International Journal of Information Technologies and Systems Approach
Volume 18 • Issue 1 • January-December 2025

The Analysis of Product Marketing Strategy and Strategic Innovation in Market Segmentation Based on Deep Learning

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ABSTRACT

In order to evaluate the effects of a marketing strategy based on market segmentation, this paper compares four models: transformer, temporal convolutional networks, self-attention sequential recommendation, and the optimized model. In the experiment, six core indicators, such as customer conversion rate, market penetration rate, customer satisfaction rate, sales growth rate, brand awareness improvement, and customer retention rate, are scored and analyzed. Each indicator is divided into three dimensions and scored on a scale of one through five. The results show that the optimized model performs well in many dimensions. In the dimension of customer conversion rate, the scores of the optimized model in product attractiveness, marketing channel effect, and pricing strategy matching degree are four points, five points, and four points, respectively. In the dimension of market penetration, the optimized model scores five points, four points, and four points, respectively, in terms of market coverage, brand influence expansion, and competitive advantage establishment.

KEYWORDS

Brand Perception, Deep Learning, Market Segmentation, Marketing Strategy, Strategic Innovation

INTRODUCTION

In the face of intensifying global market competition and continuous technological advancements, companies are encountering unprecedented challenges and opportunities when developing product marketing strategies (Sudirjo, 2023; X. Wu et al., 2022). Traditional marketing approaches can no longer meet the ever-changing consumer demands and rapidly shifting market environments. As a result, more companies are adopting strategic innovations to navigate market uncertainties. In particular, the rapid growth of the digital economy has brought new consumer behavior trends, such as personalization, diversification, and dynamism. Consumers now gather information, express needs, and make purchasing decisions through multiple channels, including social media, e-commerce platforms, and mobile devices, within nonlinear and multi-scenario consumption pathways. This complexity and uncertainty present significant challenges to traditional market segmentation

DOI: 10.4018/IJITSA.384611

logic: the boundaries of consumer groups are increasingly blurred, demand structures are evolving rapidly, and static segmentation methods based on characteristics like age and gender can no longer accurately capture target customers. Meanwhile, the rapid development of artificial intelligence (AI) and deep learning technologies has provided companies with powerful tools, enabling the shift from “experience-driven” to “data-driven” marketing strategies (De Ruyter et al., 2022; Piranda et al., 2022). By mining vast amounts of consumer behavior data, deep learning can uncover potential consumption preferences, supporting more precise, dynamic market segmentation and personalized marketing. Furthermore, market segmentation is a crucial element of a company's marketing strategy, helping companies identify the distinct needs of various consumer groups and develop targeted product promotion strategies (Purnomo, 2023). In this environment, integrating strategic innovation, market segmentation, and deep learning has become a key path to enhancing market competitiveness and gaining consumer recognition.

Building on this, this study explores how deep learning can optimize market segmentation strategies and, in combination with strategic innovation logic, provide theoretical support and practical guidance for companies in constructing more accurate and efficient product marketing systems.

Research Objectives

By thoroughly examining the advantages of deep learning in data processing and consumer behavior analysis, this study develops a market segmentation model capable of accurately identifying the characteristics of different consumer groups. The proposed model aims to assist enterprises in better understanding their target markets and provides a data-driven foundation for formulating personalized marketing strategies.

This study investigates the role of strategic innovation in enterprise marketing and explores how deep learning technologies can be organically integrated with strategic innovation to enhance the scientific rigor and effectiveness of marketing decision-making. Through both theoretical analysis and empirical research, the study examines how deep learning can optimize market segmentation and marketing strategies.

Furthermore, the study advances the application of deep learning in the domain of personalized marketing by exploring how automated data processing and analysis technologies can provide more accurate predictions of consumer behavior. It aims to support personalized product recommendations and the optimization of marketing content, thereby improving customer satisfaction and strengthening brand loyalty.

LITERATURE REVIEW

In previous studies, Hancu and Modroiu (2022) proposed that market segmentation was the core of marketing strategy. By dividing the whole market into different consumer groups, enterprises can formulate targeted marketing strategies according to the unique needs of each group, thereby effectively improving marketing efficiency and customer satisfaction. Timoumi et al. (2022) showed that market segmentation can not only enhance the efficiency of enterprise resource utilization, but also help enterprises better identify and target potential markets, thus gaining an advantageous position in fierce market competition. They stressed that the accuracy of market segmentation determines the success or failure of a marketing strategy. Rivaldo and Amang (2022) found that the powerful capabilities of deep learning in large-scale data analysis provided a new tool for consumer behavior prediction and product recommendation in marketing. By handling complex nonlinear relationships, deep learning can help enterprises better understand consumer needs and make accurate predictions. Aripin et al. (2023) showed that deep learning models can automatically extract hidden patterns from data—especially in personalized marketing and real-time data processing—and demonstrated significant advantages, greatly improving marketing automation and the accuracy of marketing decisions. Alzoubi (2022) found that strategic innovation was a key factor for enterprises to maintain their competitive advantage in highly competitive markets. Through innovative marketing strategies, enterprises can quickly adapt to market changes and find a balance between differentiation and cost leadership strategies, thereby improving market performance. Kaur et al. (2022) showed that the core competitiveness of enterprises was closely related to strategic innovation. Through innovative marketing methods and strategic planning, enterprises can not only enhance brand awareness, but also seize opportunities in rapidly changing markets, thus enhancing marketing effectiveness.

With the rise of big data and AI technologies, scholars have increasingly focused on the dynamic nature of market segmentation. Nur and Siregar (2024) argued that static segmentation models are inadequate for adapting to the rapid changes in consumer behavior, and they recommended building an adaptive segmentation framework using real-time data streams and online learning mechanisms. They developed a sustainable user profiling system based on deep neural networks, which effectively enhanced the segmentation model's sensitivity and responsiveness to market changes. Additionally, Arif et al. (2024), in their research on smart retail, emphasized that dynamic market segmentation can enable more precise personalized marketing by capturing real-time user behavior data and adjusting customer classification standards accordingly. Their adaptive segmentation algorithm, which integrates reinforcement learning and convolutional neural networks, automatically optimizes segmentation strategies based on user feedback, significantly improving conversion rates and customer satisfaction.

Although numerous studies have demonstrated the importance of market segmentation in marketing strategy, previous research has primarily focused on traditional segmentation methods, such as those based on demographic data and behavioral characteristics. These methods often lack dynamism and cannot respond quickly to market changes or the rapid evolution of consumer demand. Moreover, many segmentation approaches rely on fixed, static data, making them unable to reflect the rapidly changing market environment and digital trends. In this study, deep learning technology is innovatively introduced into the field of market segmentation, and a dynamic, adaptive market segmentation model is constructed. This model can not only process large-scale data, but also make real-time adjustments based on changes in consumer behavior. It provides more accurate and dynamic segmentation results, thereby addressing the limitations of traditional segmentation methods, such as slow response and poor adaptability (Y. Wu & Liu, 2024).

RESEARCH METHODOLOGY

Target Market Selection and Positioning Based on Market Segmentation

Market segmentation refers to dividing the entire market into several sub-markets with common needs based on the differing characteristics of consumers. This approach helps enterprises meet the needs of various groups in a targeted manner while making efficient use of limited resources (Rahman & Nguyen-Viet, 2023). It enables businesses to identify their own competitive advantages within a complex and ever-changing market environment, thereby avoiding direct and broad-based competition with other firms across a large, undifferentiated market (Hanis & Yusuf, 2022; Saura et al., 2023). Market segmentation not only contributes to optimizing resource allocation and improving marketing efficiency, but also enhances customer satisfaction, thereby fostering brand loyalty (Sungkawati et al., 2023; Yusuf et al., 2022). Once segmentation is completed, enterprises must evaluate the various market segments and select the one with the highest potential as the target market. The principles guiding target market selection are outlined in Table 1.

