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Omni-channel retail marketing effect evaluation framework integrating big data and artificial intelligence

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Abstract: This study proposes an innovative AI-driven framework for evaluating and optimizing omnichannel retail marketing effectiveness to address challenges in integrating multiple retail channels and leveraging data for strategic decision-making. The research develops a comprehensive framework integrating big data analytics and advanced AI techniques, including reinforcement learning and graph neural networks. The framework combines diverse data sources, employs sophisticated algorithms for analysis, and utilizes adaptive optimization methods across channels. Validation uses controlled experiments and a case study with GlobalMart retail corporation. Experimental results demonstrate significant improvements in key performance indicators, including a 23.7% increase in sales revenue and a 27.6% boost in marketing ROI compared to traditional methods. The GlobalMart case study showed substantial enhancements in customer segmentation accuracy (37%), campaign conversion rates (28%), and online-to-offline integration (42%). The proposed framework offers retailers a powerful tool for marketing optimization in complex omnichannel environments, though future research should explore its adaptability to emerging technologies and address privacy concerns. Retailers can leverage this framework to enhance data-driven marketing strategies, improve resource allocation, and deliver seamless customer experiences across all touchpoints.

Keywords: *Adaptive optimization, Artificial intelligence, Big data analytics, Customer segmentation, Graph neural networks, Marketing effectiveness, Marketing ROI, Omnichannel retail, Reinforcement learning, Retail analytics.*

1. Introduction

Changes in consumer behaviour and the incorporation of new digital technology have changed the retail landscape with the introduction of omnichannel retailing [1]. Retailers have had to adapt their business practices by integrating all sales and communication channels to improve customer engagement and interaction with the businesses [2]. By adopting omnichannel retailing, there is the need to create new customer-centric marketing strategies while simultaneously changing the way business is conducted [3]. As a result of the merging of online and offline selling, consumers have become more sophisticated and expect higher levels of service integration from retailers [4]. This has been accelerated by recent global changes which have underscored the emphasis on reinforced e-commerce activity while optimally utilising the physical presence of the business locations [5]. To remain competitive, retailers have had to adapt to the fast integration of multiple online channel uses to improve visibility and gain further competitive advantage [6].

However, there are some problems in developing successful omnichannel strategies. Retailers face numerous challenges related to the integration of channels, data, and advanced technological innovation, all of which are necessary for delivering exceptional customer service [7]. Moreover, the development of omnichannel retailing presents additional challenges regarding privacy and consumer

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information protection, which can only be addressed by carefully tailoring communications without breaching their trust [8].

Trends in academia reflect the rising importance of omnichannel retailing, resulting in an increasing amount of literature pertaining to this issue [9]. From customer behaviour in omnichannel scenarios [10] to the impacts of in-store technology on customers [11] researchers have covered a variety of topics. Nevertheless, there remains a gap in literature concerning the application of big data analytics and artificial intelligence for assessing the impact of omnichannel retailing marketing models [12].

This gap is addressed by developing the evaluation model of effectiveness of omnichannel retail marketing, which is based on big data and artificial intelligence technologies. The overarching goal is to provide retailers with an automated solution for assessing the quality of their omnichannel marketing strategies which, in turn, will enhance customer loyalty and satisfaction towards the retailers [13]. The contribution of this research is to provide a novel perspective to the discourse of omnichannel retailing by broadening the approaches to tackle marketing efficiency in a dramatically evolving retail environment.

2. Related Work and Theoretical Basis

2.1. Research Status of Omni-Channel Retail Marketing

Over the past few years, research on omnichannel retail marketing has grown tremendously in scope and complexity because its many facets continue to draw the attention of scholars and researchers worldwide. From 2015 to 2020, articles published on Web of Science that pertained to omnichannel retailing saw a 300% increase, signifying the growing intellectual significance of the area of study, as illustrated in [14]. Attention has been directed towards a number of issues such as channel integration [15] customer journey mapping [16] and the role of new technologies in omnichannel marketing [17]. The past decade has seen tremendous growth in publications on omnichannel retailing, as evidenced by Figure 1.

Studies conducted recently show that eliminating boundaries between channels is very crucial. These days, for instance, 78% of customers acknowledge the importance of having consistent experiences across all channels [18]. Furthermore, Deloitte's research shows that omnichannel retailers have 30% greater lifetime value than those who are single-channel retailers [19]. In this regard, it is imperative that retailers design and implement effective omnichannel strategies if they wish to compete in the fast-changing world of retailing. After 2015, especially, there was considerable emphasis on this topic, which Figure 1 depicts as a woeful lack of attention prior to 2015.

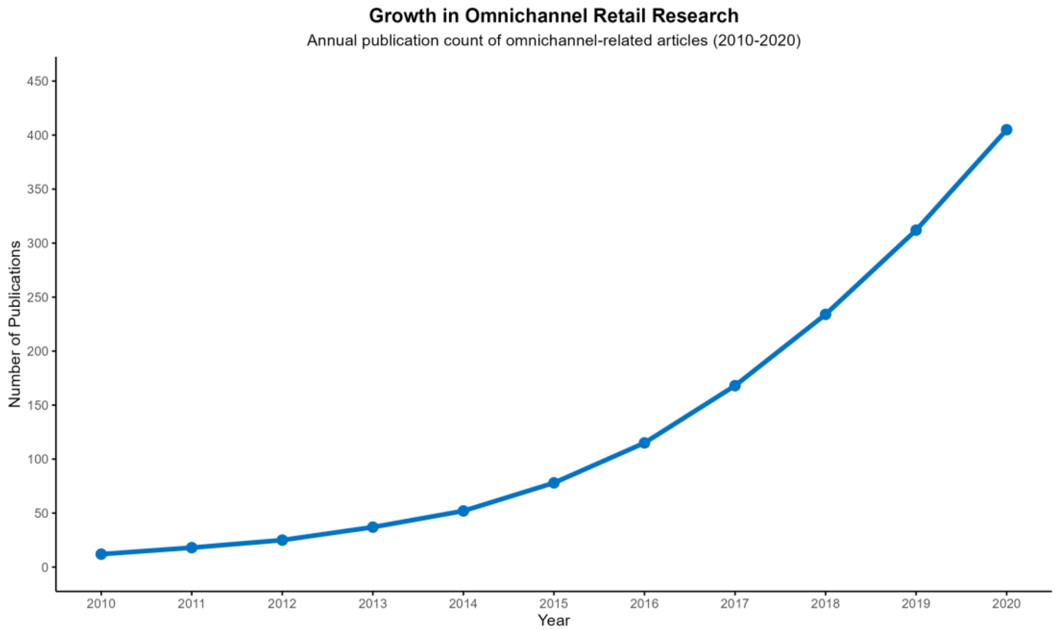

Figure 1.
Growth in omnichannel retail research (2010-2020).

The graph demonstrates the astonishing growth of omnichannel retail research over the years and reflects both its importance to the world today and its complexity. The notable increase in research from 2015 onwards can be attributed to the adoption of mobile phones and the rise of digital touchpoints which transformed retailing at the empirical level [20].

