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Navigating the platform economy: Crafting a customer analytics capability instrument

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ABSTRACT

The prevalence of the platform economy is rapidly increasing, primarily driven by the incorporation of big data into the digital business environment. Big data contains substantial customer information, necessitating analytics to process such data. Despite the acceleration in customer data, researchers lack knowledge about the tools that constitute Customer Analytics Capability (CAC) within the online retail business context. Through a multi-phase research design, we develop and test an instrument for CAC within the spectrum of the platform economy. We validate a multidimensional and higher-order CAC framework comprising value creation, delivery, and management. We establish the nomological validity by identifying the instrument's significant impact on customer-related performance. This research contributes to a deeper understanding of the role of CAC in shaping customer-centric outcomes within the expanding platform economy.

1. Introduction

The landscape of retail has experienced a transformative shift, with the proportion of online sales relative to total retail sales witnessing a substantial surge. Over the years, this proportion has risen dramatically from 2.7 % in 2006 to an impressive 16.9 % in 2019. Notably, giants in the online retail space, such as Amazon and eBay, propelled this growth, amassing a staggering $154.5 billion in sales during the third quarter of 2019 in the United States alone (Jiang & Zou, 2020). The momentum of this transition gained further impetus amidst the COVID-19 pandemic, leading to an accelerated expansion of online retail. In 2020, global online sales surged by 32 % to reach $2.6 trillion, with projections forecasting their contribution to encompass 20 % of all retail sales by 2025 (Wang & Liu, 2023). An encompassing survey spanning 25 countries revealed that 43 % of consumers intend to intensify their online shopping activities within the upcoming six months (PWC, 2023).

Driving this paradigm shift is the profound emergence of big data, an asset that holds a significant stake in shaping future retail dynamics. Projections indicate a substantial escalation in the market value of big data, catapulting from $70.5 billion in 2020 to a projected $243.4 billion by 2027, with an impressive compound annual growth rate (CAGR) of 19.4 % within this period (Research & Markets, 2021). Within this data expanse, a substantial portion is dedicated to customer-centric insights (e.g., Hossain, Akter, & Yanamandram, 2020a). Anticipating this data influx, it is foreseen that by 2025, around 30 % of all data will necessitate advanced real-time digital processing (Seagate, 2021).

In this transformative scenario, industry giants like Amazon have demonstrated a keen interest in deciphering customer behaviour within their online retail domains, meticulously tracking purchasing patterns, product views, shipping addresses, and feedback (Marr, 2021). However, amidst a plethora of options, customers can be overwhelmed, leading to frequent disappointment (Gray, 2021; Inman & Nikolova, 2017). To navigate this complex landscape, Customer Analytics (CA) capability has emerged as a potential solution, offering the means to predict customer preferences by creating profiles and analysing the buying behaviours of similar niches (Fallon, 2020; Giri, Thomassey, & Zeng, 2019). This capability is embodied in a platform's or firm's capacity to scrutinise customer-centric data, personalize communications, and offer a tailored value proposition.

Yet, amidst the evident significance of CA capability, empirical studies lag in unravelling its precise manifestation within the context of online retail (Germann, Lilien, Fiedler, & Kraus, 2014; Griva, Bardaki, Pramatari, & Doukidis, 2021). Consequently, the development of scales to gauge Customer Analytics Capability (CAC) becomes paramount. The

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exploration of how specific customer-centric analytics capabilities augment customer-related performance, scrutinising a 360-degree perspective of customer interactions, holds immense value for both practitioners and scholars alike (Diorio, 2020; Marketing-Science-Institute, 2020).

Platform ecosystems universally encompass a foundational structure composed of four key actors (Van Alstyne, Parker, & Choudary, 2016). Platform owners wield governance and intellectual property rights, while service providers facilitate interactions between the platform and users. Producers and retailers craft offers, which customers then embrace. The ubiquity of platforms has sparked intensified competition across industries (Rietveld & Schilling, 2021). Traditionally, value creation followed established chains, but platforms have disrupted these pathways. Notable examples include Apple's integration of the App Store as an intermediary marketplace and Walmart's expansion into online marketplaces. This platform-driven transformation has fundamentally reshaped business strategies (Gregurec, Tomičić Furjan, & Tomičić-Pupek, 2021; Helo & Hao, 2021).

Within this evolving landscape, the focus of this study centres on the potential of customer data analytics to amplify value for retail enterprises catering to customers through online platforms. A notable void in the empirical exploration of this specific facet is evident, particularly in the context of data-driven retail platforms (Kitchens, Dobolyi, Li, & Abbasi, 2018; Rahman, Hossain, Fattah, & Akter, 2020a). Thus, this research aims to address the gap by developing an instrument for measuring CAC within the context of platform-driven, data-rich retailing.

RQ: What are the key steps in conceptualizing and validating a CAC instrument within the domain of platform-driven, data-rich retailing?

To address the research question, this study establishes its theoretical underpinning by drawing upon the foundational concepts of Resource-Based View (RBV) capability (Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Kraaijenbrink, Spender, & Groen, 2010) and market orientation (Alnawas & Hemsley-Brown, 2019; Bhattarai, Kwong, & Tasavori, 2019). The study synthesizes the perspectives of market orientation and RBV to construct the CAC of firms, encompassing both internal capabilities and external market insights (Day, 2014; Kohli & Jaworski, 1990). This integration of internal and external viewpoints is particularly crucial because it enables a firm to achieve a strategic fit between its capabilities and the demands of its market environment. This alignment enhances a firm's ability to create value, maintain competitiveness, and navigate changing market dynamics successfully. Furthermore, this study extends the domains of RBV capability and market orientation by introducing a novel set of instruments to measure CAC in the context of online retail platforms.

This study presents a rigorous methodological contribution, employing both multiphase techniques to develop a higher-order CAC framework and outcome variables, and advanced PLS-SEM technique for analysing a third-order reflective-formative research model. Methodologically, the study encompasses multiple processes for data analysis and the presentation of a novel instrument, particularly aimed at validating CAC and its effects—a pioneering effort within the annals of marketing and management literature. The application of PLS-SEM serves as a robust technique to affirm the complex model's validity. In practical terms, this research has tangible implications for managers utilizing online retail platforms, equipping them with the tools of CA to foster value formation and enhance customer satisfaction.

2. Literature review

2.1. The significance of customer analytics orientation in the platform economy

Advancements in digital technology, coupled with the vast collection of data through smart devices, have ushered in a revolutionary shift in the architecture of value-generating businesses (Correani, De Massis, Frattini, Petruzzelli, & Natalicchio, 2020). The global big data market has experienced exponential growth, with projections indicating further acceleration (Dwivedi et al., 2021; Ghobakhloo, 2020; Gupta, Kar, Baabdullah, & Al-Khowaiter, 2018). Notably, a substantial share of this data is market-oriented and customer-centric (Hossain et al., 2020a). By 2025, this data is expected to connect 75 % of the global population, fostering data interactions every 18 s per connected individual (Coughlin, 2018; Seagate, 2021). The rapid proliferation of digital technology has compelled organisations to re-evaluate their business models, creating new processes, products, and services (Wu, Kozanoglu, Min, & Zhang, 2021). These technological shifts redefine business operations (Jonsson, Mathiassen, & Holmström, 2018), necessitating the effective utilization of digital tools to manage these changes (Kallinikos, Aaltonen, & Marton, 2013).

Emerging as a result of advancing digital platforms and technology, the platform economy leverages global internet and data connectivity to facilitate agile collaboration within and across industries, paving the way for new market opportunities. This economy serves as a catalyst for profitability and rapid expansion. During McKinsey Technology's 16th Annual IT Conference in 2020, top CIOs engaged in discussions about their efforts to promote organizational agility and generate new value through a transformative shift to a platform-based approach (Blumberg, Bossert, Kürtz, & Richter, 2020). A firm's success within this landscape hinges on its integration of platforms with its business strategy and holistic information management (Chen et al., 2020; Hossain, Agnihotri, Rushan, Rahman, & Sumi, 2022). The benefits of platform-driven service extend across diverse industries, including banking, automotive, pharmaceuticals, airlines, and retail (Blumberg et al., 2020). Stitch Fix, a US-based online personal styling service, employs analytics-driven personalized offers, scrutinizing customer preferences (Hossain, Akter, Yanamandram, & Gunasekaran, 2021b). Similarly, Amazon's cashier-less store and diverse retail platforms emphasize the pivotal role of advanced CA (Fallon, 2020; Gray, 2021).

The literature on the platform economy is multifaceted, with researchers exploring various aspects of this emerging paradigm. For instance, Chatterjee, Chaudhuri, Mikalef, and Sarpong (2023) undertook a study on coopetition within the platform economy, focusing their investigation on ethical considerations and their consequential impact on firm performance. Thorhauge (2022) explored the platform economy's evolution, scrutinizing its shift from retail-centric frameworks to player-driven economies. In another line of inquiry, Cao, Su, Xu, and Guo (2022) examined channel selection strategies pertinent to retailers operating within the platform economy, with particular emphasize on scenarios involving cap-and-trade policies and the intricate interplay of power dynamics. In a distinct but interconnected vein, Belhadi et al. (2023) delved into the influence of strategic management of digital technologies on electronic word-of-mouth and customer loyalty. Taking a more subtle approach, Raguseo, Pigni, and Vitari (2021) investigated the mediation effects of process efficiency and product effectiveness within the context of digital data streams and competitive advantage. Collectively, these studies contribute insights to the burgeoning body of research concerning the platform economy, illuminating various dimensions and implications, albeit without explicitly addressing the context of CA.