Table 1. Principles of Target Market Selection

Principle	Analysis
Market scale	If the target market is too small or subdivided, it may be difficult for enterprises to obtain enough profits from it, resulting in a waste of resources (Amoako et al., 2022; Gunawan, 2022).
Market growth	A market with high growth means that it may bring more opportunities and profits in the future, so enterprises can gain a competitive advantage by entering the market at an early stage.
Competitive situation	If the competition in the target market is too fierce, it may be difficult for enterprises to gain significant market share.
Accessibility	In some markets, due to policy restrictions, technical requirements, or cultural differences, the entry cost of enterprises is too high and the risk is too high (Rachmad, 2022b; Z. Xu et al., 2022).
Matching and resource advantages	Enterprises need to evaluate whether they have unique resources or advantages in a specific market, can meet the needs of this market segment, and can differentiate themselves from competitors.

Once an enterprise selects its target market, the next step is to accurately position itself within that market (Istikomah et al., 2022; Nnaji et al., 2024). Target market positioning refers to the process by which enterprises communicate the unique value of their brands or products to consumers through a series of strategies and actions, thereby securing a distinct position in consumers' minds—one that differentiates them from competitors. The ultimate goal of positioning is to establish a unique brand image, enhance brand awareness, and build customer loyalty (Shi et al., 2022; Suherlan, 2023).

In the process of positioning the target market, enterprises first need to clarify their core competitiveness—that is, the unique advantages of the enterprise or its products compared with competitors. These advantages may include a combination of product quality, price, service, brand reputation, and other factors. Enterprises must select the most representative and attractive aspect as the core of their market positioning. They should formulate a clear value proposition based on the needs of the target market, clearly conveying to consumers why they should choose their products or services. The value proposition should clearly express the enterprise’s unique advantages, emphasize how the products or services meet the specific needs of consumers, and highlight the differentiation from competitors. When positioning in the market, enterprises need to thoroughly analyze competitors' positioning strategies and identify the differences between their own offerings and those of competitors. By comparing competitors’ market performances and brand positionings, enterprises can uncover market gaps and develop positioning strategies that distinguish them. For example, if competitors focus on the high-end market, enterprises may consider positioning themselves in the mid-range or budget segment to avoid direct confrontation. Ultimately, enterprises need to combine the characteristics of the target market with the competitive landscape to select the most appropriate positioning strategy.

Target market selection and positioning based on market segmentation are core steps in modern enterprise marketing strategy. Through in-depth analysis of different market segments, enterprises can identify the most promising market as their target and occupy a unique position through well-designed positioning strategies. Accurate market positioning not only helps enterprises stand out from the competition, but also enhances brand value and customer loyalty, thereby achieving long-term market success. Driven by digitalization and technological innovation, the integration of market segmentation and positioning with deep learning and other advanced technologies will further improve the accuracy and adaptability of marketing strategies (A. Xu et al., 2024).

Data Processing and Analysis of Deep Learning in Marketing

With the advent of the data-driven era, data has become a crucial resource for enterprises to formulate marketing strategies. In the vast and complex market environment, factors such as consumer behavior, market trends, and competitors' strategies are changing rapidly, making traditional marketing analysis tools insufficient (Lina, 2022). As a cutting-edge technology in the field of AI, deep learning offers innovative solutions for modern marketing with its powerful data processing and pattern recognition capabilities. Deep learning's data processing and analysis in marketing help enterprises extract valuable insights from massive datasets and make accurate predictions of consumer behavior and market decisions (Aripin & Yulianty, 2023). The data generated by modern marketing activities are diverse and complex, mainly including the following categories, as shown in Table 2.

Table 2. Data Types

Type	Analysis
Structural data	Such as sales data, customers' purchase history, click rate of websites, conversion rate of advertisements, etc. (Heryadi et al., 2023).
Unstructured data	Includes text comments on social media, customer feedback, pictures and video content, dialogue records between customers and customer service, etc. (Fachrurazi et al., 2022; Liu et al., 2022).
Time series data	Such as user behavior trajectory, consumer purchase frequency, market trend fluctuation, and other data; they show a specific law with the change of time (Azimovna et al., 2022).

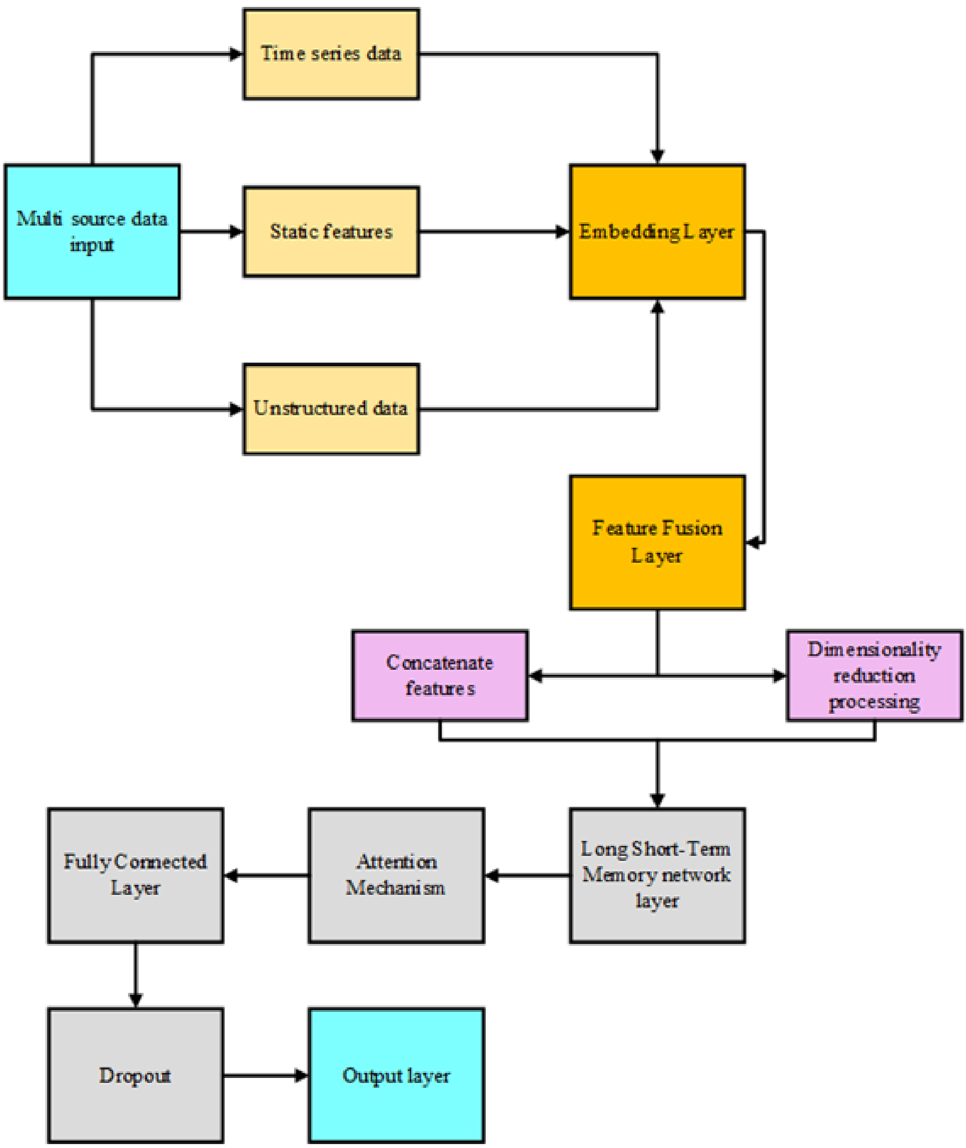
Deep learning models can automatically extract meaningful features from diverse data. Especially when dealing with complex unstructured data, traditional machine learning methods often require manual feature extraction, whereas deep learning can complete this process automatically through multi-layer neural networks, significantly improving the efficiency and accuracy of data processing (Rizvanović et al., 2023; Shaik, 2023).

