Analyzing Consumer Behavior through Organizational Capabilities and Digital Technologies: The Mediating Role of Proactive Marketing

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ABSTRACT

The study highlights the importance of proactive marketing, which links organizational resources and capabilities to influence consumer behavior. Using Partial Least Squares Structural Equation Modeling (PLS-SEM) and data from 454 respondents, it was found that proactive marketing served as a mediating variable in aligning organizational resources and competencies with customer behavior. This research emphasized the significance of proactive marketing in leveraging organizational strengths to analyze and influence consumer behavior, informing strategic decisions and improving business performance. Future research may explore how proactive marketing strategies affect different organizational competencies and consumer segments, helping firms navigate the digital business landscape. The value of a company's stock rises in tandem with its level of dynamic capability. Our understanding of user behavior, adaptability, and value to many businesses is greatly enhanced by these findings. The study theoretically enhanced existing literature by expanding the concept of dynamic capabilities to incorporate intelligence and information-processing abilities that are aligned with culture. The findings provide important insight in assisting the management in aligning technology adoption and integrating dynamic capabilities. Therefore, the research highlighted the need for managers to invest more in facilities that have dynamic capabilities.

Keywords: Social Media Technologies; Culture of Intelligence; Information Processing Capabilities; Proactive Marketing; Consumer Behavior; Dynamic Capability.

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INTRODUCTION

The advent of digital technologies has transformed corporate efficiency and consumer engagement in the digital age. Strategic, data-driven decision-making is pivotal to maximizing the potential benefits of digital technologies (Hazzam, Wilkings & Strong, 2022). However, organizations face significant hurdles, such as adapting to market dynamics, meeting global customer expectations, and addressing infrastructural gaps like inadequate waste management systems. Firms operating in culturally diverse markets encounter additional challenges related to cross-cultural communication, consumer awareness, and organizational hesitations. Addressing these complexities requires a synthesis of innovative business strategies, advanced digital tools, and an intelligence-driven organizational culture. While previous studies have explored the role of market orientation and dynamic marketing capabilities (Kohli & Jaworski, 1990; Narver & Slater, 1990; Teece et al., 1997), limited attention has been given to the intersection of cultural intelligence, digital technologies, and proactive marketing. Organizational cultural intelligence (OCI), derived from frameworks by Ang and Inkpen (2008), highlighted the importance of managing culturally diverse encounters, yet its integration with emerging digital platforms remains underexplored. Similarly, proactive marketing strategies and information processing capacities have been shown to influence consumer decision-making (Hien et al., 2022; Homburg & Wielgos, 2022; Jamaludin et al., 2022; Song & Montoya-Weiss, 2001; Li et al., 2021; Zahra et al., 2023), but their implications in digitally enabled, cross-cultural contexts are not fully understood.

This study addressed these gaps by investigating three key research questions. First, how do OCI and digital technology (DT) influence proactive marketing? Second, how does proactive marketing affect consumer behaviour? Third, how does proactive marketing (PM) explain the relationship between organizational cultural intelligence (OCI) , Digital technology (DT) and consumer behaviour (CB)? By exploring these questions, this research sought to provide a comprehensive understanding of how organizations can leverage cultural intelligence and digital tools to thrive in increasingly complex and globalized markets (Ma'aji, Shrubsall, & Anderson, 2023; Sani et al., 2019). The primary objectives of this research were threefold. The first was to analyze the interplay between digital technologies, OCI, and consumer behavior in diverse settings. The second was to evaluate the impact of proactive marketing strategies on customer engagement and organizational performance, particularly in B2B and multicultural contexts. Finally, the study aimed to provide insights into building intelligence-driven cultures that optimize the use of digital platforms, such as social media, business intelligence (BI), and the Internet of Things (IoT), for product innovation and market success.

This research makes significant contributions to literature. Theoretically, it extends the concept of OCI by integrating its role in digital technology adoption and information processing for product development. Empirically, it offers data-driven evidence on how OCI and proactive marketing strategies influence consumer behavior and organizational performance in culturally diverse markets. From a managerial perspective, the findings offer actionable insights for businesses to enhance their use of digital platforms, foster cultural intelligence, and adopt proactive marketing approaches to gain a competitive advantage. In summary, this research addressed critical gaps in the literature by focusing on the interconnections between OCI, digital technologies, proactive marketing, and consumer behavior. By doing so, it provides a comprehensive framework for understanding how organizations can succeed in culturally diverse and digitally enabled markets.