A recent report indicates that 64 % of customers desire swift responsiveness from firms to meet their diverse needs, while 88 % of executives acknowledge that customer reactions are evolving more rapidly than anticipated, posing a challenge for firms to react promptly

(Accenture, 2022). The strategic complexity of addressing customer needs has been compounded by intense competition, leading to swift customer attention capture (Gupta et al., 2006; Kitchens et al., 2018). In bridging this research gap, a firm's capability in CA emerges as a pivotal tool for data analysis. CA represents an advanced data analytics tool firms use to extract insights from customer touchpoints. The three-dimensional nature of a firm's CAC spans value creation, value delivery, and value management (Hossain et al., 2020a). Consequently, the implication of CA stands as a transformative strategic move (Braun & Garriga, 2018; Giri et al., 2019; Gray, 2021), enabling a nuanced understanding of market demand through insights gleaned from diverse customer data sources. Therefore, cultivating a comprehensive understanding of CA implications becomes essential for maximizing benefits from platform-driven services. In significantly contributing to the platform economy, firms must adeptly wield CAC instruments (Cohen, 2017; Mansell & Steinmueller, 2020; Yerpude & Singhal, 2021). However, there remains a dearth of academic studies that substantiate these instruments' efficacy within the platform economy's context (Beverungen et al., 2021; Liu et al., 2023).

3. Methods for developing instruments of CAC

The prevailing body of literature concerning marketing and CAC remains largely conceptual in nature (Germann et al., 2014; Gray, 2021; Wedel & Kannan, 2016). Within the marketing discipline, there exists a dearth of established scales for quantifying constructs related to analytics capability. Recognizing this gap, the current study examines several papers on scale development for marketing concepts (e.g., Böttger, Rudolph, Evanschitzky & Pfrang, 2017; Lu, Cai & Gursoy, 2019; Sweeney & Soutar, 2001; Walsh & Beatty, 2007). Many of these works adhere to the instrument development steps outlined by Churchill (1979). However, other scholars, such as Sarstedt, Hair, Ringle, Thiele, and Gudergan (2016) and Yi and Gong (2013), advocate for the utilization of Partial Least Squares (PLS) estimation. Further refinement of this process has been proposed by Motamarri, Akter, and Yanamandram (2020), accentuating the use of PLS in developing scales for higher-order

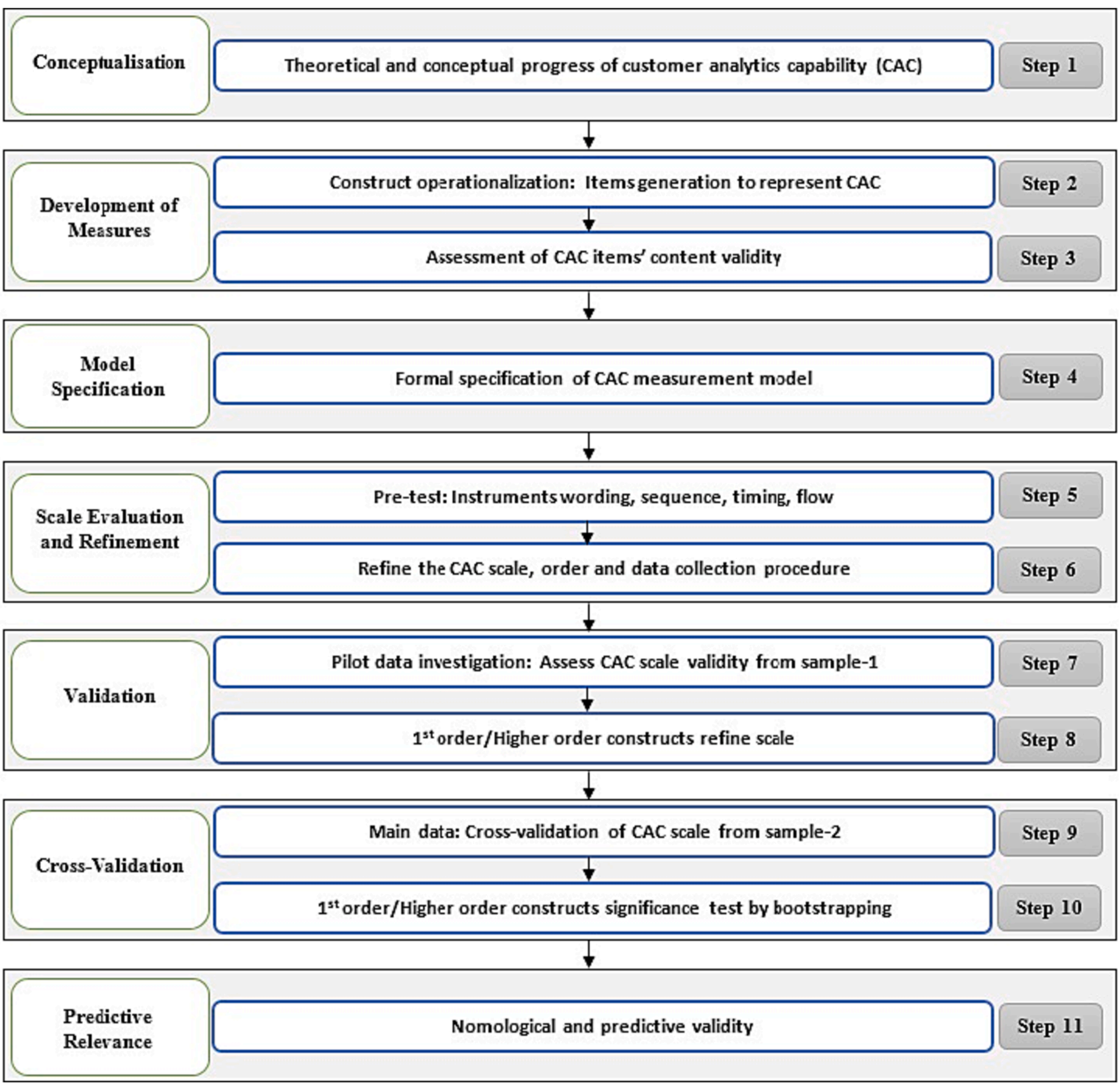

Fig. 1. Scale development process.

constructs. Additionally, we considered scale development guidelines from eminent journals (e.g., Bagozzi, 2011; Wetzels, Odekerken-Schröder, & Van Oppen, 2009). This study introduces a comprehensive 11-step approach encompassing essential aspects to validate the operationalization of CAC instruments (see Fig. 1).

3.1. Step 1: Theoretical and conceptual foundation of CAC development

In the context of analytics capability, extant business research has embraced the RBV as a framework for modeling firms' capabilities (e.g., Rahman et al., 2021a; Santiago Rivera & Shanks, 2015; Wamba et al., 2017). RBV underscores the significance of resources that are valuable, rare, inimitable, and non-substitutable (VRIN) in shaping competitive firm performance (Barney, 1991). From the perspective of RBV, it is crucial to incorporate assets that exert significant influence on processes, enabling platform-driven enterprises to generate distinctive value for their end consumers (Vargo, 2008; Zeng, Yang, & Lee, 2022). The advancement of analytics-driven processes has engendered continuous change (Davenport, Guha, Grewal, & Bressgott, 2020; Hossain et al., 2021b). A firm's performance is differentiated by its ability to leverage heterogeneous resources (Akter et al., 2016). Given the dynamic nature of the environment, the exclusive reliance on RBV might not suffice to meet evolving customer needs. Consequently, the amalgamation of RBV and firm proficiency has garnered scholarly attention, manifesting as RBV-capability (Hossain, Akter, & Yanamandram, 2021a; Yang, Jiang, & Zhao, 2019). Thus, the study integrates the perspective of market orientation alongside RBV to advance CAC from both internal and external standpoints (Day, 2014; Day & Moorman, 2010; Kohli & Jaworski, 1990). In this regard, the study contends that dynamic capability, akin to RBV, commences from within the organization, aligning with the inside-out concept reminiscent of RBV (Kraaijenbrink et al., 2010; Rahman et al., 2021a). Notably, dynamic capabilities enable firms to sense, seize, and reconfigure market dynamics (Teece, 2007; Teece, Pisano, & Shuen, 1997), which is pertinent to contemporary ambidextrous firms that simultaneously explore and exploit opportunities (Buccieri, Javalgi, & Cavusgil, 2020; Pereira et al., 2021). Thus, the study considers the synergy between RBV-capability and a firm's market orientation, fostering progression based on market demands and expectations. CAC signifies a firm's advanced capability for customer data analysis, encompassing value creation, delivery, and management (Hossain et al., 2020a). Building upon these theoretical and definitional underpinnings, the study formulates CAC's dimensions and sub-dimensions through a systematic literature review, interviews, and surveys.

3.1.1. CAC's dimensions

The research began by drawing on existing theories and initiating a systematic literature review (SLR) to establish an initial conceptual model. The SLR process unveiled the dimensions of trend detection, proposing, learning, and tailoring as constituents of CA-driven value creation capability. Similarly, facets such as process consistency, content consistency, support and recovery, and order fulfillment emerged as components of communication and distribution, reflecting CA-driven value delivery capability. Moreover, data integration, quality, privacy, and security were identified as imperative for data-centric value management capability. Detailed insights into this initial conceptual model can be found in the study by Hossain et al. (2020a). Building upon the future research trajectory outlined in Hossain et al. (2020a), this study proposes the CAC scale as a timely and crucial tool for the platform economy, bolstering performance and precision across customer interactions. To advance the scale development process, the study engaged in interviews and surveys to re-evaluate CAC's SLR-based findings.