Consumer Behavior Prediction Model Based on Deep Learning

The theory of dynamic capabilities emphasizes that, in rapidly evolving market environments, businesses must develop dynamic mechanisms to continuously identify opportunities, integrate resources, and reconfigure capabilities. Strategic innovation is a core element of this theory, requiring companies to consistently update their strategic direction and technological pathways to navigate external uncertainties and complexities (Nyagadza, 2022; Rauschnabel et al., 2022). In the model presented in this study, strategic innovation is reflected not only in the adoption of deep learning technologies as a form of technological advancement but also in the shift from "static segmentation" to "dynamic adaptation" in segmentation logic. The model adjusts segmentation structures based on real-time data, demonstrating strategic flexibility. This flexibility embodies the "sensing—integrating—reconfiguring" process of dynamic capabilities: continuously sensing changes in consumer behavior via deep learning models, integrating historical and real-time data for pattern recognition, and adjusting segmentation strategies in real time to ensure precise responses (Leung et al., 2022). Both theoretically and empirically, this process illustrates the practical value of strategic innovation in enhancing a company's market adaptability and competitiveness.

With the rapid development of big data and AI technologies, enterprises are increasingly relying on the accurate prediction of consumer behavior to inform their marketing strategies (Astini et al., 2022; Hicham et al., 2023; Wichmann et al., 2022). By understanding and anticipating consumer behavior, businesses can better formulate personalized marketing strategies, thereby improving customer conversion rates and satisfaction (Haleem et al., 2022; Rachmad, 2022a). In this context, deep learning technology has gradually become a core tool for predicting consumer behavior due to its exceptional performance in large-scale data processing, pattern recognition, and predictive analysis (Erlangga, 2022; Keke, 2022; Muttaqien & Sulistyan, 2022). A consumer behavior prediction model based on deep learning equips enterprises with strong analytical capabilities, enabling them to detect potential consumption trends and behavioral patterns within complex market environments and to make data-driven decisions (Lopes & Casais, 2022). The structure of the proposed prediction model is shown in Figure 1.

Figure 1. Consumer Behavior Prediction Model



This study presents a consumer behavior prediction model based on a deep learning architecture that integrates multi-source data processing, embedding representation learning, feature fusion, and an attention mechanism. The model is designed to accurately capture user behavior trajectories and generate personalized predictions in real time. It comprises five primary stages: data input, feature processing, temporal modeling, attention mechanism, and prediction output. The model ingests heterogeneous data from e-commerce platforms, including time-series data, static features, and unstructured data. Categorical and sequential data are first transformed into low-dimensional dense vectors via embedding layers to facilitate streamlined downstream modeling. These vectors are then integrated into a unified representation through a feature fusion layer followed by dimensionality reduction to eliminate redundancy and enhance computational efficiency. The unified vector is subsequently fed into a long short-term memory (LSTM) network to model sequential behavior and capture long-term user dependencies (Ma et al., 2024). To improve the model's sensitivity to key behavioral signals, an attention mechanism is introduced. For instance, in a common "browse–add-to-cart–purchase" trajectory, standard LSTM models treat all actions equally, whereas the attention layer assigns greater weight to the "add-to-cart" step due to its higher predictive value, thereby enhancing both accuracy and interpretability.

To support flexible deployment, the model adopts a modular design, allowing adaptation to various hardware environments. For deployment in small and medium-sized enterprises or edge computing scenarios, the model can be optimized through lightweight strategies such as:

1. Knowledge distillation to train compact student models as substitutes for the full architecture.
2. Reducing embedding dimensions and LSTM units to lower memory consumption.
3. Converting the model to formats like open neural network exchange for efficient operation on low-power devices.

These optimizations ensure practical usability without compromising accuracy. To support seamless system integration, the model provides a standardized RESTful API interface, enabling smooth data exchange with CRM systems and marketing automation platforms. User behavior logs are extracted daily and processed through an extract–transform–load pipeline. The model's predictions—such as purchase intent scores, conversion probability labels, and activity level forecasts—can be directly utilized by CRM platforms for applications including customer segmentation, personalized recommendations, and real-time updates to dynamic marketing strategies.

The proposed model effectively combines the representational power of deep learning with the precision of attention mechanisms. Furthermore, it addresses practical challenges related to integration, deployment, and resource efficiency, making it highly applicable and scalable for real-world business environments.

EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

Datasets Collection, Experimental Environment, and Parameters Setting

The dataset used in this study is from the Alibaba Tianchi "Alibaba Cloud Recommendation Algorithm Competition." It consists of recommendation system data from a large-scale e-commerce platform provided by Alibaba and contains extensive user behavior information. Using this dataset, researchers can analyze user activities on the platform, including browsing, clicking, adding to favorites, adding to cart, and making purchases. This dataset is highly suitable for studies on consumer behavior prediction, recommendation systems, and other related experiments.

The following are user behavior types:

- Page view (pv): Approximately 84.5%

- Add to cart (cart): Approximately 5.6%
- Favorite (fav): Approximately 5.1%
- Purchase (buy): Approximately 4.8%
- Click: Merged into the page view category and not labeled separately

This distribution aligns with the typical "long-tail" pattern observed in real-world consumer behavior—characterized by high browsing frequency and low purchase conversion. It provides a realistic foundation for behavior prediction and conversion modeling. To ensure data quality and enhance the effectiveness of model training, the following preprocessing steps were applied:

1. Missing value handling: Records with missing critical fields (e.g., user_id, item_id) were removed to maintain data integrity.
2. Behavior filtering: Only major behavior types were retained. Behavior weights were adjusted based on task relevance—for example, emphasizing the transition from pv to buy in conversion prediction tasks.
3. Timestamp normalization: The timestamp field was converted to a standard datetime format to support the construction of user behavior sequences and time-based trend analysis.
4. User filtering: Users with fewer than five behavior records were excluded to reduce cold-start effects and prevent sparse data from skewing model training.
5. Item filtering: Items with no conversions during the observation period were removed to reduce noise and enhance model focus.
6. Data splitting: The dataset was chronologically divided into a training set (first seven days) and a testing set (last two days), ensuring temporal consistency between training and evaluation phases and improving the simulation of real-world deployment scenarios.
7. Feature construction: Each behavior record was enriched with fundamental features such as user identification, item identification, behavior type, and timestamp. These were later used to build sequential behavior vectors for model input.

The experimental environment was configured as follows: the processor was an Intel Xeon Gold 6248R (3.00 GHz, 24 cores) paired with an NVIDIA Tesla V100 GPU (32GB GDDR6). The system included 256GB of DDR4 memory, 2TB of SSD storage, and an ASUS ROG Zenith II Extreme Alpha motherboard. A wired network connection was used. The operating system was Ubuntu 20.04.5 LTS (64-bit), with Python 3.8.10 and TensorFlow 2.9.1 as the deep learning framework.