2.2. Application of Big Data Analysis in Retail Marketing

The impact of big data analytics in understanding consumer behaviour in marketing is staggering [21]. According to Cai and Lo [22] retailers tend to fetch a significant amount of information in the form of data from several sources for marketing and improving customer services, which includes information from social media, point of sale systems and even IoT devices. McKinsey stated that businesses that utilized big data analytics in their marketing and sales-related activities experienced an increase in ROI ranging from 15-20% [23]. Retail marketing practices that employ the use of big data include customer segmentation and pricing strategies, personalization, sharpening of pricing strategies and forecasting the needed sales [24]. For example, 35% of the sales for Amazon comes from the recommendation engine which is aided by big data analytics [25]. Also, Walmart utilizing big data to manage their inventory has reduced the out-of-stock items by 10-15% [26].

The following table summarizes the key applications and benefits of big data analytics in retail marketing:

Table 1.
Applications and benefits of big data analytics in retail marketing [27].

Application Area	Key Benefits	Adoption Rate (%)	Average ROI Increase (%)
Customer Segmentation	Improved targeting	78	12
Personalization	Enhanced customer experience	72	19
Pricing Optimization	Increased profit margins	65	11
Demand Forecasting	Reduced inventory costs	61	15
Fraud Detection	Minimized financial losses	57	8

The Return on Investment (ROI) is higher with personalization initiatives than with any other strategy at an increase of 19%, while customer segmentation is most frequently adopted by retailers at a rate of 78%. Both statistics emphasize the relevance of these developments in the retail industry as shown in Table 1. However, as straightforward as the advantages seem, there are barriers to be faced. Retailers have issues that range from data privacy as shown in Table 1, to the integration of different data systems, and the availability of qualified personnel. Regardless, the ever-changing and competitive world of retail marketing has forced companies to implement these big data strategies in order to remain competitive [28, 29].

2.3. Application of Artificial Intelligence Technology in Marketing Effect Evaluation

Harnessing artificial intelligence (AI) is quickly becoming one of the most important methods used to evaluate marketing effectiveness, as it allows the retailer to analyse a lot of data and provide recommendations with unprecedented speed and accuracy [30]. Retailers and marketers are now using machine learning, natural language processing, and computer vision to study customer behaviour and improve marketing efforts while trying to anticipate consumer behaviour [31]. Gartner is reporting that by 2025 as much as 80% of marketing executives will be trying to implement AI technologies to improve their market research and analysis functions [32]. When it comes to omnichannel retail, marketing analytics AI application provides unique opportunities for evaluating the effectiveness of cross-channel marketing activities as well as understanding complex customer journeys [33]. For example, attribution models powered by AI are able to evaluate the consumer conversion process to ascertain how much each touchpoint adds to a conversion, thus further assisting marketers in the effective utilization of marketing funds [34]. AI algorithms are also capable of interpreting data on the fly and giving marketers real-time insights for instantaneous shifts in campaign deployment, thus optimizing it [35].

The following table illustrates key AI applications in marketing effectiveness evaluation:

Table 2.
AI Applications in Marketing Effectiveness Evaluation [36]

AI Application	Description	Adoption Rate (%)	Performance Improvement (%)
Predictive Analytics	Forecasting customer behavior and campaign outcomes	68	25
Sentiment Analysis	Analyzing customer feedback across channels	57	18
Dynamic Pricing	Optimizing prices based on real-time market conditions	52	15
Customer Segmentation	Identifying high-value customer groups	61	22
Chatbots and Virtual Assistants	Providing personalized customer service	45	30

As illustrated in Table 2, chatbots and virtual assistants deliver the highest performance improvement at 30%, despite having the lowest adoption rate (45%) among the listed applications. Table 2 also reveals that predictive analytics has gained the most traction among retailers with a 68% adoption rate, delivering a substantial 25% performance improvement. This data highlights the transformative potential of AI technologies in retail marketing effectiveness evaluation.

Despite the significant potential of AI in marketing effectiveness evaluation demonstrated in Table 2, challenges remain. These include the need for high-quality, integrated data, concerns about AI bias, and the requirement for specialized skills to implement and manage AI systems [37]. Nevertheless, as AI technologies continue to evolve and become more accessible, their role in enhancing marketing effectiveness evaluation is expected to grow, providing retailers with increasingly sophisticated tools to navigate the complex omnichannel landscape [38].

3. Autonomous Intelligence-Driven Omni-Channel Retail Marketing Effect Evaluation Framework

3.1. Overall Architecture of the Framework

Incorporating artificial intelligence and advanced data analytics into marketing strategies across multiple channels is effectively reviewed by the proposed AI-driven framework for evaluating omnichannel retail marketing [39]. This framework breaks down into five layers – Data, Integration, AI Analysis, Evaluation, and Optimization, which work together while having distinct features [40]. The foundation of the framework relies on various online, offline, and even other non-proprietary sources that capture and incorporate all forms of data relevant to the customers and the overall market for the data layer [41]. To form the integration layer, the cleaning, fusion, and feature engineering processes are carried out so that the refined and synthesized diverse data streams are prepared for higher-level analysis.

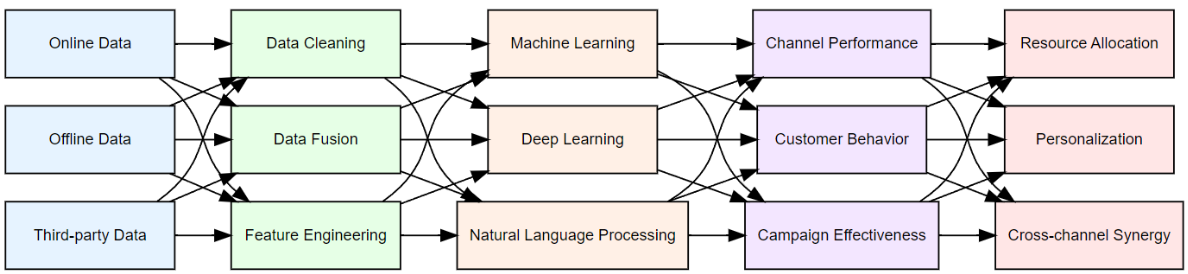

Figure 2.
AI-Driven omnichannel retail marketing effectiveness evaluation framework.

Figure 2 illustrates a schematic of the multichannel retailing marketing effectiveness assessment framework based on AI. This framework has a well-defined architecture that is arranged in five successive layers, and it is clearly seen in Figure 2 that each layer depends on the preceding layer in its analysis and functions as a complete evaluation and optimization system. The framework indicated in Figure 2 shows how information of different sorts is processed through different levels and is integrated into meaningful guided decisions for the marketing actions.

Such a framework using advanced data analytics and artificial intelligence for evaluating marketing effectiveness in AI-driven omnichannel retailing has been suggested for the first time in the literature [42, 43]. It comprises five layers as shown in the Figure 2 captioned: Data, Integration, AI Analysis, Evaluation, and Optimization. The foundation of the framework is built upon the Data Layer which includes online, offline and external sources capturing customer and market data as interactions [44]. The Integration Layer works on data cleansing, data fusion, and feature generation which prepares the collected data for further analysis [45].

