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CLICKS VS. BRICKS: A SYSTEMATIC REVIEW OF RETAIL SEGMENTATION STRATEGIES IN OMNICHANNEL CONTEXTS

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Abstract

Retailers face increasing difficulty in aligning segmentation strategies across online and offline environments amid rapid technological change. This study adopts a qualitative design using PRISMA guidelines, reviewing 46 peer-reviewed articles (2015–2024) from an initial pool of 68. Findings show that online segmentation is driven by real-time behavioral data and AI-based personalization, while offline segmentation remains largely demographic and geographic. However, cross-channel consumer behavior is creating overlap, with emerging technologies such as IoT, edge computing, and federated learning narrowing the data gap between both environments. The paper also revealed several major obstacles, including data silos, excessive personalization, and privacy threats, as well as potential convergence in the form of unified CRM platforms. The implication of this results is that both theory and practice must shift toward holistic, cross-channel frameworks that better capture dynamic consumer behavior and support more effective strategic decision-making. It was therefore concluded that retail segmentation is evolving from distinct online and offline approaches toward integrated, data-driven strategies shaped by omnichannel behavior. Hence, retailers should invest in unified data systems, advanced analytics, and context-sensitive models. The originality of this study lies in its contribution towards clarifying the evolving divide in retail segmentation and identifying pathways toward integrated, technology-driven segmentation frameworks.

Keywords: Consumer segmentation, Online (clicks) retail, Offline (bricks) retail, Omnichannel strategy, Personalization, Dual-channel marketing.

Introduction

The retail landscape has undergone a profound transformation driven by rapid technological advancement and shifting consumer expectations, resulting in the coexistence and increasing interdependence of online and offline shopping channels. While traditional brick-and-mortar retail continues to offer sensory engagement, immediate product evaluation, and interpersonal interaction, digital platforms provide convenience, scalability, and highly personalized experiences enabled by data analytics (Verhoef *et al*., 2021; Chaffey & Smith, 2022). These structural differences are not merely operational but fundamentally shape consumer decision-making processes, influencing how value is perceived, how information is processed, and how purchasing choices are made.

Consequently, retailers are required to adapt their strategic tools, particularly segmentation, to reflect the complexities of this dual-channel environment.

Segmentation remains a cornerstone of marketing strategy, traditionally categorized into demographic, geographic, psychographic, and behavioral dimensions (Kotler & Keller, 2016). However, its operationalization differs significantly across retail contexts. In online environments, segmentation is increasingly driven by real-time behavioral data, predictive analytics, and algorithmic profiling, allowing for dynamic personalization and targeted engagement (Costa & Castro, 2021; Miao *et al*., 2022). In contrast, offline retail continues to rely on more static and observational forms of segmentation, including location-based insights, in-store behavior, and customer interactions (Lindblom, 2023; Singh & Basu, 2023). These divergent approaches reflect disparities in data availability and technological infrastructure, but they also highlight a broader methodological divide in how consumer heterogeneity is understood and addressed across channels.

Despite the extensive body of literature on consumer behavior in both online and offline settings, there remains a notable lack of integrative research that systematically examines how segmentation strategies can be aligned across these environments. Existing studies tend to adopt a siloed perspective, focusing on either digital or physical retail without adequately addressing their intersection. This limitation is particularly significant in the context of contemporary retailing, where consumers increasingly exhibit cross-channel behavior, moving fluidly between online and offline touchpoints throughout their purchase journey. The absence of integrated segmentation frameworks not only constrains theoretical development but also limits practical application, as retailers struggle to reconcile fragmented customer insights into a coherent strategic approach.

Retailers operating within this dual-channel context therefore face a critical strategic challenge in developing unified segmentation models that account for differences in data richness, behavioral patterns, and technological capabilities. Online channels benefit from extensive, real-time data that enable precise targeting and continuous optimization, whereas offline channels often lack comparable analytical depth, resulting in less adaptive segmentation practices (Costa & Castro, 2021; Lindblom, 2023). This asymmetry is further complicated by the rise of omnichannel retailing, where consumers expect seamless, consistent, and personalized experiences across all touchpoints (Chaffey & Smith, 2022). In the absence of integrated segmentation strategies, firms risk delivering inconsistent messaging, undermining customer satisfaction, and weakening brand loyalty. Accordingly, the central problem addressed in this study is the lack of a coherent and adaptable segmentation framework capable of capturing and responding to consumer behavior across both online and offline retail environments, thereby bridging the gap between theoretical understanding and practical implementation.