In an effort to re-evaluate the initial conceptualization, this project involved interviews with 20 experienced customer data analysts. The interview recordings were transcribed using Rev Software. The results reinforced the overarching themes of CAC: customer data-driven value creation, value management, and value delivery capability. The interviews elucidated that (1) customer data-driven value creation hinges on the firm's aptitude for trend-based offerings, personalized learning, and tailoring, (2) customer data-driven value delivery encompasses aspects like process consistency, content consistency, and support and recovery, and (3) ensuring proper data integration, privacy, and security is essential for data-centric value management. Subsequently, we proceeded to distribute a survey link to 185 analytics managers to assess the dimensions of customer-centric analytics capability. Out of these, we received responses from 43 managers, representing a response rate of twenty-three percent. The outcomes revealed that a substantial eighty-three percent of these responses aligned with the foundational dimensions of CAC. Integrating the insights garnered from the SLR findings, interviews, and survey results, the study establishes CAC as a higher-order construct (see Fig. 2).

3.2. Step 2: Construct operationalization: Items generation

In the present study, we identified relevant items from established literature sources, tailoring them to align with the sub-dimensional context of CAC. Specifically, for the domain of analytics-driven value creation across various channels, our investigation delved into literature concerning customer-centric learning (De Luca, Herhausen, Troilo, & Rossi, 2020; Kitchens et al., 2018; Wedel & Kannan, 2016), tailoring/personalization (Goic, Rojas, & Saavedra, 2021; Tofangchi, Hanelt, Marz, & Kolbe, 2021; Tran, 2017; Wedel & Kannan, 2016), and trend-based offering (Andreassen, Lervik-Olsen, & Calabretta, 2015; Boone, Ganeshan, Jain, & Sanders, 2019; Davenport, Mule, & Lucker, 2011; Israeli & Avery, 2018). In the context of analytics-driven value delivery across diverse channels, our inquiry encompassed literature examining process consistency (Lee, Chan, Chong, & Thadani, 2019; Shen, Li, Sun, & Wang, 2018; Wu & Chang, 2016), content consistency (Lee et al., 2019; Shen et al., 2018; Wu & Chang, 2016), as well as support and recovery (Rosenmayer, McQuilken, Robertson, & Ogden, 2018; Smith, Karwan, & Markland, 2009). To address the management of value within a data analytics-rich environment, we explored literature concerning data integration (Jayachandran, Sharma, Kaufman, & Raman, 2005; Nam, Lee, & Lee, 2019), privacy (Chiu, Chang, Cheng, & Fang, 2009; Greenaway, Chan, & Crossler, 2015; Li, Sarathy, & Xu, 2011), and security (Bansal & Zahedi, 2014; Fernando, Chidambaram, & Wahyuni-TD, 2018; Huang, Niu, & Pan, 2021; Meholick, Jesneck, Thanawala, & Seymour, 2020; Rtayli & Enneya, 2020). These initial scales were adapted and refined from existing literature to suit the specific study context. Additionally, modifications were made to eliminate social desirability and unclear wording (See Table 1). Given that several of these instruments were being applied within the CAC context for the first time, we assessed their reliability and validity by following the necessary steps.

3.3. Step 3: Assessment of CAC items' content validity

Content validity serves as a crucial measure to assess the extent to which selected research instruments effectively represent the conceptual scope of the study, encompassing its main dimensions (Hair Jr, Hult, Ringle, & Sarstedt, 2016; Motamarri et al., 2020; Straub, Boudreau, & Gefen, 2004). To ensure content validity, the study employed the Q-sorting methodology, which aids in determining the alignment of a measure with its designated concept domain and the collective encapsulation of the concept domain by the set of measures (Fitzpatrick, 1983; Lundberg, de Leeuw, & Aliani, 2020; MacKenzie, Podsakoff, & Podsakoff, 2011). For the Q-sorting method, three (3) academic experts were selected through a judgemental sampling technique in accordance with previous research practices (e.g., Rahman et al., 2020a; Rahman, Hossain, Fattah & Mokter, 2021b). These panel members horizontally grouped all items and vertically arranged the CAC dimensions in columns. Each item was then matched to the corresponding dimension by

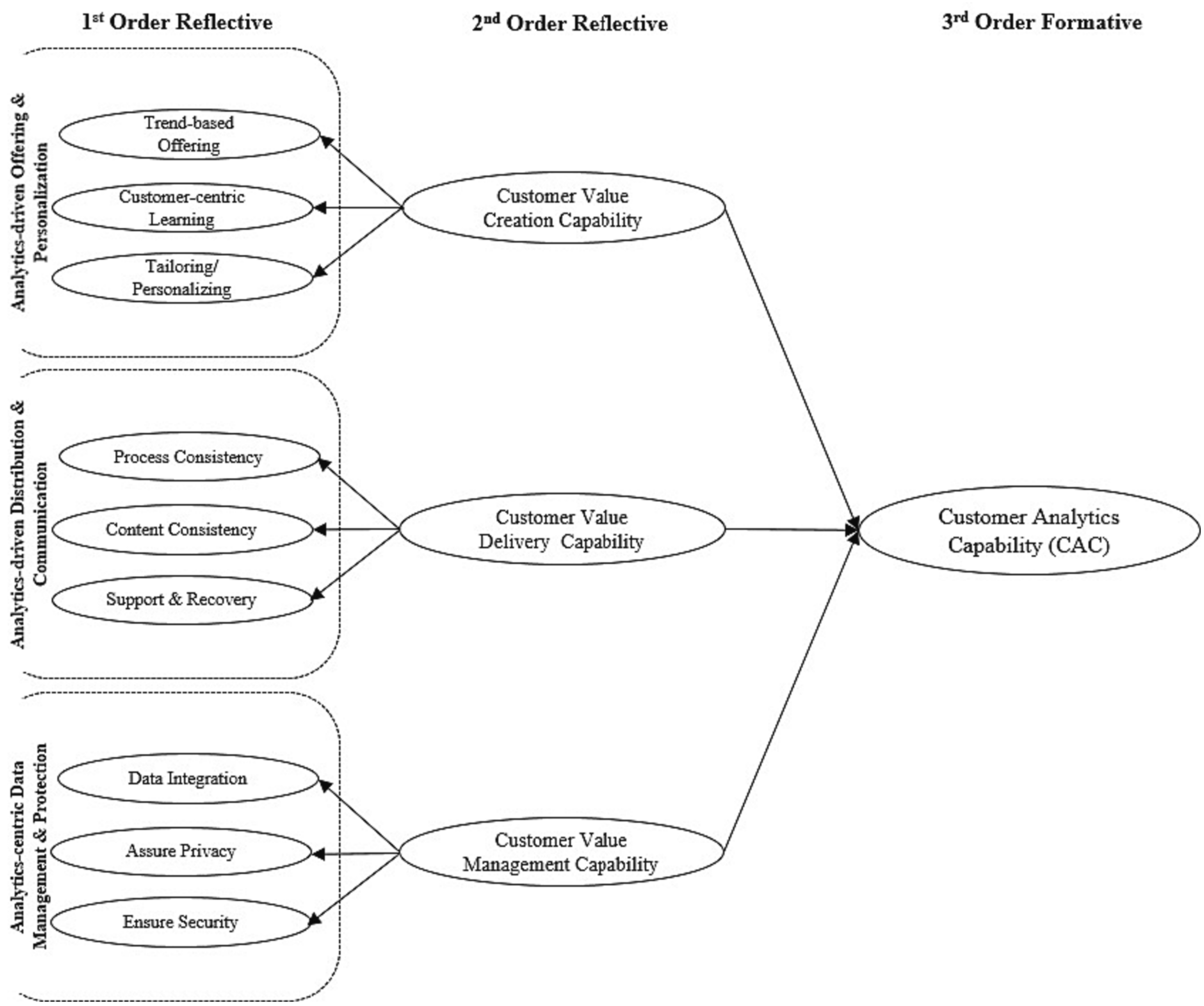

Fig. 2. Hierarchical CAC model.

the panel members, ensuring the coverage of the item pool and instrument. Subsequently, two key researchers engaged in one-on-one discussions with the investigators to further establish the content validity of the construct's items. Incorporating the valuable insights of these experts, adjustments were made to the wording of certain questions to enhance clarity and alignment.

3.4. Step 4: Formal specification of the CAC measurement model

Upon initial exploration of CAC dimensions and items, this study confirms the firm's CAC as a higher-order multidimensional construct, employing both reflective and formative elements (Becker, Klein, & Wetzels, 2012). Adhering to guidelines from impactful research works (e.g., Akter, Gunasekaran, Wamba, Babu, & Hani, 2020; Becker et al., 2012; Hossain, Akter, Kattiyapornpong, & Dwivedi, 2020b; Sarstedt, Hair, Cheah, Becker, & Ringle, 2019), this study adopts a third-order reflective-formative framework to conceptualize CAC. In this structure, the third-order CAC construct emerges from three reflective second-order constructs: customer value creation capability, customer value delivery capability, and customer value management capability. These second-order constructs are, in turn, reflected by nine first-order constructs, encompassing elements like trend-based offering, customer-centric learning, tailoring/personalizing, process consistency, content consistency, support and recovery, data integration, assuring privacy and ensuring security.