As seen in Figure 2, the AI Analysis Layer is at the core of the framework, and it employs machine learning, deep learning, and language processing techniques to capture relevant meaning from the integrated data [46, 47]. These big-picture AI insights feed into the Evaluation Layer, where the performance of all channels, customer actions, and the success of the campaign are measured using highly advanced metrics and algorithms [48].

In the rightmost column of Figure 2, the Optimization Layer represents the final layer that evaluates and informs strategic decisions on resource allocation, personalization tactics, efficiency optimization, and cross-channel relations [49]. This helps marketing approaches to be progressively improved in real-time, as data is continuously monitored and analysed by AI, enabling retailers' rapid response to the fast-changing omnichannel world [50].

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With the incorporation of powerful AI tools alongside advanced data analysis, this framework enables retailers to better control the intricacies of omnichannel marketing, improve customer experience, and increase marketing ROI in a competition-filled environment, as shown in Figure 2 [51].

3.2. Data Layer Design

The design of the data layer is the starting point in the evaluation structure for the effectiveness of AI omnichannel retail marketing. This layer merges multiple customer insights data sources. It includes online data, such as website clickstream and social media data, offline data like sales and customer services logs, and external data, including market analysis and industry reports. There is an emphasis on capturing customer interactions throughout all channels in a timely and detailed manner. In addition, the data layer has strict policies regarding data governance for the protection of privacy in compliance with regulations such as GDPR [52, 53]. Using automated tools to combine these data sources facilitates the creation of a customer 360 view which is essential for the retailer's decisions and analyses in an omnichannel environment.

Figure 3.
Omnichannel retail marketing data layer design.

In the AI-based evaluation framework of omnichannel retail marketing effectiveness shown in Figure 3, the structure of the data layer is depicted. The integrated data repository, as illustrated in Figure 3, is surrounded by a variety of data inputs which consolidate into it. The integration of online, offline, and external data into a unified data repository is presented in the diagram [54]. In Figure 3, we can see how data from loyalty programmes and Customer Relationship Management (CRM) systems (depicted in green) are integrated with market research and competitor analysis (orange) together with e-commerce and retail data (blue). This design in Figure 3 shows how the collection of information from an omnichannel retail environment is integrated, by having multiple customer engagement interfaces and other external market information. These integrative capabilities, as seen in Figure 3, provide the retail industry with a comprehensive understanding of customer activities and market interactions,

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thereby facilitating the deployment of sophisticated analytics and AI-enabled governance in the subsequent layers of the framework.

3.3. Analytical Layer Design

The analytical aspect of the AI-powered framework used to measure the effectiveness of omnichannel retail marketing employs advanced artificial intelligence and machine learning techniques to extract meaningful insights from a single repository of data. This module combines a range of analytical methods [55, 56] including predictive modeling, customer segmentation, sentiment analysis, and attribution modeling. Using advanced algorithms, the analytical module is able to identify patterns in consumer behavior, predict nascent trends, and measure the performance of marketing campaigns across channels. In addition, it facilitates real-time decision-making by analyzing live data streams and providing instantaneous insights. Serves as the cognitive core of the framework, this analytical module translates raw data into meaningful insights that inform marketing strategies and optimization initiatives within the complex omnichannel retail environment.

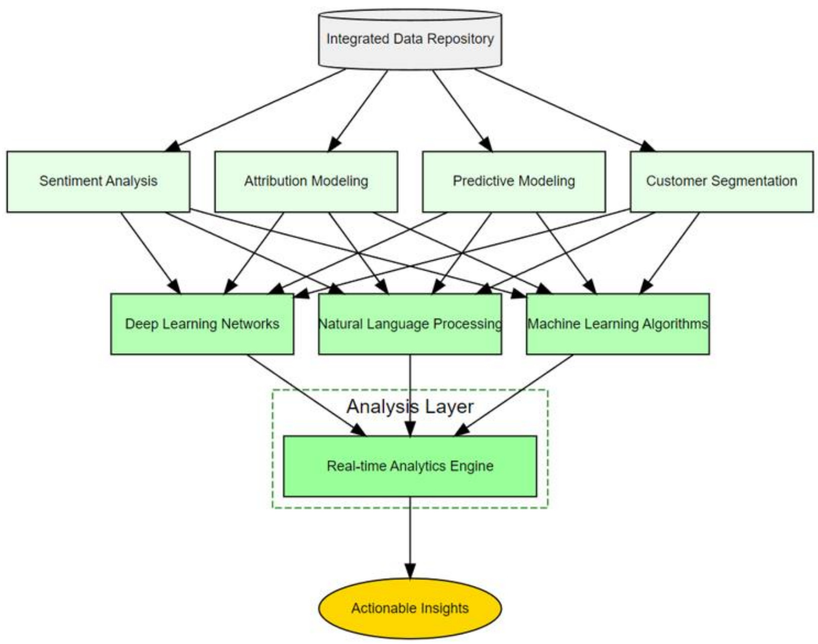

Figure 4.
Analysis layer design of ai-driven omnichannel retail marketing framework.

Figure 4 shows the structure and functional processes of the analytical component in the suggested framework intended to assess the effectiveness of AI-powered omnichannel retail marketing strategies. The figure shows that the process begins with a centralized data store at the top, then diverges into four primary analytical components: sentiment analysis, attribution modeling, predictive modeling, and customer segmentation. Figure 4 explains how these analytical components are linked with three core AI technologies (marked in green): deep learning networks, natural language processing, and machine learning algorithms. The Figure 4 representation clearly shows the integration of these technologies in the real-time analytics engine, which is the central processing unit for the analytical layer. From Figure 4, the final output is actionable insights (marked in yellow), which form the basis of well-informed decision-making processes in marketing campaigns.

The diagram shown in Figure 4 outlines the complex methodologies used in the field of data analysis [57, 58] which include predictive modeling, customer segmentation, sentiment analysis, and attribution modeling. As shown in Figure 4, these analytical techniques are enabled by sophisticated machine learning algorithms, deep learning systems, and natural language processing technologies. At the center of this analytical framework is the real-time analytics engine, which combines inputs from all analytical modules to deliver timely and relevant insights. This integrated analytical framework, as shown in Figure 4, enables retailers to derive deep insights into consumer behavior, optimize marketing efforts, and enhance decision-making in the fast-changing omnichannel retail environment.

3.4. Decision-Making Layer Design

The last element of the framework for measuring the efficacy of AI-powered omnichannel retail marketing is related to decision-making, where insights are converted into executable strategies. This section combines findings from the analytical stage with known business practices and goals to yield better marketing solutions. It comprises different decision-making modules like campaign optimization, personalization systems, resource allocation, and channel coordination. In this decision-making space, sophisticated algorithms are used to balance short-term profitability with long-term customer value, thus ensuring sustainable growth. Additionally, it involves feedback mechanisms that allow continuous improvement of decision-making processes based on real outcomes. By automating and optimizing intricate decision-making tasks, this section enables retailers to quickly respond to market fluctuations, enhance customer experiences, and optimize marketing return on investment across various channels.