In the deep learning model developed for this study, parameter settings were carefully selected based on the characteristics of the dataset, model functionality requirements, and insights from relevant literature. The objective was to balance representational power and computational efficiency. At the input layer, the number of unique user and item identifications was set to 100,000 and 50,000, respectively, reflecting the dataset's scale and ensuring full coverage within the embedding layer. The embedding vector dimension was set to 128—a commonly adopted size in behavior prediction and recommendation systems—offering sufficient representational capacity while keeping the parameter size manageable to reduce overfitting risk. Weights were initialized using the Glorot Uniform method to maintain stable variance across layers and accelerate convergence. L2 regularization with a coefficient of 0.001 was applied to the embedding layer, a well-established practice in recommender systems used to enhance generalization. In the attention mechanism module, the number of hidden units was set to 256 to strengthen the model's ability to extract informative features from user behavior sequences. A two-layer attention structure was adopted to strike a balance between expressiveness and training stability—avoiding underfitting from shallow architectures and computational instability from deeper ones. The ReLU activation function was used to mitigate vanishing gradient issues. A dropout rate of 0.3 and a recurrent dropout rate of 0.2 were applied to improve generalization and robustness, particularly in the sequential modeling layers. To preserve the full temporal dynamics of user behavior, the return_sequences parameter was set to true, enabling the model to retain hidden states across all time steps for downstream attention weighting and prediction aggregation.

The contrast models set in the experiment were the transformer model, temporal convolutional networks (TCN), and self-attention sequential recommendation (SASRec). Several advanced sequence modeling baselines were considered for comparison. The transformer is known for its multi-head attention mechanism and global modeling capability and excels in capturing long-range dependencies in consumer behavior. It is widely applied in e-commerce recommendation and dynamic user preference modeling. TCN replaces recurrent structures with dilated convolutions, offering efficient sequence modeling with improved parallelism and long-sequence handling. Its stability has been validated in tasks like clickstream prediction and sales forecasting. SASRec is a self-attention-based sequential recommendation model tailored for modeling short-term user interests and has demonstrated strong performance in personalized recommendation scenarios on platforms like Amazon. These three models were selected as technical baselines due to their demonstrated success in tasks closely aligned with this study's focus on consumer behavior modeling and dynamic market segmentation. They provide a robust benchmark for evaluating the proposed model's improvements in adaptive capability and behavioral prediction accuracy.

Traditional baseline models commonly used in the industry, such as recency, frequency, monetary and clustering algorithms, were not included for comparison in this study for two main reasons:

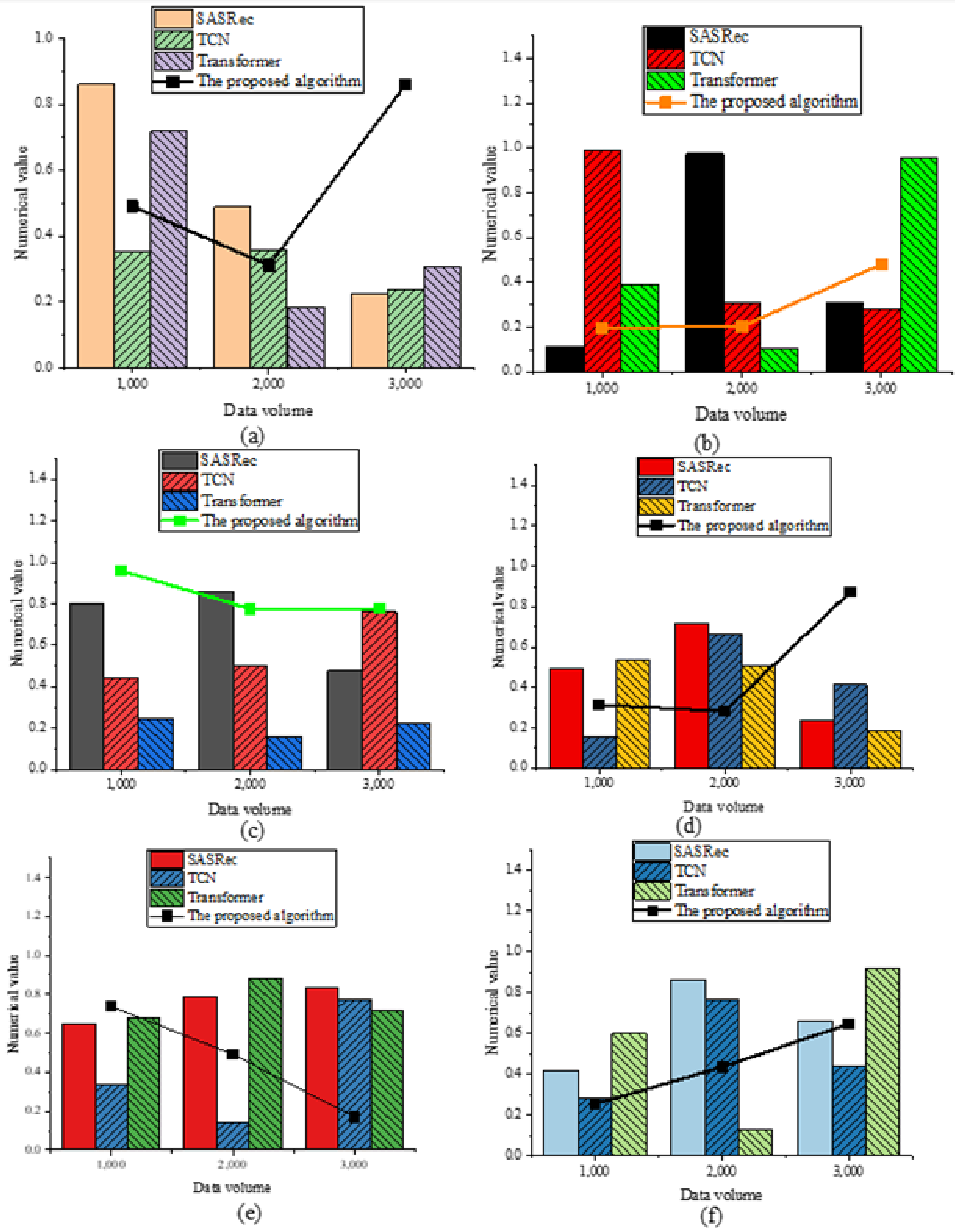
1. Differences in research focus: Traditional models rely on static attributes and are typically applied to infrequent segmentation tasks (e.g., monthly or quarterly customer grouping). They lack mechanisms for modeling continuous behavioral change and real-time feedback, whereas this study focuses on dynamic segmentation and real-time behavior prediction.
2. Differences in technical depth: Rule-based methods, while computationally inexpensive and easy to implement, lack the expressive power required for high-dimensional, multi-source behavioral data. In contrast, deep learning models excel at extracting complex features and modeling nonlinear behavior patterns. They support richer interactions among segmentation variables and offer superior scalability and adaptability.

Performance Evaluation

Model Performance Comparison Experiment

The metrics selected for comparison in the experiment include execution efficiency, computational complexity, data processing speed, memory usage, training time, and model stability. The experimental results are presented in Figure 2.