Applying the approach outlined by Becker et al. (2012), this study employs a repeated indicator methodology for measuring CAC. Instead of separately estimating lower-order and higher-order constructs, this approach simultaneously assesses and measures all constructs, effectively capturing their interrelationships (Hossain et al., 2020b). Given the reflective-formative nature of CAC conceptualization, the first-order and second-order reflective constructs are modeled using mode A (automatic option in PLS). Meanwhile, the third-order construct is represented in mode B, aggregating formative item contributions within the PLS model (Chin, 2010; Ringle, Sarstedt, & Straub, 2012b). The best parameters of path weighting scheme in the hierarchical reflective-formative model are generated through the repeated indicators approach (Becker et al., 2012). In total, the measurement of CAC is represented by 30 indicators, all assessed using a 7-point Likert scale format.

3.5. Steps 5 and 6: Evaluation of scales: Items pre-test and refinement

The CAC assessment tools were translated into a survey questionnaire format and administered through the Qualtrics platform. Qualtrics, a widely employed tool for creating and distributing survey instruments (Chambers, Nimon, & Anthony-McMann, 2016; Molnar, 2019), facilitated the implementation of the pretesting phase, which encompassed three distinct stages. To enhance the questionnaire's quality and validity, the Qualtrics version of the survey questionnaire was shared with 20 academics and business analysts using a judgmental sampling approach. Throughout the pretesting process, a thorough assessment of questionnaire formatting, word choices, clarity, completeness, question sequencing, procedure, and timing was

Table 1
Initial items created for higher-order CAC.

Theme	Constructs/Items code	Items/Concepts in literature	Items adapted	Sources
Customer Value Creation Capability	***Trend-based offering (TBO)***		***Customer-centred analytics facilitates our firm to:***	
	TBO_1	Trend spotting direct managers toward innovations that are more in accordance with specific customer needs.	Execute segment-wise offers predicting trends accurately.	Andreassen et al. (2015)
	TBO_2	Know your offerings by understanding the word of mouth or customers' buying intentions.	Execute offers anticipating customers' word of mouth or propensity to buy.	Boone et al. (2019); Davenport et al. (2011)
	TBO_3	Data helps to offer by analysig market trends.	Execute offers detecting current market trends.	Israeli and Avery (2018)
	Customer-centric learning (CCL)		***Customer-centred analytics allows our firm to:***	
	CCL_1	Individual-level data can generate extensive customer value.	Discover individual customer value.	Wedel and Kannan (2016)
	CCL_2	Specify patterns of competitive actions influencing customers.	Learn the designs of competitive actions influencing customers.	De Luca et al. (2020)
	CCL_3	Understand potential actions dealing with customers' data.	Understand the best next action in customer interaction.	Kitchens et al. (2018)
	CCL_4	Comprehend disfavoured customer behaviours, for example, complaints or churn.	Understand customers' problems, possibilities, or actions.	De Luca et al. (2020)
	Tailoring/ personalizing (TAI)		***Customer-centred analytics permits our firm to:***	
	TAI_1	Configure personalized recommendations based on customer preferences.	Design tailor-made recommendations based on customer choices.	Wedel and Kannan (2016)
	TAI_2	Trigger automatic emails with personalized messages to recommend cross selling and cart abandonment reminders.	Send personalized emails to the selected customer.	Goic et al. (2021)
	TAI_3	Create real-time personalized advertisements on customers' preferred products, prices, and places.	Generate real-time customized promotions on the product, price, and place, linking customer choices.	Tran (2017); Tofangchi et al. (2021)
Theme	**Constructs/Items code**	**Items/Concepts in literature**	**Items adapted**	**Sources**
Customer Value Delivery Capability	***Process consistency (PRC)***		***Customer-centred analytics enables our firm to:***	
	PRC_1	The service execution is uniform across various channels.	Maintain a consistent service process across all the channels (e.g., online, mobile, offline channels).	Shen et al. (2018)
	PRC_2	Customers' feelings are consistent in multiple channels for invariant performance and timeliness of services.	Meet customer needs in multiple channels consistently.	Wu and Chang (2016)
	PRC_3	Customers' service levels are consistent across all the channels.	Perform customer-related activities in all the channels simultaneously.	Lee et al. (2019)
	Content consistency (COC)		***Customer-centred analytics allows our firm to:***	
	COC_1	Provide consistent information about products through various channels.	Provide consistent information about our product/service features in multiple channels (e.g., online, mobile & offline).	Wu and Chang (2016)
	COC_2	Provide uniform promotion information through various channels.	Provide consistent information about promotional offers across channels.	Lee et al. (2019)
	COC_3	Receive the identical response through various channels.	Present overall consistent information in multiple channels.	Shen et al. (2018)
	COC_4	Provide consistent stock details through all channels.	Present overall consistent stock information across different channels.	Wu and Chang (2016)
	Support & recovery (SRC)		***Customer-centred analytics empowers our firm to:***	
	SRC_1	Assist customer queries in various channels (e.g., internet, telephone, and in-person).	Support customer inquiries in multiple channels (e.g., online, mobile, offline channels).	Smith et al. (2009)

(*continued on next page*)

Table 1 (*continued*)

Theme	Constructs/Items code	Items/Concepts in literature	Items adapted	Sources
	SRC_2	Ability to identify customer complaints in multi-channel.	Track customer complaints across channels.	Rosenmayer et al. (2018)
	SRC_3	Monitor failure data frequently in service recovery.	Examine possible odds across channels during problem recovery.	Smith et al. (2009)
Theme	**Constructs/Items code**	**Items/Concepts in literature**	**Items adapted**	**Sources**
Customer Value Management Capability	***Data integration (DIN)***		***Our firm's advanced system can:***	
	DIN_1	Our firm adequately utilizes different tools to integrate data from diverse sources.	Utilize various tools to integrate customers' data from multiple sources.	Nam et al. (2019)
	DIN_2	Integrate internal data of customers with customer data from external sources.	Combine in-store customers' transaction data with online data sources efficiently.	Jayachandran et al. (2005)
	DIN_3	Our firm incorporates customer data from customer's single view.	Integrate customer's data from a customer's single view.	Nam et al. (2019)
	Assure privacy (ASP)		***In the presence of customer-centred analytics, our advanced system enables our firm:***	
	ASP_1	Site effort to protect customer information.	To protect customers' personal information.	Li et al. (2011)
	ASP_2	Do not disseminate customers' personal information to others.	Not to share customers' personal information with others.	Chiu et al. (2009)
	ASP_3	An unauthorized entity cannot access customers' financial information.	Not to share the customers' financial information with any other unauthorised sources.	Greenaway et al. (2015)
	Ensure security (ENS)		***In the presence of customer-centred analytics, our advanced system enables our firm to:***	
	ENS_1	Our firm can satisfactorily secure customer data.	Ensure adequate security for customers.	Fernando et al. (2018)
	ENS_2	A properly developed system can secure customers' credit card transactions.	Ensure security during the customers' credit card transactions.	Rtayli and Enneya (2020)
	ENS_3	Provide someone assurance not to misuse their personal, health, or financial information.	Provide individual assurance not to misuse their personal, health, or financial information.	Bansal and Zahedi (2014)
	ENS_4	A secure and comprehensive platform-based support can appropriately serve customers.	Provide a comprehensive, secure platform for all our customers.	Huang et al. (2021); Meholick et al. (2020)

undertaken. Respondents were actively encouraged to provide feedback and suggestions for improvement. This iterative pretesting phase played a pivotal role in refining the questionnaire's structure, addressing presentation-related concerns, and ensuring the logical arrangement of survey items for optimal comprehension by the intended research participants. Based on the feedback received, certain questions were rephrased to enhance their clarity and simplicity. We also adjusted the sequence of questions to ensure a coherent flow within the survey. Additionally, the pre-test participants were engaged in discussions regarding screening questions and exit messages aimed at facilitating clear comprehension of questionnaire instructions for future respondents. Redundant questions were eliminated to streamline the questionnaire. The overarching objective was to create a well-organized survey instrument that respondents could conveniently complete within approximately fifteen minutes. The sequence of survey questions was optimized based on the insights provided by expert pre-test participants.

3.6. Steps 7 and 8: Pilot study for items validation

As a pivotal phase in the scale development process, we conducted a pilot study. While the pre-test phase refined the instrument, the pilot-test phase aimed to gauge expected response rates and outcomes while verifying scale reliability. Within this phase, we formulated a questionnaire on the Qualtrics platform and distributed it to a smaller sample size compared to the main survey. The participants' backgrounds and criteria mirrored those of the main survey precisely. For data collection, we collaborated with an internationally recognized Australian market research firm that possesses an extensive database of business analytics managers. A representative sample was drawn from this pool using a simple random sampling technique. The participants selected were business analysts with experience in handling substantial volumes of customer data on online retail platforms. Out of the 570 potential respondents, 70 met the eligibility criteria and participated in the survey. To facilitate analysis, the research data collected via Qualtrics was exported to Excel. In the process of evaluating attention checker questions and speeders, responses from 15 participants were omitted. Consequently, the analysis focused on the responses of 55 participants, which were then considered for pilot test analysis. The findings of this analysis are detailed in the subsequent scale purification and refinement phase.

3.6.1. Confirmatory analysis using PLS-SEM

Confirmatory factor analysis is commonly used to examine reflectively measured constructs. However, in exploratory research, the measures and conceptual frameworks of the constructs may need to be well-established. Recently, an extension of primary element analysis has proposed confirmatory analysis using PLS Structural Equation Modeling (PLS-SEM)—which treats observed variables and constructs proxies as composites—offering distinct advantages. Scholars have highlighted that PLS-SEM and factor-based SEM are fundamentally distinct methods, and the choice between them should be guided by research objectives, measurement properties, and model configuration (Hair, Hult, Ringle, Sarstedt, & Thiele, 2017; Hair et al., 2021). A comprehensive comparison between these methods is presented by Hair et al. (2016). PLS-SEM confirmatory analysis brings multiple advantages, including the capacity to incorporate a greater number of indicators in nomological models to estimate contingencies, ensure functional determinant construct ratings, and accommodate both reflective and formative applications (Hair et al., 2021). Rigorous simulation studies have established that PLS-SEM confirmatory analysis outperforms factor-based methods when the causal population prototype is composite (Hair et al., 2017; Sarstedt et al., 2019).