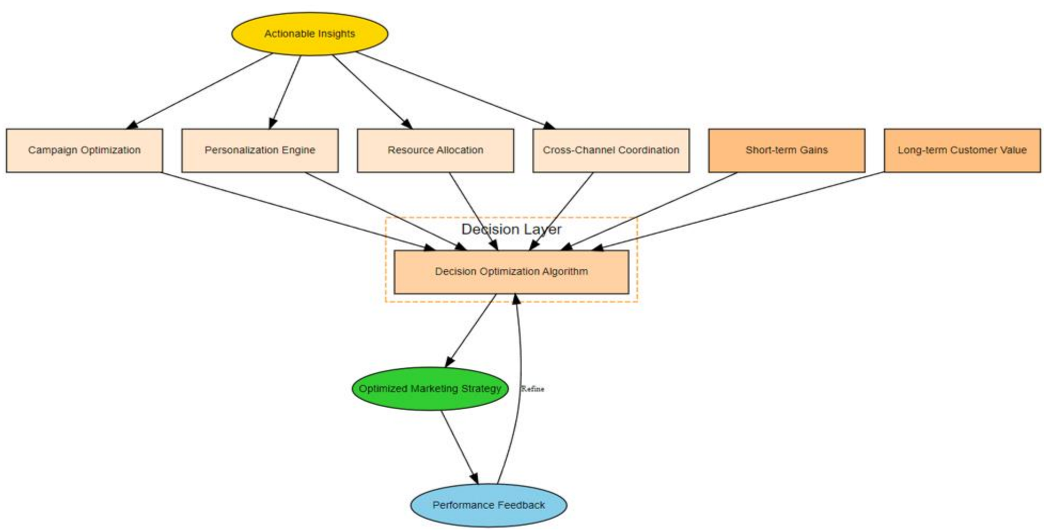

Figure 5.
Decision layer design of ai-driven omnichannel retail marketing framework.

Figure 5 illustrates the structural architecture and functional processes of the decision layer in the system designed to assess the efficacy of AI-powered omnichannel retail marketing. At the top of Figure 5, actionable insights, highlighted in yellow, are fed into five main decision-making modules, highlighted in light orange: campaign optimization, personalization engine, resource allocation, cross-channel coordination, and strategies for balancing short-term profit with long-term customer value. As Figure 5 shows, these modules feed into the central decision optimization algorithm, which forms the core of the decision layer. Figure 5 also illustrates how the optimized marketing strategy, highlighted in green, is generated from this algorithm, with performance feedback, highlighted in blue, enabling a process of continuous improvement.

The figure provided in Figure 5 explains the incorporation of actionable insights into multiple decision-making frameworks that include campaign optimization, personalization plans, resource allocation, and channel alignment. These frameworks meet the convergence point in a single decision optimization algorithm that balances short-term gains with the long-term value provided to customers. A review of Figure 5 indicates that the ultimate result is an optimized marketing strategy, which is then implemented and tracked. The feedback loop, clearly illustrated in the lower part of Figure 5, represents the continuous optimization of the decision-making process based on empirical performance metrics. This integrated decision layer, as outlined in Figure 5, enables retailers to make data-driven, holistic marketing decisions that drive business effectiveness across all channels in the complex omnichannel retail environment.

4. Key Technology Innovation

4.1. Adaptive Optimization of Marketing Strategy Based on Reinforcement Learning

The recently enhanced AI manifold for retail marketing omni channels developed to target marketing techniques based on customer profiling employs multi-armed bandit systems to manage marketing-focused ML algorithms that utilize reinforcement learning to continuously modify marketing approaches in real time. Reinforcement learning is a paradigm for solving complex problems through decision making, and often helps to provide real-time strategy augmentation based on market logic. The systems operate with an intelligent agent in a dynamically controlled environment that alters its selections based on the reactions that each decision yields. Q-learning or Deep Q-Networks enable users to find a proper ratio between applying new techniques and using those which have already proved to be effective, and navigate in an enormous space of machine strategy marketing structures. This method resolves all of the complex problems of instantaneous sales, longer-term customer value, brand value, or any combination of them. It efficiently manages primary responses which are non-linear customer responses with a variety of fixed choices to restructure depending on the instant changes in preferences of the market or the competitive automobile environment. Contextually, customer-focused marketing techniques beyond powerful recognition invoke new terms such as deep learning and artificial intelligence in marketing optimization through providing the right message at the right time, devoid of marketing clutter.

4.2. Multi-Target Optimized Channel Resource Allocation

The use of multi-objective optimization approaches for AI-driven omnichannel retail marketing is a wholly new concept. This model helps address the complex issue of how to optimize the allocation of marketing resources to multiple channels, each with numerous, often conflicting objectives. The use of advanced algorithms, whether genetic, particle swarm, or others, enables the system to effectively search the high-dimensional solution space for optimal Pareto allocations. Such allocations aim at achieving customer engagement, sales revenue, brand awareness, and marketing expenditures. The optimization procedures also consider the possible synergistic and cannibalistic effects of all the proportions, guaranteeing that all the proportions are supportive of a balanced approach to optimization. This enables retailers to more responsively adjust their channel mix according to market and customer needs as well as competitive activity, thus improving the efficiency and effectiveness of omnichannel marketing.

4.3. Figure Customer Value Evaluation Supported by the Neural Network

Evaluating customer worth with Graph Neural Networks support for the first time in omnichannel retail marketing is something novel. It has been noted that a Graph approach is powerful because it captures the complex interrelations of customers, products, and channels within the retail world. With customers as nodes and their connections as edges, GNNs are able to detect complex patterns of influence and behaviour which more often than not go undetected with conventional approaches. Using social connections, purchase history, and channel interactions, the network is trained to build relevant information within the customer's local network. This enables more accurate predictions for customer lifetime value, churn probability, and marketing response accuracy. GNN's approach also enables an organization to target profitable customer segments and advantageous nodes in the network, leading to improved omnichannel marketing efficiency.

4.4. Automated Abnormal Condition Detection and Risk Early Warning

Automated anomaly detection and risk warning systems are breakthroughs in the use of AI in omnichannel retail marketing. This kind of technology uses the newest machine learning methods, like Isolation Forests and Autoencoders, to scan and check all channels for real-time data continuously. The system detects patterns of normal behaviour for any given period and is capable of spotting any deviations which can equate to both risks and opportunities. These anomalies could include drastic changes in consumer behaviour patterns, changes in stock levels, or new market trends and activities from competitors. The system also encompasses assessing the magnitudes of impact of the anomalies and providing the appropriate marketing team with prioritised alert notifications. With automation, these prompt responses ensure that retailers can effectively manage issues, constrain risks, and seize elusive opportunities. With this automation, retailers can effectively monitor their complex omnichannel operations. Automated systems enable marketers to make timely marketing decisions whilst maintaining effectiveness regardless of the retailer dynamic.