Objectives

The research aims to discuss the rationale behind the rising sophistication experienced by retailers as they stratify their customers across the twin retail platforms, online (clicks) and offline (bricks). In order to do that, the following research objectives are going to be worked out:

i. To explore the differences and overlaps in segmentation strategies between online (clicks) and offline (bricks) shoppers. This objective aims to analyze how consumers' motivations and behaviors vary across physical and digital retail settings and how these differences influence the formulation of segmentation strategies.

ii. To evaluate the role of technology in shaping segmentation strategies across both retail contexts. This objective focuses on examining how advancements in data collection, algorithmic personalization, and digital tracking influence segmentation efforts.

Conceptual Foundation of Consumer Segmentation

Consumer segmentation has long been established as a central marketing strategy, enabling firms to tailor offerings to distinct customer groups based on shared characteristics. The foundational work of Smith (1956) challenged the logic of mass marketing by proposing that markets are heterogeneous and can be divided into meaningful segments. This conceptual shift reoriented marketing toward differentiation and customer-centric strategies. Subsequent developments by Kotler (1989) formalized segmentation into four principal dimensions: demographic, geographic, psychographic, and behavioral. These dimensions remain widely adopted in both academic and practical contexts, providing a structured basis for understanding consumer heterogeneity and guiding strategic decision-making.

These segmentation categories support alignment between organizational offerings and consumer expectations by enabling targeted communication, product positioning, and service delivery (Osei *et al*., 2021). Demographic segmentation focuses on measurable population characteristics such as age, income, and occupation, while psychographic segmentation captures attitudes, values, and lifestyle orientations (Naong & Makhoali, 2024; Kotze, 2022). Behavioral segmentation, often considered the most actionable, examines patterns of interaction, including usage frequency, brand loyalty, and responsiveness to marketing stimuli. Although these approaches remain relevant, they are increasingly constrained by their static nature, particularly in environments characterized by rapid technological change and evolving consumer behavior.

The contemporary retail context, marked by the integration of online and offline channels, exposes the limitations of traditional segmentation models. Consumers now engage in complex, non-linear purchase journeys that span multiple touchpoints, challenging the effectiveness of fixed and single-dimensional segmentation frameworks (Verhoef *et al*., 2021). As a result, segmentation has shifted toward more dynamic and data-driven approaches. Digital technologies, including artificial intelligence and machine learning, enable the analysis of large-scale behavioral data, allowing for real-time segmentation and continuous refinement of customer profiles (Garlet *et al*., 2024; Yoo *et al*., 2023). This transition reflects a broader movement from descriptive categorization toward predictive and adaptive segmentation strategies.

Online (Clicks) Segmentation Approaches

The emergence of e-commerce has transformed segmentation practices by enabling the collection and analysis of granular, real-time consumer data. Unlike traditional approaches that rely on static attributes, online segmentation is driven by behavioral and interactional data generated through digital platforms. This shift allows retailers to identify patterns of engagement and tailor marketing strategies with a high degree of precision. The integration of data analytics, artificial intelligence, and machine learning has further advanced this process, enabling continuous segmentation updates based on evolving consumer behavior (Dwivedi *et al*., 2021; Mariani *et al*., 2022).

Central to online segmentation is the ability to process diverse data sources, including clickstreams, browsing histories, search queries, and purchase records. These data enable the formation of nuanced consumer segments based on behavioral tendencies and engagement patterns (Garlet *et al*., 2024; Yoo *et al*., 2023). Recommendation systems, particularly those based on collaborative filtering and deep learning, play a significant role in operationalizing segmentation by delivering personalized product suggestions. While such systems enhance customer experience and conversion rates, they also reinforce algorithmic dependence, raising concerns about transparency and bias.

Dynamic pricing and journey tracking further illustrate the sophistication of online segmentation. Pricing strategies are increasingly individualized, reflecting demand patterns and consumer profiles, while clickstream analysis enables the mapping of customer journeys and identification of friction points (Tuanrat *et al*., 2021). However, the extensive reliance on data collection introduces critical challenges related to privacy and ethical data use. As regulatory frameworks become more stringent, retailers must balance personalization with responsible data governance (Dwivedi *et al*., 2022). This tension underscores the need for segmentation models that are not only effective but also ethically grounded.