In PLS-SEM, indicators are specified as Mode-A (reflective) representing correlational weights or Mode-B (formative) representing regression weights (Rigdon, 2012). Rigdon and other scholars emphasize that PLS-SEM is fundamentally a composite-based method, regardless of the model specification as Mode-A or Mode-B (Rigdon, 2012, 2014; Sarstedt et al., 2019). When applying PLS-SEM, researchers need to consider four crucial points: data, model properties, PLS-SEM algorithms, and model evaluation issues (Hair, Ringle, & Sarstedt, 2011; Ringle, Sarstedt, & Straub, 2012a). PLS-SEM demonstrates particular strengths when dealing with complex models and small sample sizes, as it makes minimal assumptions concerning the underlying data (Cassel, Hackl, & Westlund, 1999). Additionally, PLS-SEM is suitable for higher-order models, irrespective of their reflective or formative nature (Hossain et al., 2021a). The scale development and validation in the present study follow the guidelines proposed by Hair, Page, and Brunsveld (2019) and Motamarri et al. (2020). PLS-SEM requires careful consideration of confirmation, explanation, and prediction aspects (Hair et al., 2020). The confirmatory analysis includes the estimation of loadings and significance, item reliability, construct reliability, average variance extracted (AVE), discriminant validity (Fornell Larcker, HTMT), nomological validity, and predictive validity (Hair et al., 2020).

3.6.2. Scale purification and refinement

Scale purification is considered one of the primary choices researchers incorporate in scale development within the marketing stream (Böttger et al., 2017). The study uses Smart PLS 3.0 software for empirical analysis purposes. This study checked first-order constructs' reliability, convergent validity and discriminant validity as part of the confirmatory factor analysis (MacKenzie et al., 2011; Straub et al., 2004). Initially, 30 reflective items were considered under 9 first-order constructs. PLS algorithm's basic setting was a path weighting scheme, maximum iterations: 300, stop Criterion (10ˆ-X): 7.

In PLS, an item remains reliable if its loading surpasses the threshold value of 0.7 (Hair et al., 2021; Sarstedt et al., 2019). The pilot study data showed 3 itmes out of 30 failed to meet the threshold criteria; that is CCL3, COC_4, and ENS_3 (See Table 2). Therefore, for reliability and quality purposes, these items were dropped. The analysis was then conducted on the refined set of 27 items, and the results are presented in Table 2. This study also assessed construct reliability (CR) to examine the latent constructs. Table 3 confirms all scales' reliability with CR values surpassing the cut-off of 0.80 (Hair et al., 2017). The AVE are above 0.5 (See Table 3), confirming the convergent validity (Hair et al. (2016)). To test discriminant validity, Fornell and Larcker (1981) criteria and Heterotrait-monotrait ratio of correlations (HTMT) were employed. The inter-construct correlations were found to be smaller than the square root of each construct's AVE, and all HTMT values were below 0.90, affirming discriminant validity.

As a third-order concept, CAC necessitated evaluation at different levels. For the lower-order components (LOCs), characterized by reflective nature, the study assessed *internal consistency* (e.g., items loading, composite reliability), *convergent validity* (e.g., AVE), and *discriminant validity* (e.g., HTMT). As the second order is reflective, the focus shifted to assessing the internal consistency of indicators, where Cronbach's alpha and composite reliability scores exceeded 0.80, and convergent validity was confirmed with AVE values above 0.50. Discriminant validity was established through HTMT values below 0.90. The third order is formative; hence the study also demonstrates the

Table 3
Refined instruments scores.

Items	Loading	CR	AVE	Items	Loading	CR	AVE
TBO		0.948	0.858	**PRC**		0.911	0.774
TBO_1	0.922			PRC_1	0.881		
TBO_2	0.930			PRC_2	0.870		
TBO_3	0.928			PRC_3	0.889		
CCL		0.934	0.826	**COC**		0.921	0.796
CCL_1	0.904			COC_1	0.915		
CCL_2	0.899			COC_2	0.861		
CCL_4	0.923			COC_3	0.900		
TAI		0.870	0.691	**SRC**		0.924	0.803
TAI_1	0.804			SRC_1	0.908		
TAI_2	0.782			SRC_2	0.897		
TAI_3	0.902			SRC_3	0.883		
DIN		0.883	0.716	**ASP**		0.921	0.795
DIN_1	0.842			ASP_1	0.869		
DIN_2	0.880			ASP_2	0.881		
DIN_3	0.815			ASP_3	0.925		
ENS		0.908	0.767				
ENS_1	0.898						
ENS_2	0.803						
ENS_4	0.921						

Table 2
First reliability evaluation.

Items	Pilot result	Decision	Refined value	Items	Pilot result	Decision	Refined value
TBO_1	0.922	Keep	0.922	PRC_1	0.881	Keep	0.881
TBO_2	0.930	Keep	0.930	PRC_2	0.870	Keep	0.870
TBO_3	0.928	Keep	0.928	PRC_3	0.889	Keep	0.889
CCL_1	0.893	Keep	0.904	COC_1	0.907	Keep	0.915
CCL_2	0.901	Keep	0.899	COC_2	0.869	Keep	0.861
CCL_3	−0.144	Drop	N/A	COC_3	0.888	Keep	0.900
CCL_4	0.917	Keep	0.923	COC_4	−0.235	Drop	N/A
TAI_1	0.804	Keep	0.804	SRC_1	0.908	Keep	0.908
TAI_2	0.782	Keep	0.782	SRC_2	0.897	Keep	0.897
TAI_3	0.902	Keep	0.902	SRC_3	0.883	Keep	0.883
DIN_1	0.842	Keep	0.842	ASP_1	0.869	Keep	0.869
DIN_2	0.880	Keep	0.880	ASP_2	0.881	Keep	0.881
DIN_3	0.815	Keep	0.815	ASP_3	0.925	Keep	0.925
ENS_1	0.899	Keep	0.898	ENS_2	0.802	Keep	0.803
ENS_3	−0.140	Drop	N/A	ENS_4	0.921	Keep	0.921

validity of the third-order formative construct. For the higher-order component (HOC), where LOCs represent the indicators of the HOC formatively, we used mode B in PLS, which counts all the items as formative in the third order (Hossain et al., 2020b). For the formative third-order component, validation encompassed convergent validity (e.g., redundancy analysis), collinearity between indicators, and the significance and relevance of outer weights, following Sarstedt et al.'s (2019) guideline. Convergent validity was assessed through a redundancy analysis, involving the use of a formatively measured construct, such as CAC, as an exogenous latent variable to predict the same construct measured by a single global item, known as the CAC global single item. This modern validation approach is well-recognized in current research (Sarstedt et al., 2019). The path coefficient connecting the two constructs, CAC (including formative items) and CAC global single item, surpassed 0.70, confirming the convergent validity of the measurement model (Hair et al., 2020). Furthermore, the PLS algorithm demonstrated lower collinearity, satisfying the variance inflation factor threshold (VIF < 5). Additionally, bootstrapping results revealed significant weights for the higher-order CAC (Hossain et al., 2021a). Specifically, the outcomes validated that Variables VCC ($\beta = 0.369$, $p < 0.01$), VDC ($\beta = 0.349$, $p < 0.05$), and VMC ($\beta = 0.353$, $p < 0.001$) are meaningful antecedents of CAC.

3.7. Step 9: Main study population and sample size

The study's focus is on managers, specifically those well-versed in handling customer data from various platforms. To establish a robust sample, the study collaborated with a reputable Australian research firm. This collaboration facilitated the selection of managers possessing the required expertise. Initially, approximately 2000 managers expressed interest in participating in the survey. After a stringent screening process, 387 managers met the eligibility criteria. Further assessments were carried out to address factors like straight-lining, attention check responses, and survey completion time. Ultimately, the study analyzed the responses of 353 managers. In line with the research insights of Hair et al. (2016), which indicate that a minimum of 150 observations is necessary to attain a statistical power of 80 % for detecting effect sizes of at least 0.10 when there are a maximum of 9 independent variables in the measurement and structural models, our study's CAC model benefits from a sample size of 353, surpassing this threshold level.

The demographic data shows the majority of the respondents were male (53.3 %) than female (46.7 %). Respondents aged between 25 and <45 years constituted 51.2 % of the sample, while those above 45 years accounted for 43.1 %. Regarding educational background, the majority held bachelor's degrees (42.2 %), followed by a Diploma certificate (29.5 %). In terms of job titles, senior managers comprised 37.1 % of the respondents, while operations managers constituted 23.2 % (see Table 4).

3.8. Step 10: Cross validation of CAC instruments

3.8.1. First-order measurement model specification

First-order item loadings exceed the threshold value of 0.7 (Hair et al., 2021; Sarstedt et al., 2019). This study checked construct reliability (CR) to examine the latent constructs. Table six displays all scales as reliable, as CR value exceeds the cut-off value 0.80 (Hair et al., 2017). The AVE scores are above 0.5 (See Table 6), confirming convergent validity (Hair et al., 2016). This study used Fornell and Larcker (1981) criteria and HTMT to test the discriminant validity. The inter-construct correlations were smaller than the square root of the specific construct's AVEs in the diagonals (See Table 5). HTMT's all values are below 0.85, confirming discriminant validity (See Table 7). Table 8 presents cross-loading indicators (See Table 8).