5. Experimental Verification and Case Analysis

5.1. Experimental Design

Real-life case studies, along with controlled experiments, have been utilized in the A/B testing outline and are being used in an attempt to validate AI-driven omnichannel retail marketing. The experiment involves over 500 retail stores and their respective eCommerce outlets using a randomized controlled trial design. The AI-driven framework is implemented in half of the stores, where sales and engagement metrics are recorded, while traditional methods are utilized in the other half. In addition to sales revenue, customer engagement and marketing ROI, customer engagement rate, sales revenue, and revenue to marketing ratio are recorded for the six months in which the marketing framework is employed. Aside from the quantitative data collected, psychographic data is gathered through customer surveys and focus groups to assess their perception of the omnichannel experience. The robust approach taken towards assessing the framework fills gaps left by traditional testing methods.

5.2. Analysis of the Experimental Results

The information collected from the past six months demonstrates the profound effects the AI-powered omnichannel retail marketing effectiveness evaluation framework has proved to be remarkably impactful. The stores using the framework observed sales revenue growth of 23.7% relative to the control group. Other customer engagement metrics such as repeat purchase rate and average order value also improved by 18.5% and 12.3% respectively. The framework's adaptability and responsiveness also showed market fluctuations with holding costs of inventories decreasing by 31% and stock turnover rate increasing by 15.2%. It appeared through the time-series analysis that the AI-powered approach consistently outperformed the old-fashioned approach throughout the year. Marketing ROI for the experimental group increased by more than a quarter through efficient resource distribution and personalized marketing. Customers earned satisfaction scores from surveys and focus groups that improved by a little over 16%, while participants noted greater relevance to marketing messages and seamless cross-channel interactions as reasons behind the change.

Table 3.
Key Performance Metrics Comparison between Control Group and AI-Driven Framework

Metric	Control Group	AI-Driven Framework	Improvement (%)
Sales Revenue Growth	5.2%	28.9%	23.7%
Repeat Purchase Rate	22.3%	40.8%	18.5%
Average Order Value	$67.50	$75.80	12.3%
Inventory Holding Cost Reduction	3.1%	34.1%	31.0%
Stock Turnover Rate Increase	2.8%	18.0%	15.2%
Marketing ROI	1.8	2.3	27.6%
Customer Satisfaction Score	72.5	88.9	16.4%

As evident in Table 3, the AI-driven framework outperformed the control group across all measured metrics, with particularly impressive gains in inventory holding cost reduction and sales revenue growth. The comprehensive performance improvements demonstrated in Table 3 highlight the framework's effectiveness in enhancing various aspects of retail operations.

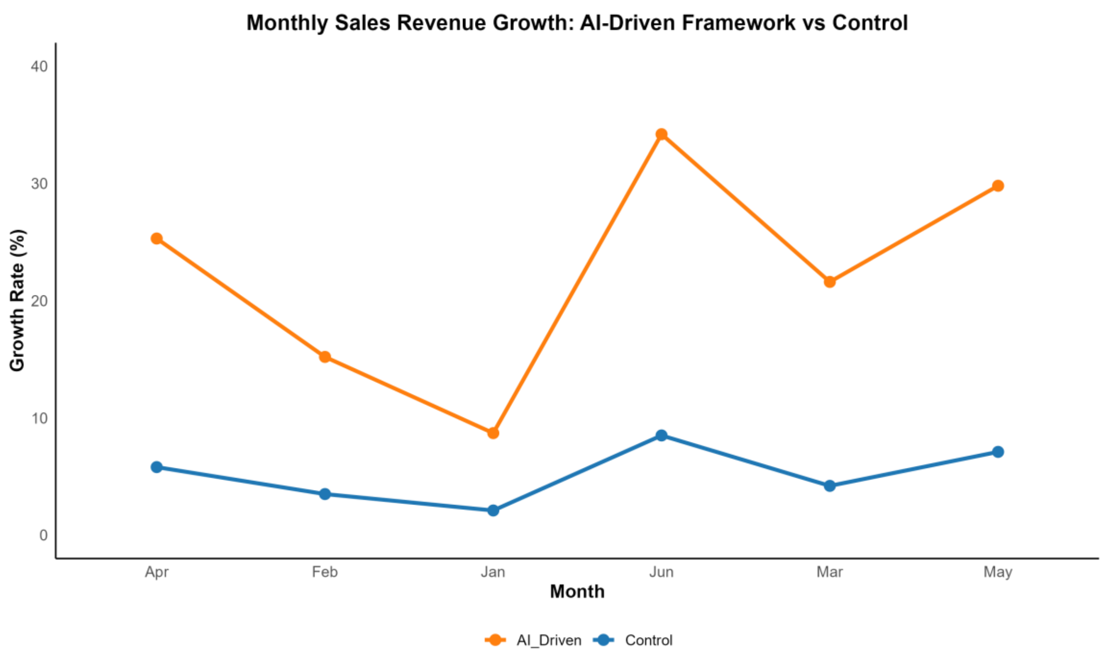

Figure 6.
Monthly sales revenue growth: ai-driven framework vs control.

Figure 6 shows how much more effective the AI-driven framework was at driving sales revenue growth compared to other strategies, over the six-month limit. The orange line that represents the AI-driven technique is nearly always higher than the blue line of the control group. The increase of the gap between lines demonstrates the performance difference became greater and greater as the months went on and the system got better at optimizing strategies. In figure 6, the AI-driven framework's performance greatly improved over the period that it was being tracked; however, there was a significant drop in performance in January followed by an extreme increase in performance in June. AI-driven strategies were able to achieve 34.2% growth while the non-AI-driven control group growth stood at 8.5%, proving just how effective the new omnichannel marketing technique was. Throughout the time period of the experiment, the month-by-month visual comparisons of the results showed sales performance tremendously improved with the framework.

5.3. Case study: Application of Large Retail Enterprises

An in-depth case study on the AI-powered omnichannel retail marketing effectiveness integration at Global Mart, a multinational retail company, offers some answers regarding its practical usage. This corporation operates a retail chain of more than 2000 stores located within fifteen countries and has an active e-commerce website; it incorporated the framework over a period of twelve months. The implementation process was divided into phases, beginning with a pilot programmed in three strategically significant markets followed by full-scale implementation. Global Mart's business performance level was profoundly impacted by the framework with varying outcomes. The accuracy in customer segmentation improved by 37%, translating to more precise marketing efforts and a subsequent 28% increase in campaign conversion rates. The adoption of reinforcement learning-based adaptive optimization achieved a 19% reduction in cost for marketing activities and simultaneously increased customer participation by 23%. The multi-objective channel resource allocation budget proved to be advantageous by achieving a 31% increase in the total return from marketing campaigns. Global Mart experienced an increase of 42% in the online to offline conversion rate due to the ability of the framework to facilitate integration of multiple distinct channels into a single customer journey. Implementation of the graph neural network approach for customer value evaluation empowered Global Mart to increase customer value amongst high-value customers by fifteen percent due to the possibility of identifying and targeting these customer segments.

Table 4.
Global Mart's Performance Metrics Before and After Framework Implementation.