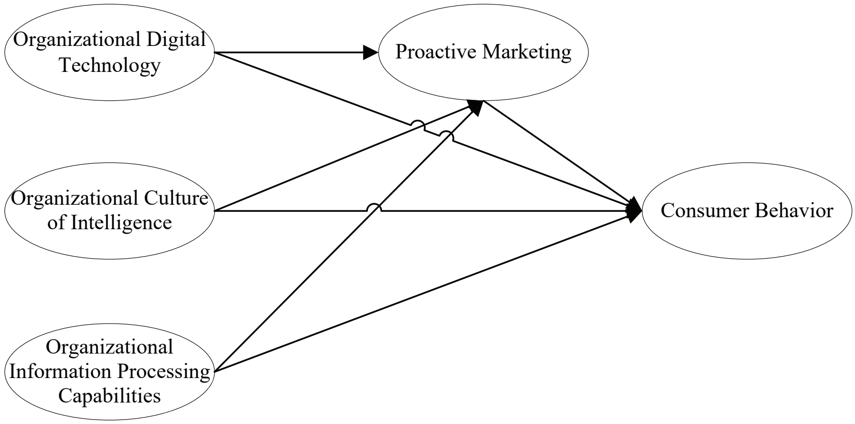

Figure 1: Conceptual Model

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

The Dynamic Capability Perspective

This study was grounded in the **Dynamic Capabilities Framework (DCF)**, a theoretical lens that emphasizes the importance of an organization's ability to adapt, innovate, and remain competitive in rapidly changing environments. Introduced by Teece et al. (1997), dynamic capabilities highlight a firm's ability to integrate, build, and reconfigure internal and external competencies to respond effectively to evolving market demands. Dynamic capabilities are particularly critical in international and cross-border markets, where competitive pressures and cultural complexities demand agility and innovation (Lin & Wu, 2014). The framework underscores the importance of fostering an innovative culture within organizations. Merendino et al. (2018) argued that innovation is central to an organization's ability to absorb, replicate, and apply new information. This culture of innovation enables firms to harness and integrate external knowledge into strategic processes, thereby improving their capacity to respond to global market dynamics. Technologies such as IT infrastructure, social media, and data analytics are critical, enabling dynamic capabilities, as they allow organizations to anticipate industry trends and consumer behavior while adapting to market developments (Erevelles et al., 2016).

Entrepreneurial innovation is another vital component of DCF, especially in culturally and economically diverse markets. Levine et al. (2017) and Warner and Wager (2019) extended the framework by highlighting its dual focus on fostering innovation and developing market performance strategies. They emphasized the critical role of dynamic capabilities in equipping organizations to thrive in complex, fast-evolving business landscapes. This included the ability to continuously evolve strategies to meet new challenges and opportunities, ensuring long-term success. This study focuses on digital technology, organizational capacities, proactive marketing, and consumer behavior aligned closely with the principles of dynamic capabilities. Digital technologies, such as real-time analytics, IoT platforms, and artificial intelligence, enhance organizations' ability to process information on customer behavior and market trends in real time. These capabilities form the backbone of dynamic organizational capacities, providing the resources and tools necessary to adapt to shifting market conditions. Proactive marketing strategies, a critical aspect of this study, are deeply tied to dynamic capabilities as they allow organizations to shape consumer behavior and influence market trends strategically. By synthesizing digital technologies, organizational skills, and strategic marketing, this research leveraged DCF to explore how firms navigate complex environments. This approach offered a comprehensive understanding of how adaptive capabilities influence consumer behavior through proactive marketing, positioning organizations to succeed in the digital age.

Digital Technologies such as Social Media Technologies (SMT) and Internet of Things (IoT)

Organizations strive to gain a competitive advantage by leveraging unique, valuable, and hard-to-imitate resources, as outlined in the Resource-Based View (RBV) (Barney, 1991). In today's digital age, technologies such as social media Technologies (SMT) and IoT play a transformative role in enabling firms to adapt to market demands. SMTs supported by business intelligence (BI) and big data analytics bridge organizational strategies with dynamic market needs (Barrales-Molina et al., 2014; Tafesse & Wien, 2018). These tools offer organizations the capability to engage stakeholders, improve strategic marketing, and enhance consumer behavior analysis. Nguyen et al. (2015) emphasized how SMTs provide timely information that organizations can use to monitor consumer preferences and anticipate trends. Similarly, IoT facilitates real-time data collection and decision-making, improving organizational responsiveness and customer engagement (Teece, 2007). These technologies are critical in culturally diverse and competitive markets, where consumer preferences are influenced by social and cultural factors.The Technology Acceptance Model and the Knowledge-Based View (KBV) also support the idea that SMT and IoT capabilities are essential for developing enterprise market-based assets and dynamic marketing capabilities (Nguyen et al., 2015; Teece et al., 2007).

Strategic social media use helps firms acquire valuable insights into customer behavior, enabling marketing capabilities to evolve in line with dynamic market demands (Srivastava et al., 2001; Tafesse & Wien, 2018). By efficiently combining and reconfiguring digital resources, as emphasized in the DCF (Teece, 2007), organizations can align their marketing efforts with evolving consumer preferences. Therefore, SMT and IoT are integral to building adaptive organizational capabilities and generating a competitive edge in fast-changing markets. Thus, the study postulated that:

H1: Organized digital technologies are positively related to consumer behavior.

Organizational Culture of Intelligence (OCI)

The concept of cultural intelligence (CQ), as defined by Earley and Ang (2003), refers to the ability to function effectively in diverse cultural contexts. This idea, extended to the organizational level by Ang and Inkpen (2008), highlights the importance of Organizational Cultural Intelligence (OCI) as a firm's capacity to navigate cultural diversity and incorporate cultural knowledge into strategic processes. OCI integrates insights from individual cultural intelligence frameworks (Earley & Ang, 2003) and resource-based perspectives (Barney, 1991), offering a theoretical foundation for understanding how cultural capabilities contribute to organizational performance.

OCI encompasses three dimensions:

1. Top Management Cultural Intelligence, which shapes global strategy and organizational performance.

2. Competitive Cultural Intelligence, which involves acquiring and integrating diverse cultural knowledge.

3. Structured Cultural Intelligence, which leverages reporting structures and norms to enhance stakeholder relationships (Ang & Inkpen, 2008; Lorenz et al., 2018).

Barrales-Molina et al. (2014) and Bruni and Verona (2009) suggested that OCI can act as a dynamic marketing tool, enabling organizations to absorb and disseminate cultural market intelligence. This capability is crucial for engaging with diverse consumer bases and adapting to evolving market conditions. The RBV positions OCI as a strategic resource that fosters innovation, reduces conflicts, and enhances international stakeholder engagement. By integrating IoT and SMT investments with OCI, firms can unlock new value for consumers while addressing cross-cultural market demands (Teece et al., 1997). Thus, the study postulated that:

H2: Organizational culture of intelligence is positively related to consumer behavior.