Table 4
Demographic profile of respondents.

Items	Categories	%	Items	Categories	%
Gender	Male	53.3	**Age**	< 25 years	5.70
	Female	46.7		25 < 35 years	28.0
	Do not wish to disclose	00.0		35 < 45 years	23.2
				45 ≤ years	43.1
Education	Diploma certificate	29.5	**Position**	Senior manager	37.1
	Bachelor's degree	42.2		Head of analytics	4.20
	Master's degree	19.3		Analytics manager	10.5
	Doctorate	2.80		Business analyst	13.6
	Other	6.20		Operations manager	23.2
				Other	11.3

3.8.2. Second and third-order measurement model specification

Given that CAC is a third-order concept, a detailed evaluation followed. For the reflective nature of lower-order components (LOCs), key assessments involved internal consistency (e.g., item loadings, composite reliability), convergent validity (e.g., AVE), and discriminant validity (e.g., HTMT). As the second order is reflective, internal consistency of indicators was validated, with Cronbach's alpha and composite reliability scores surpassing 0.80. Convergent validity through AVE exceeded 0.50, and discriminant validity, as indicated by HTMT values, was below 0.85. The third order, characterized as formative, necessitated an assessment of the third-order formative construct. For the higher-order component (HOC), where LOCs function as indicators of the HOC formatively, mode B in PLS was applied, treating all items as formative in the third order (Hossain et al., 2020b). To establish the validity of the formative construct, the guideline proposed by Sarstedt et al. (2019) was followed, involving examinations of convergent validity (e.g., redundancy analysis), indicator collinearity, and the significance and relevance of outer weights.

To evaluate convergent validity, a redundancy analysis was conducted. A formative measurement of CAC served as an exogenous latent variable, predicting the same construct represented by a single global item (CAC global single item). This contemporary validation technique, acknowledged in recent research, demonstrated a path coefficient between the two constructs exceeding 0.70, confirming convergent validity (Hair et al., 2020). The analysis conducted through the PLS algorithm indicated acceptable collinearity, meeting the variance inflation factor threshold (VIF < 3). Furthermore, the bootstrapping analysis revealed significant weights for the higher-order CAC (Hossain et al., 2021a). Specifically, the findings highlighted the variables VCC ($\beta = 0.371$, $p < 0.01$), VDC ($\beta = 0.359$, $p < 0.05$), and VMC ($\beta = 0.359$, $p < 0.001$) were significant antecedents of CAC.

3.9. Step 11: Structural model and predictive validity

3.9.1. Impact of CAC on customer-related performance

A foundational element of any study involves establishing the relationships between independent and dependent variables within the structural model. In this study, the focus canters on the newly introduced CAC scales. It is postulated that the effective application of CAC within a platform-driven digital business environment will contribute to the enhancement of customer-related performance. To measure customer-related performance, items encompassing customer satisfaction, sustainable relationships, customer attraction, and customer retention were adapted from the works of Ngo and O'Cass (2012) and Trainor, Rapp, Beitelspacher, and Schillewaert (2011). Prior research indicates that customer-centric metrics, such as customer satisfaction,

Table 5
√AVEs (on diagonal).

	TBO	CCL	TAI	PRC	COC	SRC	DIN	APR	ENS
TBO	0.868								
CCL	0.647	0.839							
TAI	0.609	0.642	0.831						
PRC	0.532	0.505	0.433	0.835					
COC	0.581	0.568	0.523	0.519	0.816				
SRC	0.587	0.606	0.531	0.506	0.549	0.862			
DIN	0.551	0.595	0.512	0.664	0.547	0.611	0.806		
APR	0.539	0.586	0.565	0.442	0.551	0.593	0.548	0.872	
ENS	0.559	0.635	0.631	0.406	0.479	0.557	0.495	0.683	0.868

correlate with heightened future sales growth (Ahearne, Jelinek, & Rapp, 2005; Trainor et al., 2011). Building and maintaining robust customer relationships at an extensive scale can yield increased revenues and a desirable market position through mechanisms such as cross-selling, up-selling, and positive word-of-mouth (Hogan et al., 2002; Trainor et al., 2011). The loyalty exhibited by satisfied customers translates into reduced expenses for repeat purchase promotion, solidifying the firm's competitive stance within the data-rich market landscape (Rahman, Hossain, Zaman, & Mannan, 2020b; Szymanski & Henard, 2001).

Although earlier studies have emphasized marketing metrics encompassing data on campaigns, channels, treatments, and customer responses to gauge the efficacy of customer relationship management (CRM) activities (Farris, Bendle, Pfeifer, & Reibstein, 2015; Farris, Bendle, Pfeifer, & Reibstein, 2010; Ling-Yee, 2011), their scope remains broad and lacks specificity to individual customers (Gray, 2021). These studies encompass the entire marketing landscape, whereas this investigation narrows its focus to the CAC of firms operating within online retail platforms. This strategic capability offers a significant avenue to bolster customer-related performance.

From a theoretical standpoint, a firm should possess a resource foundation aligned with customer service (Kraaijenbrink et al., 2010; Sedera, Lokuge, Grover, Sarker, & Sarker, 2016). A market-oriented firm consistently explores both overt and underlying customer desires (Alnawas & Hemsley-Brown, 2019; Slater & Narver, 1999). To accomplish this, the firm requires adept functional capabilities that not only address explicit customer needs but also uncover innovative solutions for intrinsic and latent needs (Ngo & O'Cass, 2012). This study lays the groundwork for a CAC framework and measurement tools that predict enhanced customer relationship performance. Existing literature underscores that a firm's remarkable relationship performance hinges on its distinct capabilities, which are not easily transferable like tangible assets and hold profound implications for value creation and capture (Hossain et al. (2020a); Ngo & O'Cass, 2012). Integrating CAC within the firm's functional repertoire empowers it to cultivate and sustain valuable customer relationships, bolstering competitiveness and fostering superior market value. Given the rationale, this study posits that CAC implications culminate in higher customer-related performance within the context of the platform economy. Thus, we propose the following hypothesis:

Hypothesis: CAC exerts a positive influence on customer-related performance.

This research considers three pivotal factors as control variables. Specifically, the study accounts for the retail category and firm size, drawing insights from prior analytical studies (e.g., Akter et al., 2020; Chen et al., 2014; Côrte-Real, Oliveira, & Ruivo, 2017). Additionally, the study controls for respondents' job titles, recognizing their potential influence on CAC perception (e.g., Cao et al., 2019).

In the structural model, the t-value's importance is determined by whether the values are>1.95, 2.68, and 3.29, which correspond to significance levels of 0.05, 0.01, and 0.001, respectively. We used PLS Bootstrapping with 5,000 subsamples (Chin, 2010; Hair et al., 2017) to calculate the t-value. The results show that the impact of CAC on customer-related performance is substantial ($\beta = 0.738$, $t > 3.29$, $p < 0.001$). This supports the hypothesis and underscores the study's findings. The R^2 value, at 0.545, further substantiates the significant influence, as illustrated in Fig. 3.

3.9.2. *Nomological assessment and robustness tests*

The present study validates the nomological soundness of the PLS-Predict stepwise process, following the framework proposed by Shmueli et al. (2019). Initially, the study calculates the PLS-SEM Q^2predict values for all items in the measurement model, which are found to be consistently>0, ranging from 0.295 to 0.628. Subsequently, the investigation examines the symmetric distribution of prediction errors and proceeds to assess the root mean squared error (RMSE) for further validation. Additionally, the study compares the PLS-RMSE values with those of LM-RMSE for the outcome construct's items, providing evidence of the superior predictive power of PLS-SEM over LM.

To ensure robustness, several data collection and analysis approaches were employed. Addressing non-response bias, the study utilized a participant information sheet to communicate the academic purpose, confidentiality, and anonymity to potential respondents. Data were collected using a Qualtrics version of the questionnaire, ensuring that respondents could not proceed without completing all questions. The study verified that responses were spontaneously collected from all samples without any biased component. A random 25 % subset from the initial and latter response halves underwent paired t-tests, revealing no statistically significant differences. Both priori and post-hoc methods were employed to address common method bias, with independent and dependent variable questions separated during data collection, and different response scales used for the dependent variable. The study also examined the correlation between the marker variable and study variables, with results indicating no significant association ($r = -0.001$ to 0.034, $p > 0.05$). Effect sizes (f^2) derived from data analysis were strong ($f^2 > 0.350$), aligning with Cohen's (2013) goodness of fit guidelines, further supporting the predictive capability of the model. Control variables, namely firm size, industry category, and respondent position, were examined and found to have no significant effect on firm customer-related performance.

4. Discussion

4.1. *Theoretical contributions*

Within the scope of modern business transformation, the role of firms' analytics capabilities has been acknowledged by academic researchers. However, there has been a noticeable gap in understanding CAC within the context of the online platform-driven retail marketplace. This study addresses this gap by presenting a robust conceptualization of a retail firm's customer value-centric analytics capability, laying the foundation for further exploration. Several noteworthy theoretical contributions emerge from this study:

Firstly, this study significantly contributes to both the business analytics and platform economy literature. In a landscape where tech-savvy

Table 6
Assessments of CAC Instruments.