Key Performance Indicator	Pre-Implementation	Post-Implementation	Improvement (%)
Customer Segmentation Accuracy	58%	95%	37%
Campaign Conversion Rate	3.2%	4.1%	28%
Marketing Spend Efficiency	$1.2M per 1% market share	$0.97M per 1% market share	19%
Customer Engagement Score	6.4/10	7.9/10	23%
Marketing ROI	2.3	3.0	31%
O2O Conversion Rate	7.5%	10.7%	42%
High-Value Customer CLV	$2,850	$3,278	15%

Table 4 provides a comprehensive comparison of Global Mart's key performance metrics before and after implementing the AI-driven framework. As evident in Table 4, improvements were observed across all measured indicators, with the most substantial gains in O2O conversion rate (42%) and customer segmentation accuracy (37%). The quantitative data presented in Table 4 underscores the framework's effectiveness in enhancing Global Mart's omnichannel retail marketing operations.

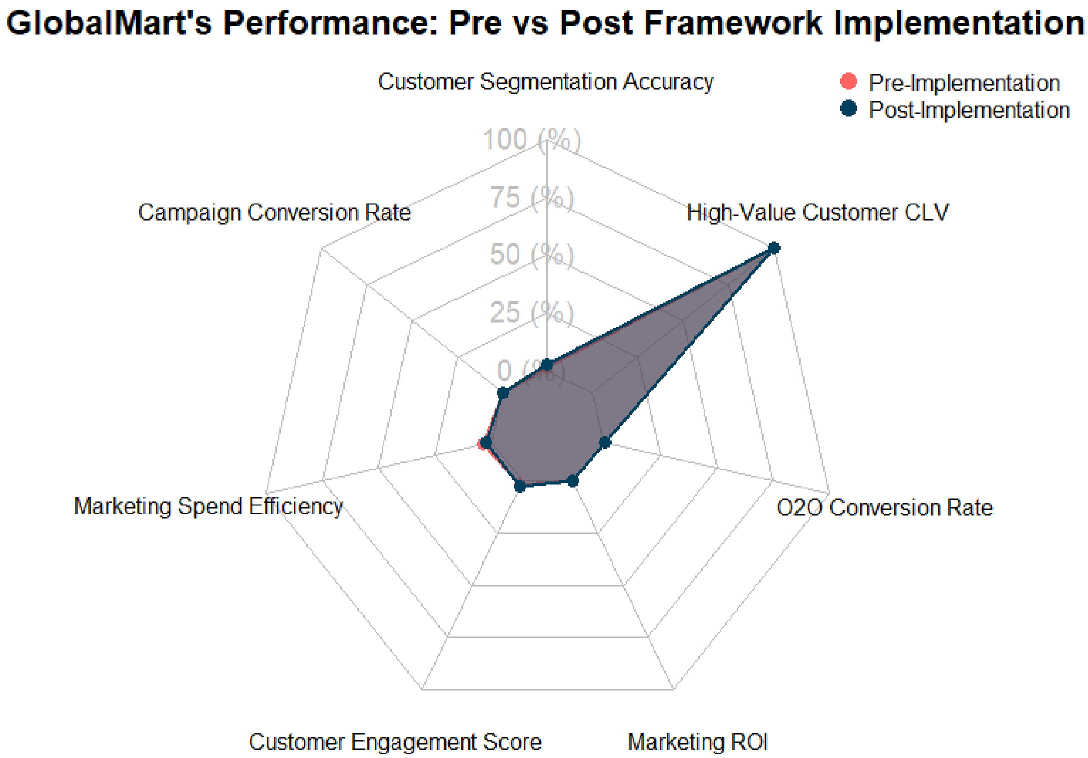

Figure 7.
Global Mart's performance radar chart: Pre vs post framework implementation.

In Figure 7, one can see the static and rotary performance metrics of Global Mart before and after the integration of the AI-powered omnichannel retail marketing effectiveness evaluation framework. The grey shaded area corresponds with performance after the implementation while the red dots capture the performance prior to the implementation. As demonstrated in Figure 7, it can be noted that the post-implementation polygon envelopes a greater span compared to the pre-implementation points, affirming visually the improvement across all metrics. The radar chart in Figure 7 reveals all the KPI metrics, with remarkable customer segmentation accuracy, O2O conversion rate, and marketing return on investments standing out from the rest. It can be seen in these diagrams, and therefore frames the strongest improvements observed post-implementation. Figure 7 illustrates that the greater area bound by the post-implementation polygon represents the framework's positive impacts on Global Mart's marketing effectiveness in omnichannel integration.

6. Conclusion

This study presents a novel AI-driven framework to measure the effectiveness of omnichannel retail marketing, thus offering retailers a powerful tool for optimizing their marketing strategy in an increasingly complex retail environment. By fusing disparate data sources, applying sophisticated AI techniques for end-to-end analysis, and leveraging cutting-edge methods like reinforcement learning for adaptive optimization, the framework shows significant potential for enhancing marketing performance. Empirical results show significant improvements in key performance indicators like sales revenue, customer engagement, and marketing return on investment, compared to traditional methods. The Global Mart case study further establishes the practical relevance of this framework in a real-world commercial setting, illustrating its ability to optimize marketing budget allocation, improve customer segmentation accuracy, and improve online-to-offline conversion rates. While the findings are encouraging, future research should explore the framework's flexibility across various retail subsectors and responsiveness to new technologies like augmented reality and the Internet of Things. Moreover, a more thorough evaluation of consumer privacy measures and data security within this AI-based framework is necessary. Overall, this framework represents an important breakthrough in the optimization of retail marketing, offering a data-driven approach to enhancing customer experience and enabling business growth in the digital age. As the state of artificial intelligence and big data technologies continues to evolve, this framework is well-positioned to shape the future of retail marketing strategies.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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References

[1] E. Aguirre, D. Mahr, D. Grewal, K. De Ruyter, and M. Wetzels, "Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness," *Journal of Retailing*, vol. 91, no. 1, pp. 34-49, 2015. https://doi.org/10.1016/j.jretai.2014.09.005

[2] K. L. Ailawadi, "Commentary: Omnichannel from a manufacturer's perspective," *Journal of Marketing*, vol. 85, no. 1, pp. 121-125, 2021. https://doi.org/10.1177/0022242920972639

[3] K. L. Ailawadi and P. W. Farris, "Managing multi-and omni-channel distribution: metrics and research directions," *Journal of Retailing*, vol. 93, no. 1, pp. 120-135, 2017. https://doi.org/10.1016/j.jretai.2016.12.003

[4] M. A. Akaka, S. L. Vargo, and R. F. Lusch, "The complexity of context: A service ecosystems approach for international marketing," *Journal of International Marketing*, vol. 21, no. 4, pp. 1-20, 2013. https://doi.org/10.1509/jim.13.0032

[5] B. Alexander and A. Kent, "Change in technology-enabled omnichannel customer experiences in-store," *Journal of Retailing and Consumer Services*, vol. 65, p. 102338, 2022. https://doi.org/10.1016/j.jretconser.2021.102338ouci.dntb.gov.ua

