading	α	CR	AVE
Customer Analytics		0.82	0.86	0.55
We use business intelligence and analytics (BI&A) to develop customer profiles.	0.70			
We use BI&A to segment markets. [a]	–			
We use BI&A to assess customer retention behaviour.	0.75			
We use BI&A to identify appropriate channels to reach customers.	0.77			
We use BI&A to customize offers. [a]	–			
We use BI&A to identify our best customers.	0.70			
We use BI&A to assess the lifetime value of our customers.	0.78			
Data-Driven Culture		0.75	0.84	0.57
We base our decisions on data rather than on instinct.	0.77			
We are willing to override our own intuition when data contradicts our viewpoints.	0.68			
We continuously coach our employees to make decisions based on data.	0.61			
We continuously assess and improve the business rules in response to insights extracted from data.	0.92			
Customer Orientation		0.81	0.83	0.54
Our business objectives are driven primarily by customer satisfaction. [a]	–			
We base our competitive advantage on understanding customer needs.	0.72			
We systematically and frequently measure customer satisfaction.	0.77			
We gather information to understand the present and future needs of our customers.	0.72			
We use our customers as important sources of new product ideas.	0.74			
Firm performance (performance of the firm relative to main competitors)		0.89	0.90	0.69
Return on investment	0.87			
Sales growth	0.82			
Profitability	0.89			
Return on assets	0.74			

[a] Removed from analysis due to low factor loading.

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