Offline (Bricks) Segmentation Techniques

Despite the rapid growth of digital retail, offline environments continue to play a significant role in shaping consumer experiences. Segmentation in physical retail settings has traditionally relied on observable and location-based data, including demographic characteristics, geographic distribution, and in-store behavior (Jayawardena *et al*., 2023). While these approaches provide valuable insights, they are generally less granular and less adaptive compared to digital segmentation methods, limiting their responsiveness to dynamic consumer behavior.

Demographic and geographic segmentation remain dominant in offline contexts, informing decisions related to store location, product assortment, and pricing strategies. Retailers often align store formats and offerings with the socio-economic profile of specific regions, reflecting localized consumer preferences. However, such approaches may oversimplify consumer behavior by relying on aggregated characteristics rather than individual-level insights. To address this limitation, retailers increasingly incorporate data from loyalty programs and transaction records to enhance segmentation accuracy. For example, loyalty schemes enable the tracking of purchase patterns, supporting more targeted promotions and customer engagement strategies (Musyoka, 2023).

Experiential factors also play a critical role in offline segmentation. Store layout, visual merchandising, and sensory cues influence consumer behavior and contribute to implicit segmentation within physical spaces. These elements guide navigation, encourage impulse purchases, and shape overall shopping experiences. Additionally, interpersonal interactions between staff and customers provide qualitative insights that are difficult to capture in digital environments. While these features represent strengths of offline retail, their limited scalability and data capture capabilities highlight the need for integration with digital systems to enhance segmentation effectiveness.

Integration Opportunities: Toward Unified Segmentation

The increasing overlap between online and offline consumer behavior has intensified the need for integrated segmentation strategies. Traditional channel-specific approaches are insufficient in capturing the complexity of modern consumer journeys, which often involve multiple touchpoints across digital and physical environments. As a result, retailers are shifting toward unified segmentation frameworks that consider the entire customer journey rather than isolated interactions (Verhoef *et al*., 2021; Melero *et al*., 2016).

Unified segmentation recognizes that consumer interactions across channels generate complementary data that, when integrated, provide a more comprehensive understanding of behavior and preferences. This approach requires the development of cross-channel customer profiles that are continuously updated based on interactions in both environments (Yoo *et al*., 2023). Technologies such as customer data platforms and advanced CRM systems facilitate this integration by consolidating data from multiple sources, enabling the creation of detailed and dynamic consumer segments. These systems support more consistent and personalized engagement strategies, enhancing both customer experience and operational efficiency.

However, achieving integration presents significant challenges. Organizational silos, legacy systems, and inconsistencies in data formats hinder the seamless flow of information across channels. Additionally, regulatory constraints and privacy concerns complicate data integration efforts. While leading retailers have demonstrated the potential of unified segmentation through omnichannel strategies, widespread implementation remains limited. This suggests that integration is not merely a technological issue but also an organizational and strategic challenge.

Challenges and Technological Enablers in Bridging Segmentation Channels

Efforts to bridge online and offline segmentation are constrained by structural, regulatory, and technological challenges. Data fragmentation remains a primary obstacle, as customer information is often stored in separate systems, limiting cross-channel visibility and hindering comprehensive analysis (Patowary, 2023). This fragmentation reduces the effectiveness of segmentation by preventing a holistic understanding of consumer behavior.

Regulatory frameworks such as GDPR and CCPA further complicate data integration by imposing strict requirements on data collection and usage. While these regulations enhance consumer protection, they also restrict the ability of retailers to implement real-time tracking and personalized targeting strategies (Dwivedi *et al*., 2022). Additionally, the integration of diverse technological systems requires substantial investment and organizational change, particularly for firms operating with legacy infrastructure (Melero *et al*., 2016).

Despite these challenges, emerging technologies offer pathways for advancing segmentation integration. Edge computing enables localized data processing, supporting real-time analytics in physical environments while preserving privacy. Federated learning allows predictive models to be developed without centralized data storage, addressing privacy concerns. Similarly, Internet of Things technologies facilitate the collection of in-store behavioral data, bridging the gap between physical and digital insights. These developments indicate that while integration remains complex, technological innovation provides viable mechanisms for enhancing segmentation across retail channels.