Organizational Information Processing Capabilities (IPC)

The concept of **Information Processing Capability (IPC)**, introduced by Tushman and Nadler (1978), refers to an organization's ability to acquire, evaluate, and synthesize information for decision-making. Digital transformation has significantly enhanced IPC by enabling firms to process large volumes of data and respond to market volatility. Tools such as social media, IoT, and big data analytics allow firms to manage consumer behavior data, improving agility and market responsiveness (Hess et al., 2016; Li et al., 2021). The Information Processing View (IPV) suggests that organizational performance improves when IPC aligns with the complexity of information-processing demands (Tushman & Nadler, 1978; Moser et al., 2017). However, rapid technological advancements and market uncertainties have created new challenges for firms, eroding their ability to generate actionable insights (Day, 2011). Firms must continuously update their digital technology portfolios to stay competitive, as outdated systems can hinder adaptability and responsiveness (Overby et al., 2006). IPC is essential for integrating digital technologies with corporate strategy, facilitating stakeholder interactions, and managing external relationships in dynamic environments. Firms with strong IPC can leverage their technological capabilities to understand consumer psychology, anticipate market trends, and adjust their strategies accordingly (Kohli & Grover, 2008). Thus, the study postulated that:

H3: Organizational information processing capabilities influence consumer behavior.

The Mediating Effect of Proactive Marketing Approach

Proactive marketing involves anticipating consumer needs and actively shaping market environments rather than simply reacting to external changes (Narver et al., 2004; Blocker et al., 2011). This approach is particularly important for B2B firms, where complex customer needs and dynamic markets demand innovative solutions and long-term engagement strategies (Avlonitis & Gounaris, 1997; Flint et al., 2002). Proactive marketing strategies are tied to dynamic capabilities, as they require firms to continuously adapt, innovate, and align their offerings with consumer expectations (Atuahene-Gima et al., 2005). Narver et al. (2004) argued that proactive market orientation fosters creativity and innovation, enabling firms to deliver greater value to consumers. This involves using advanced information-processing tools to anticipate market trends and to develop innovative products and services that address both known and latent consumer needs (Calantone et al., 2002; Stock & Zacharias, 2011). However, a proactive approach requires careful alignment with market intelligence and digital technologies. Firms that fail to understand their markets may find that aggressive strategies are less effective than more deliberate, reactive approaches (Chan, 2006).

By integrating digital technologies, OCI, and IPC with a proactive marketing approach, organizations can create innovative market offerings, gain a competitive advantage, and adapt to rapid changes in consumer behavior. This integration highlights the importance of aligning internal capabilities with external market demands for sustainable performance improvements. Thus, the study postulated that:

H4: A proactive marketing approach mediates the relationship between organized digital technologies, organizational culture of intelligence, information processing capabilities, and consumer behavior.

MATERIALS AND METHODS

Research Design and Data Collection

This study began with randomly selected participants from firms in Southern and Northern China's industrial zones. The potential of these firms to alter our key constructions drove their careful selection. The participant pool included fintech firms, banks, insurance companies, hospitals, and other service providers. The selection of these organizations was justified based on data availability and relevance to the nature of the research questions, as they were technologically inclined. We used Miles et al. (2014)'s snowballing method to find the best respondents and maintain the questionnaire's quality. We asked a core group of contacts to suggest top executives with diverse corporate expertise. The identified persons were contacted and invited to complete the survey for our study. The survey questionnaires were developed after a thorough literature analysis and feedback from prominent scholars, researchers, and management specialists. The study constructions were created through collaboration. Cronbach's alpha coefficient measured the survey's content validity and reliability, with a threshold of 0.7 or higher indicating acceptability. Our measurement tools' face and content validity were confirmed by a pilot study. We emailed each enterprise management extensively before collecting data. Their eager cooperation in our investigation was crucial. We explained the impact of the global health crisis on their firms' innovation. Stratified sampling was used to identify firms that best reflected the population from the Chinese Chamber of Commerce's online platform. Thus, we selected 480 replies from firms that performed well in their industry and markets in China's industrial regions. The number of regional branches, market presence, advertising capability, and personnel strength were carefully considered.

Companies such as Tiger Brokers and Lufax, focusing on financial technology and digital banking, were included due to their strong promotional and online advertising capabilities. First, participants needed permanent roles in their organizations. Second, they needed middle-level positions in their organizations. Thirdly, two years of tenure in the same organization were required. Our study was an academic research endeavor, and we stressed voluntary involvement. During the survey phase, participants were given an informed consent form stating they might leave the study at any time. We specifically told participants that their data would be kept secret and displayed in an aggregated form. 104 businesses in services, manufacturing, and other sectors received 480 sample survey questionnaires. The sample size was determined using Soper's (2017)'s 'A priori sample size calculator for structural equation models. ' After returning and analyzing 465 questionnaires, 454 were appropriate for our study. Mostly, marketing and operational heads were our research subjects. The present study painstakingly examined their profiles using SPSS 22, and an initial analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) via Smart-PLS 4.0 to evaluate our hypothesis. According to Hulland (1999), indicator factor loadings should be 0.5 or greater; hence, those below this criterion were eliminated from our research.

Measurement of study variables

Dependent Variable

To evaluate consumer behavior, eight variables were derived from scales developed by Unal and Tascioglu (2022), ensuring comprehensive coverage of factors influencing consumer decision-making. These variables provided critical insights into the outcomes of organizational capabilities and technological adoption.