Reflective Constructs	Items	Loadings	CR	AVE
Trend-based Offering (TBO)	*Customer-centred analytics facilitates our firm to:*		0.902	0.754
	TBO1: Execute segment-wise offers predicting trends accurately.	0.842		
	TBO2: Execute offers anticipating customers' word of mouth or propensity to buy.	0.883		
	TBO3: Execute offers detecting current market trends.	0.879		
Customer-centric Learning (CCL)	*Customer-centred analytics allows our firm to:*		0.877	0.703
	CCL1: Discover individual customer value.	0.813		
	CCL2: Learn the designs of competitive actions stimulating customers.	0.862		
	CCL4: Understand customers' problems, possibilities, and actions across touch-points.	0.840		
Tailoring/ Personalising (TAI)	*Customer-centred analytics permits our firm to:*		0.869	0.691
	TAI1: Design tailor-made recommendations based on customer choices.	0.849		
	TAI2: Send personalized emails to the selected customer.	0.774		
	TAI3: Generate real-time customized promotions on the product, price, and place, linking customer choices.	0.866		
Process Consisitency (PRC)	*Customer-centred analytics enables our firm to:*		0.873	0.697
	PRC1: Maintain a consistent service process across all the channels.	0.795		
	PRC2: Meet customer needs in multiple channels consistently.	0.844		
	PRC3: Perform customer-related activities in all the channels simultaneously.	0.864		
Content Consisitency (COC)	*Customer-centred analytics allows our firm to:*		0.856	0.665
	COC1: Provide consistent information about our product/ service features in multiple channels.	0.767		
	COC2: Provide consistent information about promotional offers across channels.	0.806		
	COC3: Present overall consistent information in multiple channels.	0871		
Support & Recovery (SRC)	*Customer-centred analytics empowers our firm to:*		0.897	0.744
	SRC1: Support customer inquiries in multiple channels.	0.838		
	SRC2: Track customer complaints across channels.	0.868		
	SRC3: Examine possible odds across channels during problem recovery.	0.881		
Data Integration (DIN)	*Our firm's advanced system can:*		0.848	0.651
	DIN1: Utilize various tools to integrate customers' data from multiple sources.	0.813		
	DIN2: Combine in-store customers' transaction data with online data sources efficiently.	0.822		
	DIN3: Integrate customer's data from a customer's single view.	0.783		
Assure Privacy (ASP)	*In the presence of customer-centred analytics, our advanced system enables our firm:*		0.905	0.761
	ASP1: To protect customers' personal information.	0.866		
	ASP2: Not to share customers' personal information with others.	0.874		
	ASP3: Not to share the customers' financial information with any other unauthorised sources.	0.876		
Ensure Security (ENS)	*In the presence of customer-centred analytics, our advanced system enables our firm to:*		0.902	0.754
	ENS1: Ensure adequate security for customers.	0.870		
	ENS2: Ensure security during the customers' credit card transactions.	0.837		
	ENS4: Provide a comprehensive, secure platform for all our customers.	0.896		

platforms dictate data-driven business transactions (Cenamor, Parida, & Wincent, 2019; Shi, Wang, & Li, 2021), this research recognizes the transformative impact of such patterns on various aspects of life and commerce. Consequently, firms gain the opportunity to thrive in this hypercompetitive marketplace (Eckhardt et al., 2019; Grandhi, Patwa, & Saleem, 2020). Although global firms aggressively deploy various digital technologies at different levels, not all businesses have accomplished the expected resilience (Li, Wang, Ye, Chen, & Zhan, 2022; Mandal, 2017). By establishing comprehensive CAC instruments tailored to retail firms operating in online platforms, this study provides a relevant framework that extends beyond overused examples like Uber, Airbnb or Netflix (Farrell and Greig, 2017; Soto-Acosta, 2020; Trabucchi & Buganza, 2020). The study highlights that retail and service industries, including banking and healthcare, rely on a mix of offline, online, and mobile channels, necessitating a strategic approach to capitalize on platforms' potential. Our conceptualization of CAC and its associated instruments serves as a guide on effectively utilizing CAC within the platform economy, highlighting its indispensability in a data-driven economy. Additionally, the integration of multichannel experiences and the significance of CAC in this context underscore the research's practical relevance.

Secondly, this study draws upon the RBV capability (Akter et al., 2016; Barney, 1991; Ngo & O'Cass, 2012), and market orientation (Alnawas & Hemsley-Brown, 2019; Day, 2011). The study contributes to the theoretical framework by introducing the concept of an "outside-in view" that builds upon prior research on marketing capabilities (Theodosiou, Kehagias, & Katsikea, 2012; Vorhies & Morgan, 2005; Vorhies, Orr, & Bush, 2011). While prior research has emphasized value creation and capture in AI platforms, this study uniquely focuses on instrument development within this specific context. The "outside-in view" aligns with the RBV's notion of firms leveraging their internal strengths to seize external opportunities, extending the application of this theory to CAC.

Finally, the study has a significant methodological contribution. Methodologically, the study outperforms many analytics capability studies in the marketing field. Employing a multi-phase approach, the study undertook the development of the higher-order CAC and its corresponding outcome variables. It then utilized the advanced PLS-SEM technique to analyse the third-order reflective-formative research model. In the context of CA, earlier investigations often adopted a qualitative approach, whereas this study employed a rigorous quantitative method (Germann et al., 2014; Giri et al., 2019; Hossain et al., 2020a). In contrast, a study on marketing analytics capability opted for

Table 7
Discriminant validity (HTMT).

	TBO	CCL	TAI	PRC	COC	SRC	DIN	APR	ENS
TBO									
CCL	0.791								
TAI	0.754	0.814							
PRC	0.658	0.641	0.558						
COC	0.733	0.737	0.693	0.672					
SRC	0.705	0.739	0.652	0.622	0.697				
DIN	0.687	0.764	0.655	0.841	0.721	0.784			
APR	0.642	0.721	0.693	0.545	0.694	0.709	0.678		
ENS	0.665	0.782	0.772	0.499	0.602	0.667	0.617	0.813	

Table 8
Cross loadings of indicators.

Dimensions	Indicators	TBO	CCL	TAI	PRC	COC	SRC	DIN	ASP	ENS
Trend-based Offering (TBO)	TBO_1	0.842	0.538	0.524	0.444	0.503	0.519	0.457	0.463	0.483
	TBO_2	0.883	0.542	0.532	0.461	0.471	0.467	0.422	0.461	0.482
	TBO_3	0.879	0.603	0.531	0.481	0.539	0.544	0.553	0.481	0.491
Customer-centric Learning (CCL)	CCL_1	0.512	0.813	0.543	0.436	0.466	0.451	0.485	0.541	0.544
	CCL_2	0.632	0.862	0.579	0.481	0.493	0.581	0.562	0.511	0.571
	CCL_4	0.472	0.841	0.491	0.351	0.471	0.484	0.443	0.438	0.482
Tailoring (TAI)	TAI_1	0.493	0.516	0.849	0.381	0.411	0.418	0.439	0.456	0.531
	TAI_2	0.485	0.495	0.774	0.348	0.501	0.422	0.428	0.417	0.432
	TAI_3	0.538	0.582	0.866	0.353	0.418	0.476	0.416	0.525	0.591
Process - Consistency (PRC)	PRC_1	0.429	0.421	0.345	0.795	0.389	0.394	0.503	0.375	0.372
	PRC_2	0.475	0.423	0.403	0.844	0.448	0.425	0.564	0.337	0.293
	PRC_3	0.431	0.424	0.337	0.864	0.461	0.448	0.593	0.396	0.353
Content-Consistency (COC)	COC_1	0.435	0.436	0.411	0.364	0.767	0.467	0.429	0.466	0.394
	COC_2	0.491	0.451	0.415	0.422	0.806	0.418	0.432	0.383	0.331
	COC_3	0.492	0.501	0.461	0.473	0.871	0.466	0.475	0.501	0.446
Support & Recovery (SRC)	SRC_1	0.499	0.475	0.407	0.404	0.449	0.838	0.511	0.518	0.451
	SRC_2	0.511	0.573	0.508	0.487	0.505	0.868	0.544	0.511	0.483
	SRC_3	0.508	0.511	0.443	0.408	0.461	0.881	0.533	0.505	0.506
Data Integration (DIN)	DIN_1	0.433	0.503	0.352	0.561	0.475	0.562	0.813	0.414	0.341
	DIN_2	0.492	0.503	0.524	0.561	0.466	0.441	0.822	0.511	0.472
	DIN_3	0.388	0.418	0.322	0.469	0.362	0.491	0.783	0.375	0.364
Assure Privacy (APR)	ASP_1	0.448	0.493	0.507	0.344	0.457	0.521	0.459	0.866	0.618
	ASP_2	0.499	0.505	0.488	0.441	0.472	0.496	0.485	0.874	0.572
	ASP_3	0.464	0.534	0.484	0.374	0.512	0.535	0.489	0.876	0.597
Ensure Security (ENS)	ENS_1	0.499	0.595	0.578	0.359	0.427	0.474	0.426	0.593	0.871
	ENS_2	0.405	0.528	0.498	0.283	0.343	0.454	0.412	0.581	0.837
	ENS_4	0.543	0.534	0.563	0.407	0.471	0.519	0.451	0.606	0.896

the Covariance-Based Structural Equation Modeling (CB-SEM) method (e.g., Rahman et al., 2021a). This choice aligned with a single-order model structure, whereas our research model's conceptualization required a more intricate multi-order framework (Becker et al., 2012). Notably, due to the inherent complexity of higher-order reflective-formative models, CB-SEM tools are unsuitable (Sarstedt et al., 2019; Wetzels et al., 2009). Consequently, the study employed PLS to validate the CAC model. This validation marks a pioneering instance in the annals of marketing and management literature. Given the intricacies of higher-order model analysis, our study surpassed the CB-SEM approach.