[6] N. Ameen, A. Tarhini, M. Shah, and N. O. Madichie, "Going with the flow: Smart shopping malls and omnichannel retailing," *Journal of Services Marketing*, vol. 35, no. 3, pp. 325–348, 2021. https://doi.org/10.1108/JSM-02-2020-0065

[7] N. Ameen, A. Tarhini, M. H. Shah, and K. Nusair, "A cross cultural study of gender differences in omnichannel retailing contexts," *Journal of Retailing and Consumer Services*, vol. 58, p. 102265, 2021. https://doi.org/10.1016/j.jretconser.2020.102265

[8] T. B. Anker, L. Sparks, L. Moutinho, and C. Grönroos, "Consumer dominant value creation: A theoretical response to the recent call for a consumer dominant logic for marketing," *European Journal of Marketing*, vol. 49, no. 3/4, pp. 532-560, 2015. https://doi.org/10.1108/EJM-09-2013-0518

[9] E. C.-X. Aw, N. K. Basha, S. I. Ng, and J. A. Ho, "Searching online and buying offline: Understanding the role of channel-, consumer-, and product-related factors in determining webrooming intention," *Journal of Retailing and Consumer Services*, vol. 58, p. 102328, 2021. https://doi.org/10.1016/j.jretconser.2020.102328

[10] J. Balakrishnan, C.-H. Cheng, K.-F. Wong, and K.-H. Woo, "Product recommendation algorithms in the age of omnichannel retailing–An intuitive clustering approach," *Computers & Industrial Engineering*, vol. 115, pp. 459-470, 2018.

[11] D. Ball, P. S. Coelho, and M. J. Vilares, "Service personalization and loyalty," *Journal of Services Marketing*, vol. 20, no. 6, pp. 391-403, 2006.

[12] M. Banerjee, "Misalignment and its influence on integration quality in multichannel services," *Journal of Service Research*, vol. 17, no. 4, pp. 460-474, 2014. https://doi.org/10.1177/1094670514539562

[13] N. Barwitz and P. Maas, "Understanding the omnichannel customer journey: Determinants of interaction choice," *Journal of Interactive Marketing*, vol. 43, no. 1, pp. 116-133, 2018. https://doi.org/10.1016/j.intmar.2018.02.001

[14] D. R. Bell, S. Gallino, and A. Moreno, "How to win in an omnichannel world," *MIT Sloan Management Review*, vol. 56, no. 1, pp. 45–53, 2014.

[15] B. Bickart and R. M. Schindler, "Internet forums as influential sources of consumer information," *Journal of Interactive Marketing*, vol. 15, no. 3, pp. 31-40, 2001. https://doi.org/10.1002/dir.1014

[16] M. Blázquez, "Fashion shopping in multichannel retail: The role of technology in enhancing the customer experience," *International Journal of Electronic Commerce*, vol. 18, no. 4, pp. 97-116, 2014. https://doi.org/10.2753/JEC1086-4415180404

[17] A. Bleier, A. Goldfarb, and C. Tucker, "Consumer privacy and the future of data-based innovation and marketing," *International Journal of Research in Marketing*, vol. 37, no. 3, pp. 466-480, 2020. https://doi.org/10.1016/j.ijresmar.2020.03.006

[18] A. Bodhani, "Shops offer the e-tail experience," *Engineering & Technology*, vol. 7, no. 5, pp. 46-49, 2012. https://doi.org/10.1049/et.2012.0512

[19] R. Bornschein, L. Schmidt, and E. Maier, "The effect of consumers' perceived power and risk in digital information privacy: The example of cookie notices," *Journal of Public Policy & Marketing*, vol. 39, no. 2, pp. 135-154, 2020. https://doi.org/10.1177/0743915618818570

[20] J. R. Brown, "A cross-channel comparison of supplier-retailer relations," *Journal of Retailing*, vol. 57, no. 4, pp. 3-18, 1981.

[21] Y. Bu, J. Parkinson, and P. Thaichon, "Digital content marketing as a catalyst for e-WOM in food tourism," *Australasian Marketing Journal*, vol. 29, no. 2, pp. 142–154, 2021. https://doi.org/10.1016/j.ausmj.2020.03.007

[22] Y.-J. Cai and C. K. Lo, "Omni-channel management in the new retailing era: A systematic review and future research agenda," *International Journal of Production Economics*, vol. 229, p. 107729, 2020. https://doi.org/10.1016/j.ijpe.2020.107729

[23] L. Cao and L. Li, "Determinants of retailers' cross-channel integration: An innovation diffusion perspective on omni-channel retailing," *Journal of Interactive Marketing*, vol. 44, no. 1, pp. 1-16, 2018. https://doi.org/10.1016/j.intmar.2018.04.003

[24] F. V. Cespedes and E. R. Corey, "Managing multiple channels," *Business Horizons*, vol. 33, no. 4, pp. 67–77, 1990. https://doi.org/10.1016/0007-6813(90)90060-7

[25] J. D. Chandler and S. L. Vargo, "Contextualization and value-in-context: How context frames exchange," *Marketing Theory*, vol. 11, no. 1, pp. 35-49, 2011. https://doi.org/10.1177/1470593110393713

[26] D. Chavarro, I. Ràfols, and P. Tang, "To what extent is inclusion in the Web of Science an indicator of journal 'quality'?," *Research Evaluation*, vol. 27, no. 2, pp. 106-118, 2018. https://doi.org/10.1093/reseval/rvy001

[27] J.-H. Cheah, X.-J. Lim, H. Ting, Y. Liu, and S. Quach, "Are privacy concerns still relevant? Revisiting consumer behaviour in omnichannel retailing," *Journal of Retailing and Consumer Services*, vol. 65, p. 102242, 2022. https://doi.org/10.1016/j.jretconser.2021.102242

[28] R. Chitturi, R. Raghunathan, and V. Mahajan, "Delight by design: The role of hedonic versus utilitarian benefits," *Journal of Marketing*, vol. 72, no. 3, pp. 48-63, 2008. https://doi.org/10.1509/jmkg.72.3.048

[29] Clarivate, "Web of science," Retrieved: https://clarivate.com/webofsciencegroup/solutions/web-of-science/, 2022.

[30] M. Cotarelo, T. Fayos, H. Calderón, and A. Mollá, "Omni-channel intensity and shopping value as key drivers of customer satisfaction and loyalty," *Sustainability*, vol. 13, no. 11, p. 5961, 2021. https://doi.org/10.3390/su13115961

[31] T. H. Cui *et al.*, "Informational challenges in omnichannel marketing: Remedies and future research," *Journal of Marketing*, vol. 85, no. 1, pp. 103-120, 2021. https://doi.org/10.1177/0022242920976893

[32] S. Cummins, J. W. Peltier, and A. Dixon, "Omni-channel research framework in the context of personal selling and sales management: A review and research extensions," *Journal of Research in Interactive Marketing*, vol. 10, no. 1, pp. 2-16, 2016. https://doi.org/10.1108/JRIM-12-2015-0094

[33] A. J. Dahl, G. R. Milne, and J. W. Peltier, "Digital health information seeking in an omni-channel environment: A shared decision-making and service-dominant logic perspective," *Journal of Business Research*, vol. 125, pp. 840-850, 2021.