Independent Variables

Organizational Cultural Intelligence (OCI) in this study referred to a company's ability to understand and adapt to the culture of its target market, consistent with the definitions provided by Ang and Inkpen (2008) and Edmondson (2019). It is conceptualized as a three-factor, second-order construct, encompassing managerial, competitive, and structural cultural intelligence. The measurement of OCI was operationalized using five items designed to capture these three dimensions, reflecting the multi-faceted nature of cultural intelligence in organizational contexts. The use of exploration and confirmatory factor analysis (EFA and CFA) to evaluate the second-order factor model ensured that the construct structure aligned with theoretical expectations and exhibited strong validity and reliability.

Organizational digital technologies (ODTs) were measured using the twelve-item scale developed by Tafesse and Wien (2018), which provided a comprehensive assessment of an organization's technological capabilities in a digital context. This scale aligned well with the study's focus on capturing diverse aspects of digital technology adoption and implementation. The additional constructs of social media technologies (SMTs), business intelligence AI, and big data analytics were measured using scales adapted from Lee and Choi (2003) and Charoensukmongkol (2022). These tools assessed the extent of technology usage in areas such as social media analytics, user engagement, and strategic implementation, aligning with current research trends in digital transformation.

To measure the implementation of OCI capabilities and SMTs, a seven-point Likert scale was used, ranging from "Strongly disagree" to "Strongly agree", with "Neither agree nor disagree" serving as a neutral midpoint. The seven-point scale provided greater sensitivity than shorter scales, allowing respondents to express nuanced opinions. This approach is widely endorsed in research for capturing attitudes, perceptions, and behaviors with enhanced precision.

The organizational information processing capacities (OIPC) scale, adapted from Li et al. (2021), was operationalized using six items and a seven-point Likert scale. This construction reflected an organization's ability to process and respond to information effectively, a critical capability for navigating complex business environments.

Mediating Variable

Proactive market orientation was measured using five items adapted from Brege and Kindström (2020) and Hazzam et al. (2022), employing a seven-point Likert scale to capture proactive and anticipatory market behaviors.

Control Variables

According to previous research (Hazzam et al., 2022; Purkayastha et al., 2023), managerial, technological, and innovation decisions, and culture can estimate the performance and international business and market capabilities of corporations. Thus, we employed the natural logarithm of the number of control variables for company size in terms of company size, market regulations, geographical location and financial capability. For instance, bigger and more financially stable corporations are better at managing organizational cultures, information, social media technology engagements, international market volatilities, and changes in terms of new consumer needs for product development and technology than smaller ones, regardless of the regional economic and market regulations.

Justification of approach

Theoretical Alignment: The selection of scales and constructs aligned with established theoretical frameworks and prior research, ensuring consistency and comparability with existing studies (Ang & Inkpen, 2008; Edmondson, 2019; Tafesse & Wien, 2018). This theoretical grounding enhanced the study's credibility and relevance.

Second-Order Construct: Defining OCI as a second-order construct reflected its inherently multi-dimensional nature, ensuring that the measurement captures the distinct but interrelated aspects of cultural intelligence (managerial, competitive, and structural). This approach aligned with advanced theoretical conceptualizations of complex constructions.

Use of Validated Scales: Adapting validated scales from established studies (e.g., Tafesse & Wien, 2018; Lee & Choi, 2003; Charoensukmongkol, 2022) ensured measurement reliability and content validity, minimizing the risk of instrument bias or measurement error.

Likert Scale Sensitivity: The seven-point Likert scale is a standard in social sciences, offering sufficient granularity for capturing subtle differences in responses. This scale improves the precision of data and aligns with best practices for psychometric measurements.

Comprehensive Assessment: By incorporating constructs such as ODTs, SMTs, OIPC, proactive market orientation, and consumer behavior, the study adopted a holistic approach to investigating the interplay between organizational capabilities and outcomes. The use of multiple validated measures ensured robust data collection.

Analytical Rigor: The use of EFA and CFA to evaluate OCI and other constructs ensured that the measurement model was statistically sound and exhibited both convergent and discriminant validity, reinforcing the reliability of the findings.

In summary, the constructs and measurement approaches in this study were theoretically and methodologically justified. They provided a rigorous foundation for examining the relationships between organizational capabilities, technological adoption, and consumer outcomes. For further details, refer to Table 6 and the Appendix.

Conceptualizing B2B

In the context of analyzing consumer behavior in B2B markets, businesses focus on understanding the needs and preferences of organizational clients rather than individual consumers. This involves studying purchasing patterns, decision-making processes, and the factors driving business-to-business transactions. Organizational capabilities, such as data analytics, customer relationship management (CRM), and operational efficiency, play a pivotal role in this analysis. These capabilities enable businesses to adapt to client demands, identify trends, and offer customized solutions that align with their clients' operational and strategic goals. Digital technologies, such as big data analytics, AI, and digital platforms, further enhance the ability of businesses to analyze and predict client behavior. These tools allow businesses to gather large volumes of data, segment clients effectively, and identify key patterns in purchasing decisions.

For example, predictive analytics can help a supplier forecast the inventory needs of a retailer or suggest maintenance schedules to manufacturing firms. Such insights empower businesses to provide tailored solutions, improving customer satisfaction and fostering long-term relationships with their B2B clients. Proactive marketing acts as a critical mediator in this process by bridging the gap between organizational capabilities, digital technologies, and consumer behavior insights. By anticipating client needs and offering value-driven solutions before demand arises, proactive marketing strengthens client engagement and loyalty. In the B2B context, this could mean delivering personalized recommendations, timely updates, or innovative solutions that align with the client's objectives. Ultimately, the integration of organizational capabilities, digital technologies, and proactive marketing allows businesses to analyze and respond to consumer behavior effectively, resulting in competitive advantages and sustainable growth in B2B markets.