Theoretical Foundations for Segmentation in Dual-Channel Retail

Two theoretical perspectives underpin this study, namely the Theory of Planned Behavior (TPB) and the Push–Pull Theory of channel preference. Both models provide a structured explanation of how consumers make channel-related decisions and offer a basis for linking segmentation variables to observed behavior across online and offline environments. Specifically, they help explain how psychographic and behavioral segmentation variables such as attitudes, motivations, and situational triggers influence consumer movement between retail channels.

Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (Ajzen, 1991) explains consumer behavior as a function of three core determinants: attitude toward the behavior, subjective norms, and perceived behavioral control. In a retail context, these constructs shape consumer preferences for online or offline channels. For instance, positive attitudes toward convenience and efficiency tend to encourage online shopping, while perceived risks or lack of trust may reinforce preference for physical stores. Subjective norms capture the influence of social expectations, which may vary across demographic or cultural segments, while perceived behavioral control reflects the individual's confidence in using technology or navigating physical retail environments.

The relevance of TPB to this study lies in its alignment with psychographic and behavioral segmentation variables. Rather than relying solely on demographic classifications, TPB highlights the importance of underlying cognitive and motivational factors in shaping channel behavior. Empirical studies show that consumers with high technological self-efficacy and favorable attitudes toward digital platforms are more likely to engage in online purchasing, whereas those who value sensory experience and interpersonal interaction tend to prefer offline channels (Salem & Nor, 2020; Al-Mamary & Alraja, 2022). This demonstrates that segmentation strategies must incorporate attitudinal and control-related variables to effectively capture differences in channel usage.

Push–Pull Theory of Channel Preference

The Push–Pull Theory provides a complementary perspective by focusing on situational and environmental drivers of channel choice. Push factors refer to negative aspects of a channel that discourage its use, such as long queues, limited product availability, or inconvenient store locations in offline retail. Pull factors, in contrast, represent attractive features of an alternative channel, such as the accessibility, variety, and price transparency associated with online platforms (Mishra *et al*., 2021; Kajol *et al*., 2022). This framework is particularly relevant in explaining dynamic switching behavior between channels.

The theory directly supports context-based and behavioral segmentation by emphasizing when and why consumers shift between online and offline environments. For example, a consumer may prefer offline shopping for product evaluation but switch to online channels due to time constraints or promotional incentives. Such behavior illustrates that segmentation cannot remain static but must account for situational variables and temporal factors. By integrating push–pull dynamics, retailers can develop more responsive segmentation strategies that reflect real-time consumer decision processes rather than fixed categorizations.

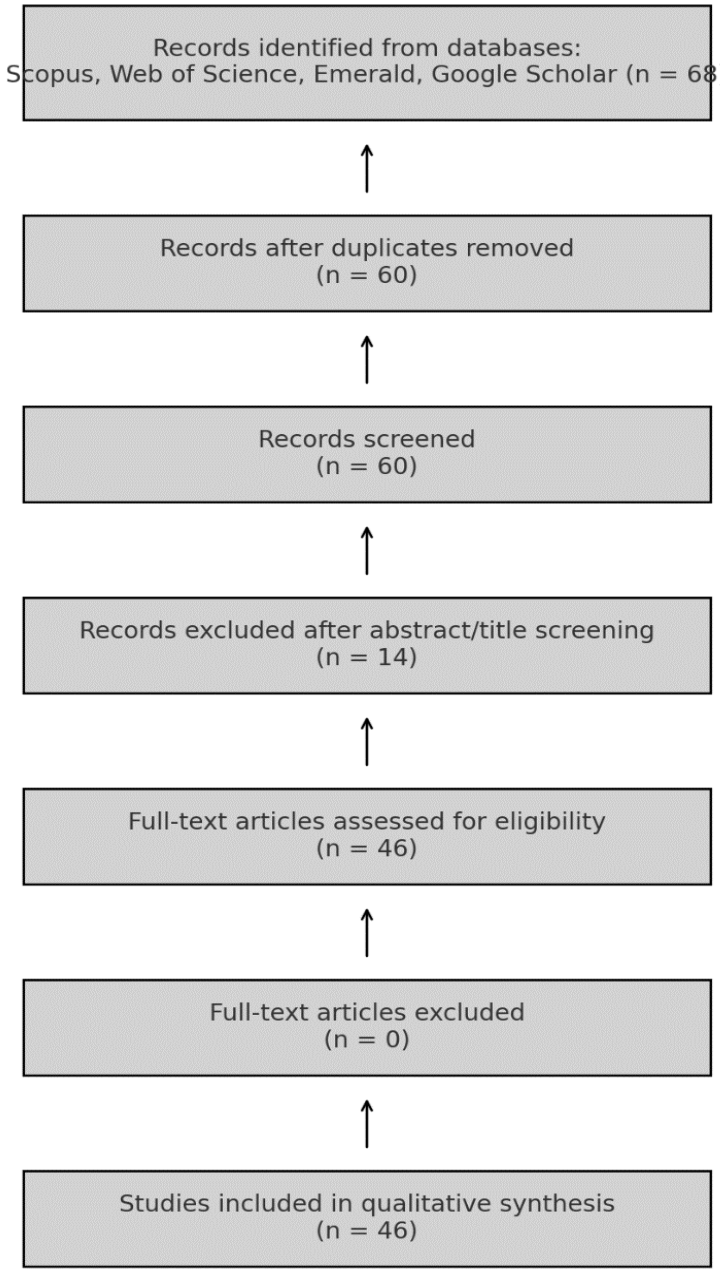
Together, TPB and Push–Pull Theory provide a coherent theoretical foundation for understanding segmentation in an omnichannel context. TPB explains the internal psychological drivers of channel preference, while Push–Pull Theory captures external situational influences. Their integration highlights the need for segmentation approaches that combine psychographic, behavioral, and contextual variables to explain consumer channel behavior more accurately. This study draws on both models to examine how segmentation strategies can be adapted to reflect the complexity of consumer interactions across online and offline retail environments.