Figure 2. Performance Comparison Results



In Figure 2, in terms of execution efficiency, the proposed optimized model achieves scores of 0.719, 0.311, and 0.647 under different data volumes, respectively. Compared with other models, it exhibits higher efficiency under small data volumes and is slightly weaker under medium volumes but improves as the data volume increases. In terms of computational complexity, the model scores

0.540, 0.282, and 0.620, indicating relatively stable performance. Even with large data volumes, the model maintains low complexity, which is beneficial for handling more complex data scenarios. In contrast, the complexity of other models is higher under certain conditions, especially with medium data volumes, and some models show slight increases in complexity. Regarding data processing speed, the proposed optimized model records values of 0.248, 0.777, and 0.436, demonstrating excellent processing capability. Especially as data volume increases, the model maintains good performance, while other models show fluctuations under large data volumes. The memory occupation of the proposed optimized model is 0.540, 0.282, and 0.620 under different data volumes. Its memory usage is reasonable, and compared with other models, it demonstrates better resource management. With large data volumes, the memory usage of some other models increases significantly. In terms of training time, the proposed optimized model achieves scores of 0.681, 0.143, and 0.422 across the three data volumes. The training time changes in line with the increase in data volume, remaining relatively stable overall and capable of completing the training task within a reasonable time. Regarding stability, the proposed optimized model scores 0.599, 0.436, and 0.436, indicating good stability under varying data volumes. Compared with some models, it shows less fluctuation when handling large data volumes.

To further analyze the impact of data volume and sparsity on the effectiveness of market segmentation, this study conducted a comparative evaluation of segmentation accuracy across different data scales (1,000, 2,000, and 3,000 records) for both the optimized model and baseline models. The F1-score was used as the primary evaluation metric, as it balances precision and recall, with higher F1-scores indicating more accurate identification of potential segmented user groups. Subsets of varying sizes were randomly sampled from the original dataset while maintaining consistency in the distributions of users, items, and behavior types to control for experimental variability. The results are summarized in Table 3.

Table 3. F1-Score Comparison Across Data Scales

Model	1,000 Records	2,000 Records	3,000 Records
Transformer	0.612	0.677	0.698
Temporal Convolutional Network (TCN)	0.587	0.659	0.684
Self-Attention Sequential Recommendation (SASRec)	0.631	0.692	0.710
Proposed Model	0.665	0.728	0.753

As the volume of data increases, all models show improvements in F1-score, indicating that larger datasets significantly enhance the accuracy of market segmentation. However, with smaller datasets (e.g., 1,000 records), overall segmentation performance declines, highlighting the adverse impact of data sparsity on model effectiveness. Notably, the proposed model consistently achieves higher F1-scores across all dataset sizes. It demonstrates strong segmentation capabilities even in sparse, small-sample scenarios, outperforming the baseline models. These results confirm that both data volume and sparsity significantly influence segmentation outcomes and further underscore the proposed model's adaptability and robustness in handling limited, sparse data.

Effect Analysis of Marketing Strategy Based on Market Segmentation

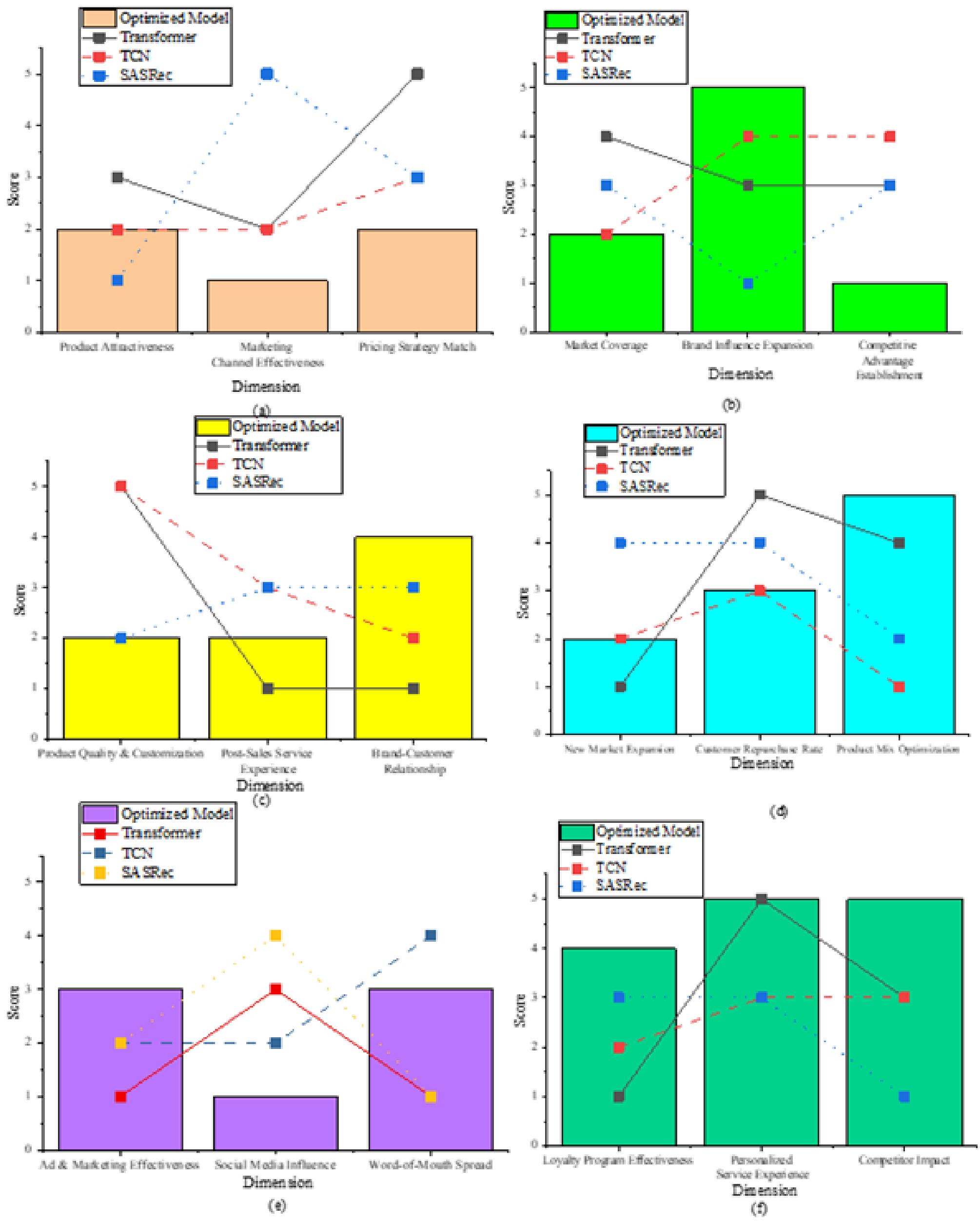
In this study, both the optimized model and the comparison models proposed marketing strategies based on the datasets, followed by an analysis of the effectiveness of these strategies. The evaluation dimensions include customer conversion rate, market penetration rate, customer satisfaction, sales growth rate, brand awareness improvement, and customer retention rate. The experiment employs a scoring system ranging from one to five.

Customer conversion rate is evaluated based on the proportion of users transitioning from browsing to purchasing, combined with changes in the number of actual buyers—greater improvements result in higher scores. Market penetration is measured by the ratio of newly acquired customers to the total potential customer base within the target segment; a higher increase corresponds with a higher score. Customer satisfaction is quantified through user feedback—such as ratings, sentiment analysis of reviews, and the proportion of positive responses—with more favorable feedback earning higher scores. Sales growth is assessed by comparing revenue before and after implementing the strategies, with larger increases indicating better performance. Brand awareness is evaluated based on growth in keyword search frequency and social media mentions; greater visibility results in a higher score. Customer retention is measured by changes in the retention rate of existing customers over a defined post-strategy period, with greater improvements leading to higher scores.