Common method variance

Owing the potential effects of CMV, we split our data collection into two distinct windows. We employed confirmatory factor analysis (CFA) and Harman's one-factor test to alleviate CMV (Podsakoff et al., 2012). Thus, we first conducted Harman's one-factor test on all first-order components. Seven factors with eigenvalues greater than one were found using EFA, and these factors explained 73.7% of the total variance. In addition, the first component explained only 26.3% of the total variation, which was considerably below the minimum acceptable 50%. The results from using the CFA single-factor measurement model were less than ideal, as were the CFA with a $\chi 2$ (1593) value of 26427.41, RMSEA of 0.16, CFI of 0.13, NNFI of 0.097, and SRMR of 0.15. Our findings confirmed the lack of CMV severity, which supported the notion that common method bias was not a problem in this study.

RESULTS AND DISCUSSIONS

Descriptive Statistics

A description of the study's findings and a demographic analysis of the sample respondents are provided in this section. Figures 2 and 3 reveal how SmartPLS 4 was used to test the study model. To calculate the values and assess the significance of the relation, the current study used samples from 454 cases. Henseler et al. (2015) asserted that by controlling errors, they reduced correlations and increased the theory's validity and PLS predicted moderator effects more accurately.

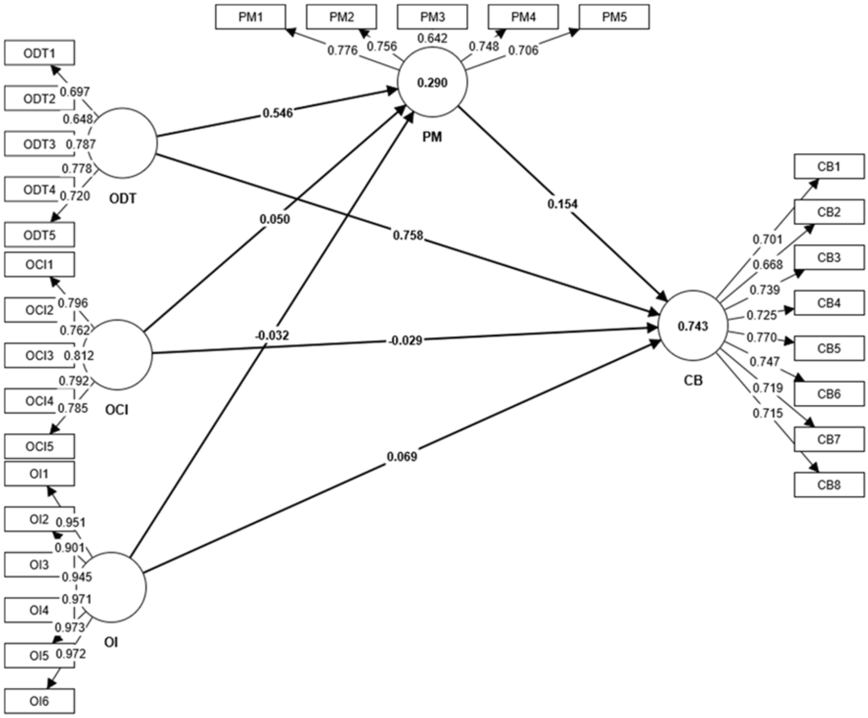

Figure 2: The Measurement Model

Respondents in this study answered four demographic questions about gender, nature of business, number of employees and service length.

Table 1: Socio-Demographic Characteristics of the Respondents

Category	**Frequency**	**Percentage** %
Gender	-	
Male	357	73.1
Female	97	26.9
Nature of Business		
IT	202	44.4
Services	87	19.3
Custom Products	79	17.4
Industrial Systems	52	11.4
Others	34	7.5

Number of Employee		
Less than 10	36	6.8
10 - 49	225	63.9
50 - 199	156	16.2
200 and above	37	13.0
Service length		
Less than five years	47	12.5
5 - 10 years	235	59.6
11 - 15 years	76	17.3
16 - 20 years	68	6.3
21 years and above	28	4.3
Total	**454**	**100**

Source: Field Survey (2022)

As shown in Table 1, there were 97 responders (26.9%) female and 357 (73.1%) male respondents. This showed that male managers outnumbered female owners. 202 (44.4%) respondents were in IT, 87 (19.3%) in services, 79 (17.4%) in custom services, 52 (11.4%) in industrial systems, and 34 (7.5%) in other specifications. This showed that most respondents worked in IT or services. As shown in Table 1, 24 (6.8%) respondents had fewer than 10 employees, 225 (63.9%) had 10 to 49, 57 (16.2%) had 50 to 199, and 46 (13%) had 200 or more. This suggested that most respondents ran micro or tiny businesses. Results indicated that 44 respondents (12.5%) had been in business for less than 4 years, 210 (59.6%) for 5-10 years, 61 (17.3%) for 11-15 years, 22 (6.3%) for 16-20 years, and 15 (4.3%) for over 20 years.