Materials and Methods

This study employs a qualitative Systematic Literature Review (SLR) to examine consumer segmentation approaches across online (clicks) and offline (bricks) retail environments, with the aim of generating both interpretive insights and practical implications. The SLR approach is appropriate given the exploratory nature of the study and the need to synthesize diverse theoretical and empirical contributions within a fragmented research domain. A structured search was conducted across major academic databases, including Scopus, Web of Science, Emerald, and Google Scholar, covering publications from 2015 to 2024. Keywords such as *consumer segmentation*, *online retail*, *offline retail*, *personalization*, *omnichannel*, and *retail technology* were used to retrieve relevant studies. The initial search identified 68 records, which were subjected to a systematic screening process based on predefined inclusion and exclusion criteria.

Inclusion criteria required studies to be peer-reviewed, published within the specified timeframe, and directly related to consumer segmentation in either or both online and offline retail contexts, with clear theoretical or practical contributions. Exclusion criteria eliminated duplicate records, non-English publications, studies lacking empirical or conceptual relevance, and those focused solely on single-channel contexts without broader applicability. Following title, abstract, and full-text screening, 46 studies met the eligibility criteria and were included in the final analysis. Data were analyzed using a six-step thematic analysis framework as outlined by Braun and Clarke (2006), supported by NVivo software. This process involved data familiarization, initial coding, theme development, refinement, and interpretation. Key themes identified include segmentation bases, technological enablers, consumer behavioral patterns, integration challenges, and emerging strategic practices. Ethical considerations were maintained through the exclusive use of publicly available data and accurate citation of all sources. A PRISMA-aligned flow diagram is presented to illustrate the study selection process.

Figure 1: Flow chart diagram of the study selection method using PRISMA guidelines.



Source: Author's Compilation (2025)

Results

Thematic analysis was employed to systematically synthesize patterns and insights from the selected literature, enabling a comparative and integrative understanding of segmentation strategies across online (clicks) and offline (bricks) retail contexts. The analysis followed the six-step inductive coding framework proposed by Braun and Clarke (2006), comprising data familiarization, initial coding, theme generation, review, definition, and interpretation. NVivo software was used to support the organization and refinement of codes. This approach facilitated a structured examination of how segmentation practices differ across channels while also identifying emerging areas of convergence, thereby directly addressing the study objectives.

Findings indicate a clear structural distinction between segmentation approaches in online and offline environments. Offline segmentation remains largely grounded in traditional demographic, geographic, and psychographic variables, reflecting its reliance on observable and location-based data. These approaches support localized decision-making related to product assortment, pricing, and service design but are inherently limited by their static and aggregated nature (Kotze, 2022; Jayawardena *et al*., 2023). In contrast, online segmentation is driven by granular behavioral data, including clickstream activity, browsing patterns, and purchase history, enabling real-time personalization and predictive targeting through advanced analytics (Dwivedi *et al*., 2021; Garlet *et al*., 2024). This divergence highlights a fundamental methodological shift from descriptive segmentation toward dynamic, data-driven models.