4.2. Managerial implications

Managerially, this study carries important implications for retail managers who serve customers through online retail platforms. By establishing a customer value-centric analytics capability, this research sheds light on how retail acceleration can be achieved while also uncovering its direct influence on customer-related performance within the fiercely competitive landscape of data-rich retail businesses. In essence, this investigation furnishes actionable marketing strategies that hold relevance for the dynamic management of platform-driven retail enterprises through the strategic deployment of value-centric CAC. Practically, the method of designing a value-centric CAC equips businesses with the means to generate value for customers from the very moment they access the online platform. The advanced CA facilitated by such a system offers avenues to create value by providing trend-based offerings, customer-centric learning, and personalising. Through robust data-driven analytics, trends and customers' buying propensity

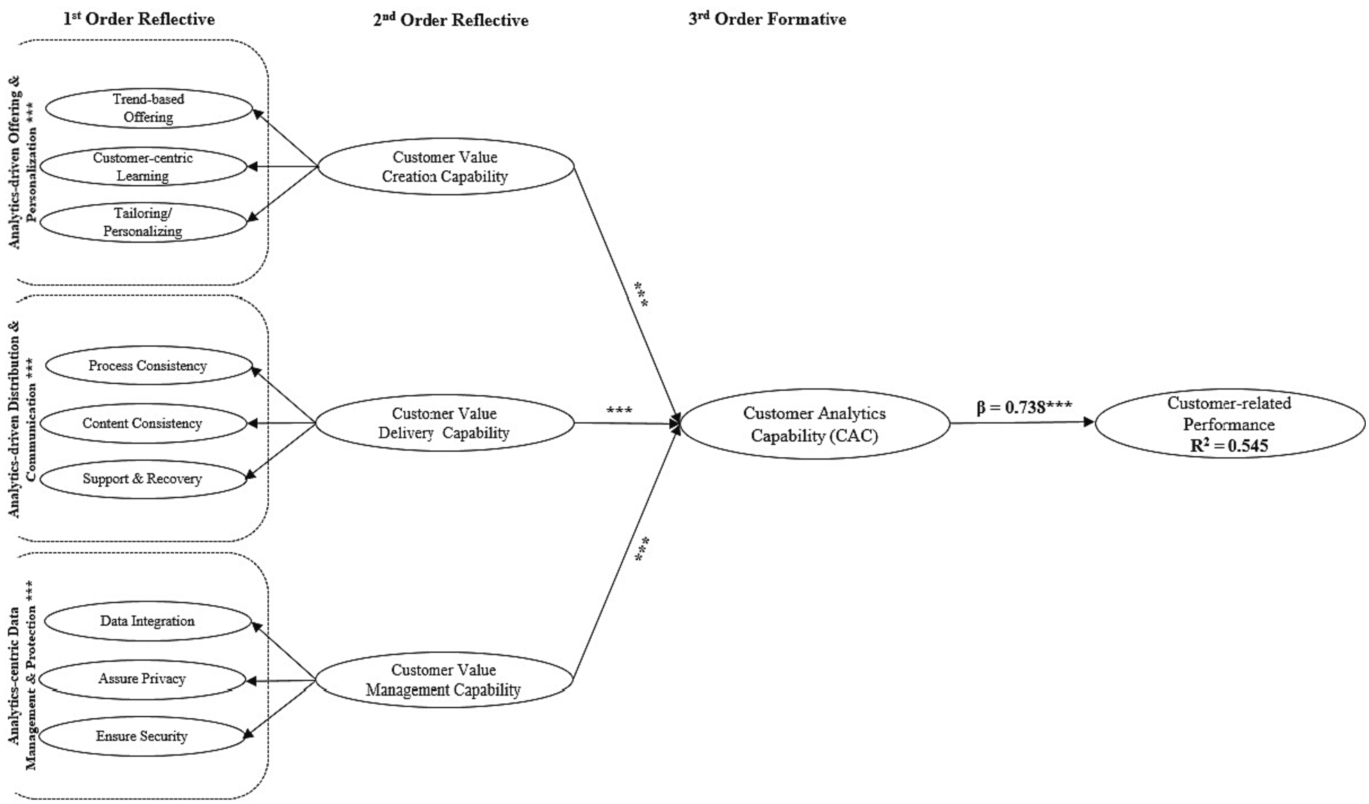

Fig. 3. Structural model. Note: $p < 0.001$***.

can be accurately identified, thereby informing targeted offerings. Noteworthy is Amazon's adept utilization of CA to enhance value on its platform. By delivering a hyper-personalized, responsive, and trend-driven user experience, Amazon meets and exceeds customer expectations, evidenced by features like expedited two-day delivery, one-click purchasing, and personalized product recommendations (Chandra et al., 2022; McKinsey & Company, 2015). Moreover, Amazon's customer-centric analytical approach has a ripple effect on customer expectations when interacting with other brands.

Further, data-driven analytics offer the means to discern individual customer value, decode the influence of competitive actions on customer behaviour, and gain insights into customer pain points, preferences, and actions. This level of sophistication empowers platforms to tailor recommendations based on specific customer preferences, send personalized communications, and roll out real-time customized promotions that align with customer choices. Furthermore, the significance of integrating customer data across platforms becomes evident in delivering a seamless customer experience (Kenney & Zysman, 2016). Seamlessly handling customer-related activities across all channels and effectively addressing customer concerns, grievances, and inquiries in real-time ensures the establishment of trust—a pivotal factor in a data-sharing environment where personal information is exchanged (Kenney, Bearson, & Zysman, 2021; Xu, Hazée, So, Li, & Malthouse, 2021).

Our data analytics-oriented CAC aligns with the United Nations (UN) Sustainable Development Goal (SDG) 9, emphasizing industry innovation and infrastructure advancement (United Nations, 2020). SDG 9 stresses resilient infrastructure, sustainable automation, and forward-looking innovation (Hossain et al., 2022). Our study introduces both a conceptual and empirical model that guides managers to use customer data in a data-rich market. By integrating customer data analytics, businesses are poised to pursue zero carbon emissions and contribute positively to society. As the pursuit of SDG 9 gains momentum, the findings of this research hold significant implications for industry policy, providing valuable insights on how to align organizational capabilities with sustainable development objectives. By leveraging data analytics effectively, businesses can play a vital role in fostering innovation, building resilient infrastructure, and driving positive societal impact.

The findings of this study yield several additional practical implications for retail managers operating in the dynamic landscape of online platform-driven business. Firstly, effective strategic data management emerges as a cornerstone for success. Retail managers should prioritize accurate data collection, secure storage, and proper governance to ensure the integrity of their CA, fostering reliable insights that inform decision-making.

Secondly, the study underscores the necessity of nurturing talent and skills in analytics. Retail managers should invest in training programs and talent acquisition to cultivate a workforce proficient in extracting meaningful insights from customer data, thus enhancing the organization's analytical capabilities.

Ethical data use emerges as a key consideration from the study's focus on data privacy. Retail managers should uphold transparent data collection practices and safeguard customer privacy, thereby building trust and avoiding potential legal and reputational challenges.

Moreover, the study underscores the significance of collaborative ecosystems. Retail managers are encouraged to explore partnerships with other businesses and technology providers to synergize data insights, amplify analytics capabilities, and co-create enhanced value for customers.

Given the real-time nature of the study's analytics, agile decision-making becomes crucial. Retail managers should adopt agile decision-making processes that allow for swift data analysis and interpretation, enabling timely responses to evolving market trends and shifting customer preferences.

Finally, the study highlights the long-term value of customer relationships. Retail managers should focus on strategies that foster customer loyalty and retention, recognizing that positive word-of-mouth and sustained customer engagement contribute to enduring business growth.

These practical implications, grounded in the study's empirical findings, equip retail managers with actionable insights to navigate the complex landscape of the platform-driven retail sector effectively.

4.3. Limitations and future research directions

While this study contributes significantly to the literature, it is not without its limitations. The data collection was confined to Australia, potentially limiting the generalizability of the findings. A promising avenue for future research lies in expanding the geographic scope to encompass both developed and developing countries, allowing for a more comprehensive assessment of the CAC's effectiveness across diverse markets.

The study's cross-sectional nature provides a snapshot of the relationships under investigation. To capture the dynamic evolution of these connections, adopting a longitudinal approach in future studies could provide deeper insights into the long-term implications of CAC on customer-related performance.

While control variables were considered, the study could delve deeper into potential moderating variables to provide a more nuanced understanding of the relationship between CAC and customer-related performance.

Furthermore, the study's exclusive focus on the retail industry's platform setting prompts the consideration of broader applications. Future research endeavours could extend their investigations to other industries, examining the applicability and effectiveness of CAC instruments in various platform contexts.

There is an opportunity for future research to delve into a comparative analysis of different platform types. By exploring e-commerce platforms and sharing economy platforms, researchers can uncover how the implementation of customer-centric analytics contributes to distinct value-creation mechanisms and performance outcomes. Identifying the critical metrics that drive success in each platform type would contribute to a more nuanced understanding of the role of analytics in driving performance.

This study has paved the way for a deeper exploration of customer-centric analytics capability in the platform-driven business landscape. We invite scholars and practitioners to continue building upon this foundation, enriching our understanding of how businesses can harness data-driven insights to create value and thrive in the dynamic world of platform-driven retail.

CRediT authorship contribution statement

Md Afnan Hossain: Conceptualization, Methodology, Formal analysis, Validation, Visualization, Writing - original draft. **Shahriar Akter:** Writing – review & editing, Validation, Methodology, Conceptualization. **Venkata Yanamandram:** Validation, Supervision, Writing - review & editing. **Carolyn Strong:** Review & editing, Methodology, Conceptualization.

Declaration of Competing Interest

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

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