Measurement Model

The measurement model assessment included key metrics such as the R^2 (coefficient of determination), which evaluated the proportion of variance in the dependent variable explained by the independent variables. According to Hair et al. (2014), R^2 values indicated the explanatory power of the model, with thresholds of substantial (≥0.75), moderate (0.50–0.75), and weak (<0.50) explanatory power. This metric is essential in structural equation modeling (SEM) to assess how well latent constructions are explained by their manifest indicators, ensuring the theoretical adequacy of the model. On the other hand, the predictive ability of the model, emphasized by Henseler et al. (2015), assessed the model's relevance for predicting outcomes in new data. The Q^2 (Stone-Geisser criterion) is commonly used, calculated through blindfolding in partial least squares SEM (PLS-SEM). A positive Q^2 value indicated predictive relevance, while non-positive values suggest the lack of predictive capability. This approach evaluated whether the model not only explained the variance in the dataset but also provided practical utility for future predictions, highlighting its real-world application. Together, these metrics served distinct but complementary purposes. R^2 focused on explanatory power, showing how well the model accounted for observed variance, while Q^2 emphasized predictive relevance, ensuring the model's utility for new scenarios. Combining these assessments provided a comprehensive evaluation of the model, aligning its theoretical robustness (via R^2) with practical predictability (via Q^2), as recommended by Hair et al. (2014) and Henseler et al. (2015).

This dual assessment enhanced confidence in the model's validity and usability. The first test, convergent validity (CV), compared questions assessing the same topic. The study next found discriminating validity (DV), which is the absence of considerable correlations between the measurement of interest and other indicators, showing that the measure does not account for other variables. The DV could also be assessed by comparing construct squared correlations to extracted variance (Henseler, et al., 2015; Hair, at al., 2014). Table 2 and Figure 2 analyzed the inter-item consistency of measuring items using Cronbach's alpha coefficient. SmartPLS V 4.0.9 helped us test the hypotheses using partial least squares–structural equation modeling (PLS-SEM) (Ringle et al., 2015). In the past, covariance-based SEM (CB-SEM) was the preferred method for studying complex latent-observable interactions. In recent years, published studies have used PLS-SEM more than CB-SEM (Hair et al., 2017). Many reasons justify using Partial Least Squares Structural Equation Modeling (PLS-SEM):

PLS-SEM enables researchers to evaluate links between items, latent constructs, and constructs, including the measurement model and structural model. Hair et al. (2017) demonstrate the framework's versatility, especially in complex models involving moderation and mediation. PLS-SEM is a statistical technique suitable for both small and large datasets. This procedure produces accurate results. According to Hair et al. (2019), PLS-SEM can accurately estimate parameters even with non-normal data distributions, unlike CB-SEM. SmartPLS, unlike LISREL or AMOS, has a user-friendly graphical interface. • This robust component-based technique has been widely used in recent scholarly research (e.g., Abid et al., 2023; Abualigah et al., 2025; Aftab et al., 2022; Aftab & Veneziani, 2023; Farrukh et al., 2022).

Table 2: Items loading, Composite Reliability and Average Variance Extracted

Construct and Items	Loading	Cronbach's α	CR	AVE
Organized Digital Technology				
ODT1	0.697	0.777	0.782	0.530
ODT2	0.648			
ODT3	0.787			
ODT4	0.778			
ODT5	0.720			
Organizational Culture of Intelligence				
OCI1	0.796	0.852	0.864	0.623
OCI2	0.762			
OCI3	0.812			
OCI4	0.792			
OCI5	0.785			
Organizational Information processing capabilities				
OI1				
OI2	0.951	0.980	1.006	0.907
OI3	0.901			
OI4	0.945			
OI5	0.971			
OI6	0.973			
	0.972			
Proactive Marketing				
PM1	0.756	0.978	0.976	0.921
PM2	0.776			
PM3	0.642			
PM4	0.748			
PM5	0.706			
Consumer Behavior				
CB1	0.701	0.989	0.995	0.953
CB2	0.668			
CB3	0.739			
CB4	0.725			
CB5	0.770			
CB6	0.747			
CB7	0.719			
CB8	0.715			

As shown in Table 2 each item had a value above 0.4 and the construct's indication substantially loaded on its parent construction, achieving CV. The current study's DV was compared to Table 2's correlation matrix for each variable using AVE. According to Fornell and Larcker (1981), the original construct's values (in bold) were greater than their connections to other constructs in Table 3. Henseler et al. (2015) recommended HTMT for DV assessment, considering Fornell and Larcker's (1981) and the cross-loading technique too liberal in validity confirmation. Table 4 shows the study's HTMT. Figure 2 shows that technology sophistication, the business model for sustainable innovation, the organizational culture of innovation, and open innovation explain 60% (R2 = 0.604) of organizational performance variance.

Table 3: Fornell-Larcker Criterion

	CB	OCI	ODT	OI	PM
CB	0.724				
OCI	-0.164	**0.790**			
ODT	0.850	-0.169	**0.728**		
OI	0.106	0.000	0.050	**0.952**	
PM	0.052	-0.042	0.536	-0.005	**0.727**

Table 4: Heterotrait-Monotrait Ratio (HTMT)

	CB	OCI	ODT	OI	PM
CB					
OCI	0.183				
ODT	1.030	0.212			
OI	0.118	0.050	0.080		
PM	0.674	0.104	0.684	0.086	

Table 5: Results of Direct and Indirect Structural Model

Relationship Variables		Beta Coefficient	Standard error	*t*-value	*P*-value	Decision
Direct	OCI -> CB	-0.029	0.028	1.059	0.290	Not Supported
	OCI -> PM	0.502	0.052	0.968	0.333	Not Supported
	ODT -> CB	0.758	0.033	22.745	0.000	Supported
	ODT -> PM	0.546	0.042	12.833	0.000	Supported
	OI -> CB	0.069	0.030	2.281	0.023	Supported
Indirect	OI - > PM	-0.032	0.052	0.620	0.535	Not Supported
	PM -> CB	0.154	0.039	3.979	0.000	Supported

Note. p < **p< .01; *** p < .001. CB= consumer behavior, OCI= organizational culture of intelligence, ODT= organized digital technology, OI= organizational information processing capability, PM = proactive marketing approach.