However, the analysis also reveals increasing convergence between the two approaches, particularly within omnichannel retail strategies. Retailers are progressively integrating online behavioral data with offline transactional and loyalty data to construct unified customer profiles. This integration enables more precise targeting and supports continuity in customer experience across touchpoints. The emergence of hybrid segmentation models, which combine spatial, behavioral, and transactional data, reflects an effort to move beyond channel-specific strategies toward a more holistic understanding of consumer behavior. These findings suggest that segmentation is evolving from a channel-bound activity to a cross-channel analytical process.

With respect to the role of technology, the analysis identifies three dominant themes: data-driven segmentation, technological enablement, and structural constraints. Advances in artificial intelligence and big data analytics have significantly enhanced segmentation capabilities, particularly in online environments where real-time data processing supports adaptive and personalized engagement (Yoo *et al*., 2023). In offline contexts, technologies such as in-store analytics, loyalty systems, and sensor-based tracking are gradually improving data capture and segmentation precision. At the same time, emerging tools including IoT, edge computing, and federated learning are enabling the development of integrated consumer profiles across channels. Despite these advancements, persistent challenges remain, including data silos, high implementation costs, and regulatory constraints related to data privacy (Patowary, 2023; Hollebeek *et al*., 2022). These limitations underscore the need for balanced segmentation strategies that combine technological capability with ethical and operational considerations.

Discussion

The findings demonstrate a clear divergence in segmentation approaches between online (clicks) and offline (bricks) retail, while also indicating a gradual shift toward convergence through hybrid strategies. In relation to Objective 1, offline segmentation remains largely anchored in demographic, geographic, and psychographic variables, reflecting its reliance on observable and location-based data. In contrast, online segmentation is driven by behavioral data and real-time interaction, enabling more adaptive and responsive targeting. This distinction aligns with Liang *et al*. (2023), who concluded that offline retail emphasizes spatial and lifestyle characteristics, whereas online environments leverage browsing behavior and algorithmic profiling. Similarly, Kotze (2022) highlights the role of sensory and emotional stimuli in shaping offline consumer segments, reinforcing the continued relevance of experiential factors in physical retail. However, while prior studies tend to treat these approaches as fundamentally distinct, the present findings suggest that this dichotomy is increasingly insufficient to explain contemporary segmentation practices.

The study further identifies a growing trend toward integration, particularly among omnichannel retailers that combine digital and physical data to enhance segmentation accuracy. This finding extends beyond the position of Jayawardena *et al*. (2023), who argue that most firms still maintain structurally separate segmentation systems. Instead, the evidence indicates that leading retailers are actively developing unified customer profiles by integrating online behavioral data with offline transactional and loyalty data. This convergence has important strategic implications, as it enables more consistent targeting and improves customer experience across channels. The effectiveness of such integration is supported by Meliawati *et al*. (2023), who demonstrate that unified segmentation contributes to improved marketing performance and customer retention. These results suggest that segmentation is evolving from a channel-specific activity toward a more holistic, data-integrated process.

With respect to Objective 2, the findings confirm the central role of technology in reshaping segmentation practices. Consistent with Garlet *et al*. (2024) and Yoo *et al*. (2023), the study shows that artificial intelligence, machine learning, and big data analytics have significantly enhanced the precision and scalability of segmentation in online environments. Technologies such as recommendation systems, sentiment analysis, and dynamic pricing enable micro-segmentation and real-time personalization, thereby improving customer engagement and conversion rates. In offline contexts, technological adoption remains comparatively limited but is gradually increasing through tools such as in-store analytics, sensors, and visual tracking systems. While these technologies improve data capture and segmentation accuracy, their impact is constrained by infrastructural and operational limitations.

Overall, the findings highlight a transition from traditional, static segmentation models toward dynamic and integrated approaches driven by technological innovation. This shift has important implications for both theory and practice. Theoretically, it challenges the continued reliance on single-channel segmentation frameworks and calls for models that account for cross-channel consumer behavior. Practically, it underscores the need for retailers to invest in data integration and analytical capabilities to remain competitive in an increasingly omnichannel environment.