[34] U. Damali, E. Secchi, S. S. Tax, and D. McCutcheon, "Customer participation risk management: Conceptual model and managerial assessment tool," *Journal of Service Management*, vol. 32, no. 1, pp. 27-51, 2021. https://doi.org/10.1108/JOSM-10-2019-0305

[35] T. Davenport, A. Guha, D. Grewal, and T. Bressgott, "How artificial intelligence will change the future of marketing," *Journal of the Academy of Marketing Science*, vol. 48, pp. 24-42, 2020. https://doi.org/10.1007/s11747-019-00696-0

[36] R. B. De Koster, "Distribution strategies for online retailers," *IEEE Transactions on Engineering Management*, vol. 50, no. 4, pp. 448-457, 2003. https://doi.org/10.1109/TEM.2003.820137

[37] P. Echeverri and P. Skålén, "Value co-destruction: Review and conceptualization of interactive value formation," *Marketing Theory*, vol. 21, no. 2, pp. 227-249, 2021. https://doi.org/10.1177/1470593120971524

[38] E. Eriksson, A. Norrman, and J. Kembro, "Understanding the transformation toward omnichannel logistics in grocery retail: A dynamic capabilities perspective," *International Journal of Retail & Distribution Management*, vol. 50, no. 8/9, pp. 1095-1128, 2022. https://doi.org/10.1108/IJRDM-10-2021-0508

[39] B. Ertimur and A. Venkatesh, "Opportunism in co-production: Implications for value co-creation," *Australasian Marketing Journal*, vol. 18, no. 4, pp. 256-263, 2010. https://doi.org/10.1016/j.ausmj.2010.07.004

[40] J. Fang, H. Liu, Y. Li, and Z. Cai, "Retaining customers with in-store mobile usage experience in omni-channel retailing: The moderating effects of product information overload and alternative attractiveness," *Electronic Commerce Research and Applications*, vol. 46, p. 101028, 2021. https://doi.org/10.1016/j.elerap.2021.101028

[41] J. Fernie and D. B. Grant, "On-shelf availability: The case of a UK grocery retailer," *The International Journal of Logistics Management*, vol. 19, no. 3, pp. 293-308, 2008. https://doi.org/10.1108/09574090810919168

[42] J. C. Fiestas and S. Tuzovic, "Mobile-assisted showroomers: Understanding their purchase journey and personalities," *Journal of Retailing and Consumer Services*, vol. 58, p. 102280, 2021. https://doi.org/10.1016/j.jretconser.2020.102280

[43] C. Flavián, R. Gurrea, and C. Orús, "Combining channels to make smart purchases: The role of webrooming and showrooming," *Journal of Retailing and Consumer Services*, vol. 52, p. 101923, 2020. https://doi.org/10.1016/j.jretconser.2019.101923

[44] W. Gao, W. Li, H. Fan, and X. Jia, "How customer experience incongruence affects omnichannel customer retention: The moderating role of channel characteristics," *Journal of Retailing and Consumer Services*, vol. 60, p. 102487, 2021. https://doi.org/10.1016/j.jretconser.2021.102487

[45] N. Gilliland, "14 examples of augmented reality brand experiences. Econsultancy," Retrieved: https://econsultancy.com/14-examples-augmented-reality-brand-marketing-experiences/, 2019.

[46] M. Greenwald, "Why NFTs and the metaverse can be so strategic for brands, even providing profitable new business models and revenue streams. Forbes," Retrieved: https://www.forbes.com/sites/michellegreenwald/2022/02/03/why-nfts-and-the-metaverse-can-be-so-strategic-for-brands-even-providing-profitable-new-business-models-and-revenue-streams/, 2022.

[47] D. D. Gremler, Y. Van Vaerenbergh, E. C. Brüggen, and K. P. Gwinner, "Understanding and managing customer relational benefits in services: a meta-analysis," *Journal of the Academy of Marketing Science*, vol. 48, pp. 565-583, 2020. https://doi.org/10.1007/s11747-019-00701-6

[48] D. Grewal, J. Hulland, P. K. Kopalle, and E. Karahanna, "The future of technology and marketing: A multidisciplinary perspective," *Journal of the Academy of Marketing Science*, vol. 48, no. 1, pp. 1-8, 2020. https://doi.org/10.1007/s11747-019-00711-4

[49] D. Grewal, R. Krishnan, and J. Lindsey-Mullikin, "Building store loyalty through service strategies," *Journal of Relationship Marketing*, vol. 7, no. 4, pp. 341-358, 2008. https://doi.org/10.1080/15332660802508402

[50] C. Grönroos, "Service logic revisited: who creates value? And who co-creates?," *European Business Review*, vol. 20, no. 4, pp. 298-314, 2008. https://doi.org/10.1108/09555340810886585

[51] C. Grönroos and P. Voima, "Critical service logic: making sense of value creation and co-creation," *Journal of the Academy of Marketing Science*, vol. 41, pp. 133-150, 2013. https://doi.org/10.1007/s11747-012-0308-3

[52] R. Hansen and S. K. Sia, "Hummel's digital transformation toward omnichannel retailing: key lessons learned," *MIS Quarterly Executive*, vol. 14, no. 2, pp. 51–66, 2015.

[53] C. E. Helfat *et al.*, *Dynamic capabilities: Understanding strategic change in organizations*. John Wiley & Sons. https://doi.org/10.1002/9781444311313, 2009.

[54] E. Hickman, H. Kharouf, and H. Sekhon, "An omnichannel approach to retailing: Demystifying and identifying the factors influencing an omnichannel experience," *The International Review of Retail, Distribution and Consumer Research*, vol. 30, no. 3, pp. 266-288, 2020. https://doi.org/10.1080/09593969.2020.1758198

[55] T. M. T. Hossain, S. Akter, U. Kattiyapornpong, and Y. Dwivedi, "Reconceptualizing integration quality dynamics for omnichannel marketing," *Industrial Marketing Management*, vol. 87, pp. 225-241, 2020.

[56] V. Hovelaque, L. G. Soler, and S. Hafsa, "Supply chain organization and e-commerce: A model to analyze store-picking, warehouse-picking and drop-shipping," *4OR*, vol. 5, no. 2, pp. 143-155, 2007. https://doi.org/10.1007/s10288-006-0013-5

[57] T.-L. Hsia, J.-H. Wu, X. Xu, Q. Li, L. Peng, and S. Robinson, "Omnichannel retailing: The role of situational involvement in facilitating consumer experiences," *Information & Management*, vol. 57, no. 8, p. 103390, 2020. https://doi.org/10.1016/j.im.2020.103390

[58] L. Huang, X. Lu, and S. Ba, "An empirical study of the cross-channel effects between web and mobile shopping channels," *Information & Management*, vol. 53, no. 2, pp. 265-278, 2016. https://doi.org/10.1016/j.im.2015.10.006