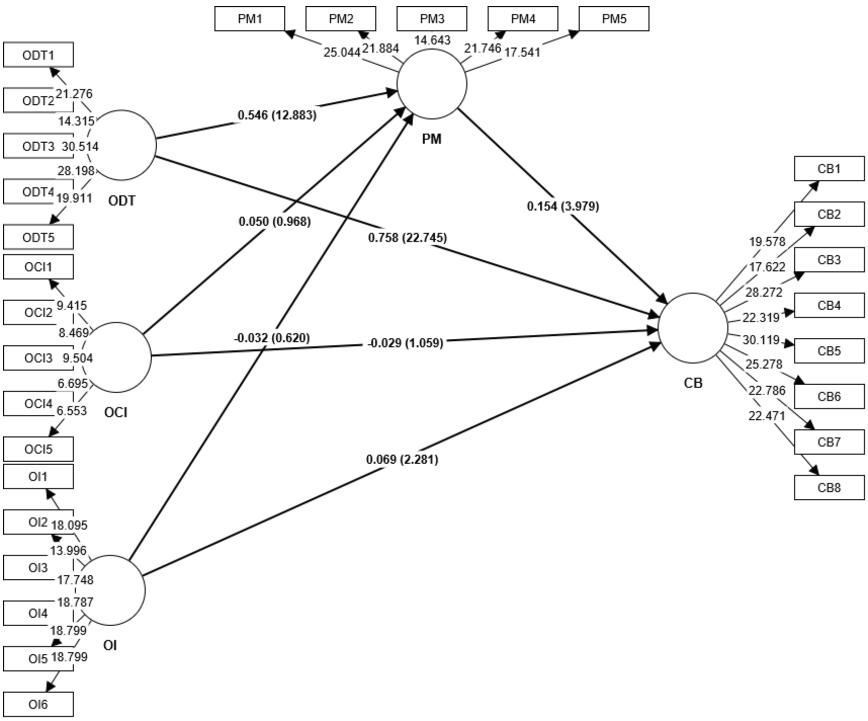

Figure 3: The Structural Paths

RESULT AND DISCUSSION

Our findings demonstrated that digital technologies, particularly social media, significantly enhanced the understanding of consumer behavior. By examining the mediation effect of proactive marketing, the study highlighted how proactive marketing influenced consumer behavior and identified consumption trends, particularly in unexplored markets like B2B. This underscored the importance of proactive strategies in adapting to changing consumer preferences and market dynamics. Moreover, the results emphasized that organizational abilities primarily impacted external factors, such as regulatory changes or technological advancements, which in turn created opportunities for innovation and reveal market vulnerabilities. This suggested that an organization's ability to process information effectively plays a critical role in shaping consumer behavior by enabling firms to develop insights into consumption patterns and market trends. H1 stated that organized digital technologies are positively related to consumer behavior. According to the results, the organizational culture of innovation did not affect consumer behavior. This suggested that SMEs were more likely to display higher levels of performance through positioning the information technology in the appropriate location and value and making use of creative ideas and technologies both inside and outside of the organization. As a result, the SME's performance was significantly increased by effective information technology. The findings were consistent with earlier research, which indicated a strong positive relationship between digital technologies.

The findings also highlighted market agility as a pivotal factor for organizations to respond to environmental changes. Market agility is defined as the ability to recognize opportunities and act swiftly, and is influenced by unpredictable factors like technological advancements, economic conditions, and customer preferences. Our results suggested that organizational responsiveness depended on the efficient use of internal data and expertise to make strategic decisions, as well as the effective allocation of resources, whether human, financial, or technological, to implement those strategies. These insights underline the necessity for businesses, particularly in B2B markets, to adopt adaptive decision-making processes tailored to environmental changes. This adaptability allowed firms to navigate uncertainties and leverage opportunities effectively, enhancing their competitive positioning and long-term sustainability.

Based on the research premise, the study's constructs were compared. The model's t-values were calculated using bootstrapping. The model's direct influence showed a strong correlation between organized digital technology and customer behavior in achieving a competitive advantage, corporate survival, and continuity. In post-pandemic digital markets, start-ups and microenterprises should prioritize the organizational culture of intelligence and information processing. Structured digital technology impacted customer behavior, per H1. These connections are shown in Figures 2 and 3. H1 was confirmed ($\beta = 0.758$, $t = 22.745$; $\beta = 0.546$, $t = 12.883$, $p < 0.000$). Digital technology, especially social media, helped understand consumer behavior and predict digital fashion trends. Social media affects performance (Kachouie et al., 2018; Purkayastha et al., 2020; Hazzam, 2022),. In contrast to our study, they did not evaluate the mediation effect of proactive marketing. Thus, proactive marketing considerably impacted client behavior and may help explain consumption trends in various industries, particularly in the uncontested B2B market.

Our second hypothesis test disagreed. Proactive marketing did not mediate the relationship between corporate intelligence and customer behavior in any market (β= -0.029, t= 1.059; β= 0.050, t= 0.968, $p > 0.000$). Thus, organizational talents can only alter external organizational issues like governmental changes or projected technical breakthroughs that cause creative destruction and market vulnerability. We found a unique result compared to other studies (Barrales-Molina et al., 2014; Bruni and Verona, 2009; Kachouie et al., 2018; Van Dyne et al., 2012), potentially expanding organizational ability research. In Hypothesis 3, we found that organizational information processing affected consumer behavior by influencing consumption choices based on knowledge of consumers and markets (β= 0.069, t= 2.281, $p < 0.000$; β= -0.032, t= 0.620, $p > 0.000$), enhancing market agility similar to Li et al (2021). Organizational agility study defines market agility as a company's ability to adapt to changing business conditions (Dove, 2001; Goldman, Nagel, & Preiss, 1995).