All evaluation scores are standardized based on actual data changes, without applying subjective weighting. Additionally, each of the six indicators is equally weighted in the final score to ensure objectivity and fairness.

A higher score indicates better performance in the corresponding indicator. The experimental results are shown in Figure 3.

Figure 3. Marketing Strategy Effectiveness



In Figure 3, the optimized model proposed in this study received a score of four in product appeal, five in marketing channel effectiveness, and four in pricing strategy alignment. This strong performance indicates the model's ability to accurately match personalized product combinations and pricing strategies to the needs of different market segments. For example, in recommendations targeting "price-sensitive user groups," the model prioritized discounted and high-value products, significantly increasing conversions from potential customers to actual buyers. In contrast, the TCN model scored only two points in marketing channel effectiveness, reflecting limitations in aligning with channel-specific delivery strategies. SASRec scored five points in pricing strategy alignment, demonstrating strong capability in delivering targeted recommendations. Regarding market penetration, the optimized model achieved scores of five, four, and four in the sub-dimensions of market coverage, brand influence expansion, and competitive advantage, respectively—indicating robust penetration capabilities. By analyzing user behavior characteristics such as active time windows and interest preferences, the model tailored push strategies for different segments. For instance, product lists pushed to "night-active" users focused on entertainment and leisure items, improving both reach and depth within these sub-markets. Although transformer scored four in market coverage, it earned only three in brand influence, revealing deficiencies in overall market penetration strategies. In the customer satisfaction dimension, the optimized model scored four, five, and four in product quality and personalization, after-sales service experience, and brand-customer relationship, respectively. Through precise segmentation-based marketing, the model was able to recommend personalized products aligned with consumer preferences and dynamically optimize after-sales service based on real-time behavioral feedback. For example, it automatically pushed service reminders to high-frequency buyers, effectively enhancing overall customer satisfaction. SASRec scored five in the brand-customer relationship sub-dimension, indicating strong capabilities in fostering emotional engagement. In terms of sales growth rate, the optimized model earned scores of five, four, and five in new market development, customer repurchase rate, and product portfolio optimization, respectively. By analyzing first-time purchase behavior among new users, the model recommended complementary items, increasing conversion in new markets. For portfolio optimization, the model mined co-purchasing patterns and designed bundled discount strategies (e.g., combo offers), effectively boosting sales revenue.

While transformer scored four in customer repurchase rate, it earned only three in new market development, suggesting weaker responsiveness to emerging segments. For brand awareness enhancement, the optimized model received scores of five, four, and four in advertising and marketing effectiveness, social media influence, and word-of-mouth promotion. The model developed differentiated promotional content based on platform preferences of segmented groups—for instance, pushing topic-driven advertisements to younger users and value-focused advertisements to mature audiences—thereby increasing brand exposure and engagement. TCN scored just three in word-of-mouth promotion, showing relatively weak performance, whereas SASRec scored five in social media influence, offering a competitive edge. In the customer retention dimension, the optimized model scored four, five, and four in loyalty program effectiveness, personalized service experience, and resistance to competitor influence, respectively. Based on segmentation tags, the model delivered tailored member benefits—such as exclusive discount coupons or personalized birthday gift recommendations for high-value customers—substantially enhancing retention intent and satisfaction. SASRec also scored five in personalized service, indicating strong customization capabilities, while transformer scored only three in loyalty program effectiveness, suggesting room for improvement in fostering long-term customer loyalty.

Key Feature Extraction and Model Interpretability Analysis

To enhance the interpretability of the proposed optimized model and address the common critique of deep learning models as "black boxes," this study integrates key feature importance analysis into the experimental framework. By combining attention weight distributions with feature attribution techniques, the analysis identifies the most influential input features in consumer behavior prediction, thereby increasing the transparency and credibility of the model's decision-making process. Specifically, an attention-based feature importance scoring method is employed alongside the local interpretable model-agnostic explanations approach to evaluate the contribution of each feature across different user behavior sequences. The feature set encompasses static user attributes (e.g., age, region), behavioral indicators (e.g., number of page views, add-to-cart actions, favorites, and purchases), temporal characteristics (e.g., active time periods), and product attributes (e.g., price range, category preferences). The top five features, ranked by their normalized importance scores, are summarized in Table 4.

Table 4. Feature Importance Scores

Rank	Feature Name	Importance Score (Normalized)
1	Number of Page Views	0.182
2	Number of Add-to-Cart Actions	0.164
3	Active Time Period	0.141
4	Product Price Range	0.132
5	Number of Favorites	0.118

The results indicate that the number of page views and add-to-cart actions are the most critical behavioral features influencing conversion prediction, as they reflect users' initial interest in products. The prominence of the active time period underscores the strong influence of temporal patterns on purchase intent, suggesting that marketing strategies should be synchronized with users' peak activity periods for more precise targeting. Furthermore, the importance of product price range and the number of favorites highlights distinct user preference patterns, offering practical guidance for developing pricing strategies and promotional recommendations. By incorporating key feature attribution analysis, this study effectively reveals the model's internal decision-making logic, thereby enhancing the transparency and interpretability of deep learning in market segmentation and consumer behavior prediction tasks. These insights ultimately provide businesses with more reliable and actionable support for real-world marketing decision-making.

DISCUSSION

From the overall data, there are obvious differences in the performance of different models in various indicators. The proposed optimized model is particularly outstanding in execution efficiency and data processing speed; especially in the case of a large amount of data, the processing speed remains efficient. In terms of memory occupation and computational complexity, the proposed optimized model also shows a good balance ability, which can reduce resource consumption while maintaining good computational performance. In contrast, other models are unstable in execution efficiency and processing speed, with some experiencing decreased processing capacity as the data volume increases. Additionally, memory usage and computational complexity fluctuate greatly among models, with some requiring long training times, indicating performance bottlenecks when dealing with large datasets.

The performance of the proposed optimized model is well balanced across all dimensions, particularly excelling in customer conversion rate and brand awareness. Its overall scores consistently range between four and five points, demonstrating strong competitiveness within the market segmentation strategy. Other models perform well in specific areas; for example, SASRec shows strengths in personalized service and social media influence but falls slightly short in other aspects. Overall, the optimized model better meets market demands by effectively driving customer conversion, enhancing brand influence, and maintaining customer loyalty.

CONCLUSION

Research Contribution

This study developed a consumer behavior prediction model that integrates deep learning with attention mechanisms from a market segmentation perspective. The model's performance was evaluated across six key metrics: customer conversion rate, market penetration, customer satisfaction, sales growth, brand awareness, and customer retention. Experimental results show that the optimized model consistently outperformed baseline models across all metrics, with particularly strong performance in customer conversion, brand awareness, and customer retention. These findings demonstrate the model's effectiveness in market segmentation and its potential to support comprehensive, data-driven marketing strategies. By dynamically modeling user behavior and identifying fine-grained customer segments, the model enhances both conversion rates and customer loyalty. For example, an e-commerce platform targeting highly active users with low purchase frequency implemented the model. Through personalized coupons and product recommendations, the platform significantly increased both conversion and repeat visit rates, validating the model's practical value in real-world retail environments. Moreover, the model demonstrated strong adaptability in complex, behavior-sensitive sectors such as electronics, FMCG, and fashion.