Conclusions

This study concludes that although online (clicks) and offline (bricks) retailers pursue similar segmentation objectives, their approaches differ significantly due to variations in consumer behavior, data availability, and channel characteristics. Online segmentation is predominantly driven by real-time behavioral data and advanced technologies such as artificial intelligence and algorithmic personalization, enabling dynamic and highly responsive targeting. In contrast, offline segmentation continues to rely largely on demographic and geographic variables, reflecting its limited access to granular customer data. The findings further reveal that these traditionally distinct approaches are increasingly converging within an omnichannel context, as retailers integrate data across platforms to create unified customer profiles. This convergence is driven by both consumer expectations for consistent experiences and organizational efforts to harmonize marketing strategies across channels.

The study also concludes that technology plays a central and transformative role in shaping segmentation practices. While digital platforms have enabled micro-level personalization and continuous behavioral tracking, offline environments are gradually adopting technologies such as in-store analytics, IoT devices, and loyalty systems to enhance segmentation capabilities. However, this transformation is uneven, as retailers face challenges related to system integration, cost, and regulatory compliance. The study contributes to existing knowledge by providing a comprehensive and integrative understanding of segmentation across dual-channel retail environments, highlighting technology as both a differentiating and unifying force in contemporary segmentation logic.

Recommendations

Based on the above conclusions, the following suggestions were put forward:

i. **Enhance Risk Identification and Classification:** Retailers should implement structured and continuous segmentation audit systems that combine demographic, behavioral, and real-time data to improve the identification and classification of customer segments across both online and offline channels.

ii. **Strengthen Data-Driven Customer Protection and Trust:** Firms should adopt transparent data governance frameworks and secure data integration systems to ensure that segmentation practices not only enhance targeting but also protect customer data and build trust, particularly in digitally intensive environments.

iii. **Improve System Reliability and Consistency Across Channels:** Organizations should invest in integrated platforms such as Customer Relationship Management (CRM) systems and Customer Data Platforms (CDPs) to ensure consistent segmentation outputs, enabling seamless customer experiences and reducing operational inefficiencies across channels.

iv. **Leverage Organizational and Technological Capabilities:** Retailers should strengthen internal capabilities through staff training, cross-functional collaboration, and investment in advanced technologies such as AI, IoT, and analytics tools to support adaptive and context-sensitive segmentation strategies.

v. **Promote Omnichannel Segmentation Integration:** Retailers should develop unified segmentation frameworks that incorporate both online and offline data streams, allowing for dynamic and context-aware customer profiling that reflects modern cross-channel behavior.

References

Al-Mamary, Y. H. S., & Alraja, M. M. (2022). Understanding entrepreneurship intention and behavior in the light of TPB model from the digital entrepreneurship perspective. *International Journal of Information Management Data Insights, 2*(2), 100106.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101.

Chaffey, D., & Smith, P. R. (2022). *Digital marketing excellence: Planning, optimizing and integrating online marketing*. Routledge.

Costa, J., & Castro, R. (2021). SMEs must go online—E-commerce as an escape hatch for resilience and survivability. *Journal of Theoretical and Applied Electronic Commerce Research, 16*(7), 3043–3062.

Dash, G., Kiefer, K., & Paul, J. (2021). Marketing to millennials: Marketing 4.0, customer satisfaction and purchase intention. *Journal of Business Research, 122*, 608–620.

Dwivedi, Y. K., Hughes, L., Baabdullah, A. M., Ribeiro-Navarrete, S., Giannakis, M., Al-Debei, M. M., ... & Wamba, S. F. (2022). Metaverse beyond the hype: Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 66*, 102542.

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., ... & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management, 59*, 102168.

Garlet, T. B., de Medeiros, J. F., Ribeiro, J. L. D., & Perin, M. G. (2024). Understanding ethical products: Definitions and attributes to consider throughout the product lifecycle. *Sustainable Production and Consumption*.

Hollebeek, L. D., Sharma, T. G., Pandey, R., Sanyal, P., & Clark, M. K. (2022). Fifteen years of customer engagement research: A bibliometric and network analysis. *Journal of Product & Brand Management, 31*(2), 293–309.

Jayawardena, N. S., Thaichon, P., Quach, S., Razzaq, A., & Behl, A. (2023). The persuasion effects of virtual reality (VR) and augmented reality (AR) video advertisements: A conceptual review. *Journal of Business Research, 160*, 113739.