Market agility involves strategic reaction to market changes, including decision-making in uncertain conditions, to ensure firm growth. Market agility requires awareness and rapid action. Recognizing environmental shifts and their opportunities raises a company's awareness (Dove, 2005). These irregular fluctuations make it difficult for enterprises to predict market conditions or plan operations. This study discussed environmental change in technology, politics and regulation, economics, international conditions, suppliers, consumer choice, the labor market, and competitor actions. How well a company adapts to external signals determines its responsiveness. Based on data and internal expertise, firms must make decisions and then allocate and acquire the human, financial, and technological resources to implement those plans. Responses vary based on context and are rarely planned (Sambamurthy, Bharadwaj, & Grover, 2003; Van Oosterhout, Waarts, & Van Hillegersberg, 2006).

Businesses adapt to environmental changes using various decision-making processes, particularly in B2B markets. However, as indicated in Table 5, predictive marketing also had a mediating effect (β= 0.154, t= 3.979, p 0.000). In line with Brege and Kindstrom (2020), we found that proactive marketing mediated the effect of intelligent organizational culture on consumer behavior. H1, H2, H3, H4, and all mediated effects. To grow market share, organizations used various strategies to influence decision-makers in their target markets and build awareness and demand. Elg et al. (2012) and Kindström et al. (2018) proposed proactive market change. Care for consumers who are directly connected with the organization's processes creates value. The proactive technique proposed by Narver et al. (2004) and the ambidextrous approach to innovation defined by March (1991) combined proactive and responsive consumer treatment. Most of the organization's activity was focused on incremental innovation, which was unrelated to innovation (Li et al., 2008). So Hypotheses 1, 3, and 4 were right and Hypothesis 2 was wrong. Despite data supporting H3, the mediating impact was not, hence H3 was dismissed (Table 5).

CONCLUSION AND POLICY IMPLICATIONS

This study examines how digital technologies, analytical and social media technologies, enhance firms' dynamic capabilities through intelligence and resource flexibility. The Theory emphasizes an organization's ability to adapt, recognize changes, and reorganize resources to stay competitive. Theoretically, the findings emphasize the necessity for enterprises to quickly modify their physical and digital resources. This integration improved our understanding of how firms traverse the digital landscape and highlight the changing nature of dynamic capabilities. Social media technologies stress resource flexibility, temporal considerations, digital ecosystem interconnectedness, and continual learning and resource transformation. Hence, firms must use digital resources effectively to stay competitive and achieve performance diversity.

In practice, managers should regularly obtain market intelligence to stay abreast of consumer behavior and market changes. Proactive marketing initiatives should reflect these trends. Organizations should also foster an informed, adaptable culture. Proactive marketing mediates customer behavior and improves organizational performance, making it relevant to management practice. Managers should monitor market developments, foster an adaptable culture, and innovate in multiple ways. These steps will provide companies with the agility and responsiveness they need to succeed in competitive markets.

The findings offered a valuable insight into the importance of managerial relevance of digital adaptation, innovation and proactive marketing strategies. Therefore, firms, through managers, are encouraged to invest in activities that facilitate market intelligence, continuous learning and responsiveness to market dynamics.

Although this research provides useful output for practice and policy decisions. Future research can prioritize a quantitative approach to studying proactive market approaches and their immediate effects on performance measurements or consumer behavior may also yield useful insights. Finding out what happens when people take initiative is intriguing. By situating proactivity and analyzing which variables affect different forms of proactivity and how they affect them, researchers and practitioners may gain new insights and improve proactivity strategies. Our research includes limitations, such as a small sample size and non-random case selection, which may limit its applicability to various firms and circumstances. Our five case studies match our framework's aspects, but more patterns may emerge. We should test our findings with larger data sets that include non-vetted companies.

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APPENDIX A: (MEASURES)

Table 6: The measurement variables for each construct

S/N	Constructs	Measurement Items	Source
1	Organized Digital Technology (DT)	1. Digitalization and IT Infrastructure. 2. Technology Partnerships and Collaborations 3. Cyber security and Data Protection 4. Customer and User Feedback Services 5. Adoption of Emerging Technologies	**Lee and Choi (2003); Charoensukmongkol (2022); Tafesse and Wien's (2018).**
2	Organizational culture of intelligence	1. Leadership Commitment 2. Knowledge Sharing 3. Open Communication 4. Data-Driven Decision-Making 5. Learning and Development Programs	**Ang and Inkpen (2008); Edmondson (2019)**
3	Information processing capabilities	1. Information Collection 2. Technology Infrastructure 3. Communication strategy with stakeholders 4. Adaptation and Learning 5. Decision-Making 6. Information Processing Capabilities	**Li et al (2021)**
4	Proactive Marketing	1. Brand Building and Reputation Management 2. Market Research and Analysis Capabilities 3. Strategic Planning 4. Innovation and Product Development 5. Content Marketing and Thought Leadership	***Brege & Kindstrom (2020) :Hazzam et al (2022)***
5	Consumer behavior	1. Purchase Volume and Frequency 2. Decision-Making Unit (DMU) Analysis 3. Customer Segmentation 4. Customer Lifetime Value (CLV) 5. Customer Satisfaction and Loyalty 6. Environmental Impact Assessment 7. Customer Feedback and Reviews 8. Supplier Performance Metrics	***Bilro et al (2023); Unal and Tascioglu, (2022)***