Theoretically, this study confirms the effectiveness of deep learning in market segmentation and precision marketing while also extending the boundaries of traditional segmentation research. Unlike conventional approaches that rely on static demographic data, the proposed behavior-driven segmentation strategy emphasizes real-time responsiveness to shifting consumer behavior. By incorporating sequence modeling and attention mechanisms, the model enables dynamic segmentation adjustments, enriching marketing theory with new insights into dynamic market responses and the development of personalized segmentation systems.

In summary, the proposed model provides a precise, adaptive, and comprehensive solution for marketing decision-making in rapidly evolving markets. As data volumes continue to grow and consumer behavior becomes increasingly dynamic, deep learning–based, behavior-driven segmentation models will remain a vital tool for businesses seeking to improve customer conversion and enhance brand influence in segmented markets.

Future Works and Research Limitations

Although this study has made significant progress in analyzing the effectiveness of market segmentation-based marketing strategies, several areas remain for improvement and further research. First, while the optimized model performs well across multiple dimensions, its structure is relatively complex, leading to high computational resource consumption. This could result in efficiency bottlenecks, especially when handling large-scale data. Future research should focus on optimizing computational complexity, reducing memory usage, and shortening training times while maintaining predictive performance. One possible approach is to introduce lightweight model designs or to combine traditional machine learning methods with deep learning techniques to create hybrid models, enabling efficient and resource-conserving market segmentation and behavior prediction. Second, the study evaluates the model's effectiveness using six core metrics. While these cover essential aspects of market segmentation, the evaluation framework remains somewhat limited. Future research could expand the set of evaluation metrics to include customer lifetime value, marketing cost-effectiveness ratios, long-term behavioral changes, and other dimensions. This would offer a more comprehensive and dynamic assessment of segmentation strategy effectiveness, enhancing both the depth and breadth of the research. Additionally, the data used in this study is primarily from a single source, which may not fully capture biases arising from regional cultural differences or varying consumer psychological preferences. Consumer behavior can differ significantly across countries, regions, or cultural backgrounds, potentially impacting the applicability and effectiveness of segmentation strategies in diverse markets. Future studies should incorporate data sets from multiple regions and cultural contexts to validate the model, systematically analyze how cultural differences affect its adaptability, and develop differentiated optimization strategies for various markets. This would improve the model's generalizability and increase its value in international applications. In conclusion, future research should focus on three key areas: optimizing model efficiency, expanding the evaluation framework, and validating cross-cultural adaptability. These steps can enhance both the theoretical contributions and the practical application value of market segmentation-based marketing strategies.

COMPETING INTERESTS STATEMENT

The authors of this publication declare there are no competing interests.

FUNDING STATEMENT

This research was supported by the Study on Environmental Auditing, Environmental Governance, and Feedback Mechanism in Hunan Regions Under the Background of Implementation of "Three Highlands and Four Novelties" [grant number 24A0658].

PROCESS DATES

07, 2025
This manuscript was initially received for consideration for the journal on 04/22/2025, revisions were received for the manuscript following the double-anonymized peer review on 06/13/2025, the manuscript was formally accepted on 06/23/2025, and the manuscript was finalized for publication on 07/01/2025

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REFERENCES

Alzoubi, H. M., Alshurideh, M., Kurdi, B. A., Akour, I., & Azi, R. (2022). Does BLE technology contribute towards improving marketing strategies, customers' satisfaction and loyalty? The role of open innovation. *International Journal of Data and Network Science*, *6*(2), 449–460. DOI: 10.5267/j.ijdns.2021.12.009

Amoako, G. K., Dzogbenuku, R. K., Doe, J., & Adjaison, G. K. (2022). Green marketing and the SDGs: Emerging market perspective. *Marketing Intelligence & Planning*, *40*(3), 310–327. DOI: 10.1108/MIP-11-2018-0543

Arif, M., Ahmed, M. P., Al Mamun, A., Uddin, M. K., Mahmud, F., Rahman, T., & Helal, M. (2024). Dynamic pricing in financial technology: Evaluating machine learning solutions for market adaptability. *International Interdisciplinary Business Economics Advancement Journal*, *5*(10), 13–27. DOI: 10.55640/business/volume05issue10-03

Aripin, Z., Mulyani, S. R., & Haryaman, A. (2023). Marketing strategy in project sustainability management efforts in extractive industries: Building a reciprocity framework for community engagement. *Journal of Development and Community Service*, *1*(1), 25–38.

Aripin, Z., & Yulianty, F. (2023). A quantitative performance management framework to improve community economy through omnichannel supply chain: A case study in the banking and marketing industry. *Journal of Development and Community Service*, *1*(1), 15–24.

Astini, R., Harwani, Y., & Soelton, M. (2022). Insights into understanding sustainable marketing management. *ICCD*, *4*(1), 244–249.

Azimovna, M. S., Ilkhomovna, U. D., & Shokhrukhovich, U. F. (2022). The concept of marketing policy in trade and service enterprises. *Central Asian Journal of Innovations on Tourism Management and Finance*, *3*(8), 1–5.

De Ruyter, K., Keeling, D. I., Plangger, K., Montecchi, M., Scott, M. L., & Dahl, D. W. (2022). Reimagining marketing strategy: Driving the debate on grand challenges. *Journal of the Academy of Marketing Science*, *50*(1), 13–21. DOI: 10.1007/s11747-021-00806-x PMID: 34426711

Erlangga, H. (2022). Pharmaceutical business competition in Indonesia: A review. *Sys Rev Pharm 2020, 11*(10), 617–623.

Fachrurazi, F., Zarkasi, Z., Maulida, S., Hanis, R., & Yusuf, M. (2022). Increasing micro small medium enteprises activity entrepreneurial capacity in the field of digital marketing. *Jurnal Ekonomi*, *11*(3), 1653–1660.

Gunawan, I. (2022). Customer loyalty: The effect of customer satisfaction, experiential marketing and product quality. *Jurnal Manajemen Organisasi dan Industri, 1*(1), 35–42.

Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*, *3*(3), 119–132. DOI: 10.1016/j.ijin.2022.08.005

Hancu, G., & Modroiu, A. (2022). Chiral switch: Between therapeutical benefit and marketing strategy. *Pharmaceuticals (Basel, Switzerland)*, *15*(2), 240. DOI: 10.3390/ph15020240 PMID: 35215352

Hanis, R., & Yusuf, M. (2022). Applying a SWOT analysis approach to a Sharia marketing perspective at Alunicorn shops in Bandung. *Proceeding of the International Conference on Economics and Business, 1*(2), 653–670.

Heryadi, D. Y., Fachrurazi, F., Nurcholifah, I., & Yusuf, M. (2023). During the Covid-19 pandemic, marketing strategy analysis for crispy MSMEs "MA ICIH". *Jurnal Publikasi Ilmu Manajemen*, *2*(1), 184–201. DOI: 10.55606/jupiman.v2i1.1335

Hicham, N., Nassera, H., & Karim, S. (2023). Strategic framework for leveraging artificial intelligence in future marketing decision-making. *Journal of Intelligent Management Decision*, *2*(3), 139–150. DOI: 10.56578/jimd020304

Istikomah, I., Saputra, G. W., & Yusuf, M. (2022). Marketing mix strategy and financial capabilities in improving Sharia stock investment. *Journal of Applied Management and Business Administration*, *1*(1), 21–27. DOI: 10.59223/jamba.v1i1.4

Kaur, B., Gangwar, V. P., & Dash, G. (2022). Green marketing strategies, environmental attitude, and green buying intention: A multi-group analysis in an emerging economy context. *Sustainability (Basel)*, *14*(10), 6107. DOI: 10.3390/su14106107