Kajol, K., Singh, R., & Paul, J. (2022). Adoption of digital financial transactions: A review of literature and future research agenda. *Technological Forecasting and Social Change, 184*, 121991.

Kotler, P. (1989). From mass marketing to mass customization. *Planning Review, 17*(5), 10–47.

Kotler, P., & Keller, K. L. (2016). *A framework for marketing management*. Pearson.

Kotze, A. (2022). *Investigating the influence of reference groups on Generation Y's social commerce buying behaviour* (Doctoral dissertation, North-West University, South Africa).

Liang, A. D., Lim, W. M., Tung, W., & Lin, S. Y. (2023). Understanding different types of consumers: A multi-group analysis based on convenience food-related lifestyle.

Lindblom, A. (2023). Identifying cues and their effects in a retail store. In *Sensory marketing in retail: An introduction to the multisensory nature of retail stores* (pp. 43–135). Springer Nature Switzerland.

Mariani, M. M., Perez-Vega, R., & Wirtz, J. (2022). AI in marketing, consumer research and psychology: A systematic literature review and research agenda. *Psychology & Marketing, 39*(4), 755–776.

Melero, I., Sese, F. J., & Verhoef, P. C. (2016). Recasting the customer experience in today's omni-channel environment. *Universia Business Review, 50*, 18–37.

Meliawati, T., Gerald, S. C., & Aruman, A. E. (2023). The effect of social media marketing TikTok and product quality on purchase intention. *Journal of Consumer Sciences, 8*(1), 77–92.

Miao, M., Jalees, T., Zaman, S. I., Khan, S., Hanif, N. U. A., & Javed, M. K. (2022). The influence of e-customer satisfaction, e-trust and perceived value on consumer repurchase intention in B2C e-commerce. *Asia Pacific Journal of Marketing and Logistics, 34*(10), 2184–2206.

Mishra, R., Singh, R. K., & Koles, B. (2021). Consumer decision-making in omnichannel retailing: Literature review and future research agenda. *International Journal of Consumer Studies, 45*(2), 147–174.

Musyoka, I. N. (2023). *Effect of competitive advantage strategies on performance of supermarkets in Kenya* (Doctoral dissertation, University of Nairobi).

Naong, M. N., & Makhoali, K. J. (2024). Influence of selected demographic variables on SMME survival: A case study of Matjhabeng district municipality. *International Journal of Research in Business & Social Science, 13*(6).

Osei, F., Ampomah, G., Kankam-Kwarteng, C., Bediako, D. O., & Mensah, R. (2021). Customer satisfaction analysis of banks: The role of market segmentation. *Science Journal of Business and Management, 9*(2), 126–138.

Patowary, N. (2023). *Post-pandemic customer experience trends in Bangladesh's retail e-commerce industry*.

Pooja, K., & Upadhyaya, P. (2024). What makes an online review credible? A systematic review of the literature and future research directions. *Management Review Quarterly, 74*(2), 627–659.

Ricci, M. (2024). *Designing next-generation retail experiences via virtual reality and pseudo-haptics*.

Rita, P., & Ramos, R. F. (2022). Global research trends in consumer behavior and sustainability in e-commerce: A bibliometric analysis of the knowledge structure. *Sustainability, 14*(15), 9455.

Salem, M. A., & Nor, K. M. (2020). The effect of COVID-19 on consumer behavior in Saudi Arabia: Switching from brick-and-mortar stores to e-commerce. *International Journal of Scientific & Technology Research, 9*(7), 15–28.

Singh, K., & Basu, R. (2023). Online consumer shopping behaviour: A review and research agenda. *International Journal of Consumer Studies, 47*(3), 815–851.

Smith, W. R. (1956). Product differentiation and market segmentation as alternative marketing strategies. *Journal of Marketing, 21*(1), 3–8.

Tueanrat, Y., Papagiannidis, S., & Alamanos, E. (2021). Going on a journey: A review of the customer journey literature. *Journal of Business Research, 125*, 336–353.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research, 122*, 889–901.

Yoo, K., Welden, R., Hewett, K., & Haenlein, M. (2023). The merchants of meta: A research agenda to understand the future of retailing in the metaverse. *Journal of Retailing, 99*(2), 173–192.