Keke, M. E. (2022). The use of digital marketing in information transport in social media: The example of Turkish companies. *Transportation Research Procedia*, *63*(2), 2579–2588. DOI: 10.1016/j.trpro.2022.06.297

Leung, F. F., Gu, F. F., & Palmatier, R. W. (2022). Online influencer marketing. *Journal of the Academy of Marketing Science*, *50*(2), 226–251. DOI: 10.1007/s11747-021-00829-4

Lina, R. (2022). Improving product quality and satisfaction as fundamental strategies in strengthening customer loyalty. *Jurnal Mahasiswa Ekonomi & Bisnis*, *2*(1), 19–26. DOI: 10.37481/jmeb.v2i1.245

Liu, Q., Qu, X., Wang, D., Abbas, J., & Mubeen, R. (2022). Product market competition and firm performance: Business survival through innovation and entrepreneurial orientation amid COVID-19 financial crisis. *Frontiers in Psychology*, *12*(1), 790923. DOI: 10.3389/fpsyg.2021.790923 PMID: 35411208

Lopes, A. R., & Casais, B. (2022). Digital content marketing: Conceptual review and recommendations for practitioners. *Academy of Strategic Management Journal*, *21*(2), 1–17.

Ma, X., Li, Y., & Asif, M. (2024). E-commerce review sentiment analysis and purchase intention prediction based on deep learning technology. *Journal of Organizational and End User Computing*, *36*(1), 1–29. DOI: 10.4018/JOEUC.335122

Muttaqien, F., & Sulistyan, R. B. (2022). Product branding training model for MSMEs in Probolinggo Regency. *Innovation Business Management and Accounting Journal*, *1*(1), 24–28. DOI: 10.56070/ibmaj.v1i1.3

Nnaji, U. O., Benjamin, L. B., Eyo-Udo, N. L., & Etukudoh, E. A. (2024). A review of strategic decision-making in marketing through big data and analytics. *Magna Scientia Advanced Research and Reviews*, *11*(1), 84–91. DOI: 10.30574/msarr.2024.11.1.0077

Nur, M. F., & Siregar, A. (2024). Exploring the use of cluster analysis in market segmentation for targeted advertising. *IAIC Transactions on Sustainable Digital Innovation*, *5*(2), 158–168. DOI: 10.34306/itsdi.v5i2.665

Nyagadza, B. (2022). Search engine marketing and social media marketing predictive trends. *Journal of Digital Media & Policy*, *13*(3), 407–425. DOI: 10.1386/jdmp_00036_1

Piranda, D. R., Sinaga, D. Z., & Putri, E. E. (2022). Online marketing strategy in Facebook marketplace as a digital marketing tool. *Journal of Humanities. Social Sciences and Business*, *1*(3), 1–8.

Purnomo, Y. J. (2023). Digital marketing strategy to increase sales conversion on e-commerce platforms. *Journal of Contemporary Administration and Management*, *1*(2), 54–62. DOI: 10.61100/adman.v1i2.23

Rachmad, Y. E. (2022a). Social media marketing mediated changes in consumer behavior from e-commerce to social commerce. *International Journal of Economics and Management Research*, *1*(3), 227–242. DOI: 10.55606/ijemr.v1i3.152

Rachmad, Y. E. (2022b). The influence and impact of the money burning strategy on the future of startups. *Adpebi Science Series*, *5*(1), 56.

Rahman, S. U., & Nguyen-Viet, B. (2023). Towards sustainable development: Coupling green marketing strategies and consumer perceptions in addressing greenwashing. *Business Strategy and the Environment*, *32*(4), 2420–2433. DOI: 10.1002/bse.3256

Rauschnabel, P. A., Babin, B. J., tom Dieck, M. C., Krey, N., & Jung, T. (2022). What is augmented reality marketing? Its definition, complexity, and future. *Journal of Business Research*, *142*(3), 1140–1150. DOI: 10.1016/j.jbusres.2021.12.084

Rivaldo, Y., & Amang, A. (2022). Influence of marketing strategy, trust, and perception service quality of purchasing decisions. *Jurnal Manajemen dan Kewirausahaan, 2*(1), 99–103.

Rizvanović, B., Zutshi, A., Grilo, A., & Nodehi, T. (2023). Linking the potentials of extended digital marketing impact and start-up growth: Developing a macro-dynamic framework of start-up growth drivers supported by digital marketing. *Technological Forecasting and Social Change*, *186*(5), 122128. DOI: 10.1016/j.techfore.2022.122128

Saura, J. R., Palacios-Marqués, D., & Ribeiro-Soriano, D. (2023). Digital marketing in SMEs via data-driven strategies: Reviewing the current state of research. *Journal of Small Business Management*, *61*(3), 1278–1313. DOI: 10.1080/00472778.2021.1955127

Shaik, M. (2023). Impact of artificial intelligence on marketing. *East Asian Journal of Multidisciplinary Research*, *2*(3), 993–1004. DOI: 10.55927/eajmr.v2i3.3112

Shi, J., Yang, D., Zheng, Z., & Zhu, Y. (2022). Strategic investment for green product development and green marketing in a supply chain. *Journal of Cleaner Production*, *366*(7), 132868. DOI: 10.1016/j.jclepro.2022.132868

Sudirjo, F. (2023). Marketing strategy in improving product competitiveness in the global market. *Journal of Contemporary Administration and Management*, *1*(2), 63–69. DOI: 10.61100/adman.v1i2.24

Suherlan, M. O. O., & Okombo, M. O. (2023). Technological innovation in marketing and its effect on consumer behaviour. *Journal Name Missing*, *1*(1), 359. DOI: 10.61100/tacit.v1i2.57

Sungkawati, E., Novitasari, D. R., & Hamad, S. B. (2023). Viral marketing: Mixue the king of snow ice cream—How does this franchise affect the market? *Revenue Journal: Management and Entrepreneurship*, *1*(2), 142–150. DOI: 10.61650/rjme.v1i2.274

Timoumi, A., Gangwar, M., & Mantrala, M. K. (2022). Cross-channel effects of omnichannel retail marketing strategies: A review of extant data-driven research. *Journal of Retailing*, *98*(1), 133–151. DOI: 10.1016/j.jretai.2022.02.008

Wichmann, J. R., Uppal, A., Sharma, A., & Dekimpe, M. G. (2022). A global perspective on the marketing mix across time and space. *International Journal of Research in Marketing*, *39*(2), 502–521. DOI: 10.1016/j.ijresmar.2021.09.001

Wu, X., Zhang, F., & Zhou, Y. (2022). Brand spillover as a marketing strategy. *Management Science*, *68*(7), 5348–5363. DOI: 10.1287/mnsc.2021.4165

Wu, Y., & Liu, Q. (2024). A novel deep learning-based visual search engine in digital marketing for tourism e-commerce platforms. *Journal of Organizational and End User Computing*, *36*(1), 1–27. DOI: 10.4018/JOEUC.361716

Xu, A., Li, Y., & Donta, P. K. (2024). Marketing decision model and consumer behavior prediction with deep learning. *Journal of Organizational and End User Computing*, *36*(1), 1–25. DOI: 10.4018/JOEUC.336547

Xu, Z., Zhu, G., Metawa, N., & Zhou, Q. (2022). Machine learning based customer meta-combination brand equity analysis for marketing behavior evaluation. *Information Processing & Management*, *59*(1), 102800. DOI: 10.1016/j.ipm.2021.102800

Yusuf, M., Saiyed, R., & Sahala, J. (2022). SWOT analysis in making relationship marketing program. *Proceeding of the International Conference on Economics and Business, 1*(2), 573–588.

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