Attention-based deep learning model to improving multi-criteria decision-making for customer loyalty

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ABSTRACT

Understanding the factors that influence product loyalty is crucial for businesses to effectively attract and retain customers. This study suggests a novel approach to assess the importance and weight of criteria that lead to product loyalty by considering the Halo effect in customer decision-making. The suggested method utilizes an attention-based deep learning model to analyze customer feedback collected through the Net Promoter Score (NPS) scale, incorporating the insights of a large number of customers. The proposed method overcomes the limitations of traditional methods that rely on expert judgments or data mining, providing a more comprehensive and customer-centric perspective. By considering the Halo effect, which can lead to biased perceptions of product features, the method offers a more accurate assessment of criteria weights and their impact on product loyalty. A case study focusing on mobile phone selection and loyalty is conducted to explain the applicability and efficiency of the suggested method. The outcomes are compared with the NPS index and several common multi-criteria decision-making (MCDM) techniques. The findings highlight the superiority of the suggested method in capturing the complex relationships between criteria and product loyalty, surpassing the limitations of expert-based approaches and outperforming traditional MCDM methods. The suggested technique provides valuable insights for companies seeking to enhance customer loyalty and optimize product development strategies. However, it is important to acknowledge limitations related to the reliance on customer feedback and the contextual specificity of the results.

Keywords: *Attention mechanism, Deep learning, Halo effect, Net promoter score, Product loyalty.*

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1. INTRODUCTION

In the rapidly evolving landscape of economic globalization, businesses are grappling with heightened competition and economic pressures. As a result, Chief Executive Officers (CEOs) face the critical task of making strategic decisions that align with product development and cater to the specific needs of target customers (Chiu, Aghaloo, & Mohammadi, 2020; Hayati, Suroso, Suliyanto, & Kaukab, 2020). Traditionally, customer satisfaction has been regarded as a measurable tool that guides businesses in reaching their customers effectively. However, differing viewpoints have emerged among researchers regarding the importance of customer satisfaction versus customer loyalty, with some arguing that loyalty outweighs satisfaction, while others emphasize the role of satisfaction in driving loyalty (Jin & Lee, 2019; Kurniawan et al., 2021).

While customer satisfaction certainly contributes to customer loyalty, it alone is insufficient to secure a long-term commitment from customers. To cultivate true loyalty, businesses must consider a range of factors and adopt a comprehensive, long-term approach. Loyal customers not only make repeat purchases but also become brand advocates, spreading positive word-of-mouth and introducing the product to their networks (Gheibdoust, Gilaninia, & Taleghani, 2023; Kurniawan et al., 2021). They choose a product because of their genuine interest and connection with the business, rather than out of necessity. Thus, acquiring and retaining loyal customers becomes the ultimate goal for businesses seeking sustainable success (Dewi & Putra, 2021; Yildiz, Temur, Beskese, & Bozbura, 2020).

To effectively pursue customer loyalty, it is crucial to employ methods that measure and evaluate the underlying factors influencing loyalty. In the realm of research on customer satisfaction and loyalty, numerous studies have explored the question of what factors impact product loyalty. These studies often utilize techniques like structural equation modeling to investigate the indirect and direct effects of various components on customer satisfaction (Karakuş, 2023; Su, Wu, & Yen, 2021). However, real-world scenarios involve complex and multifaceted criteria that influence the assessment of customer satisfaction and loyalty toward a company's products. Relying on a single criterion is deemed inadequate and risky, necessitating the adoption of multi-criteria approaches to gain a better understanding of customer behavior (Kanyama, Nurittamont, & Siripipatthanakul, 2022; Torkzadeh, Zolfagharian, Yazdanparast, & Gremler, 2022).

For CEOs to make informed strategic decisions, it is imperative to identify the criteria that significantly impact customer satisfaction and loyalty. This knowledge empowers businesses to develop future products and tailor strategies that resonate with their target market. In recent years, various multi-criteria decision-making (MCDM) methods have emerged as effective tools for evaluating these factors (Koay, Cheah, & Chang, 2022; Romdonny, Lucky, & Rosmadi, 2019; Utz, Johanning, Roth, Bruckner, & Strüker, 2023). Examples include the best-worst method (BWM), the Halo effect using convolutional neural networks (HECON), a Step-wise Weight Assessment Ratio Analysis (SWARA), analytic hierarchy process (AHP), analytic network process (ANP), and base-criterion method (BCM) (Bhowani, 2020; Dekrita, Yunus, Citta, & Yamin, 2019; Dewi & Putra, 2021; Hayati et al., 2020; Karakuş, 2023; Liang, Chen, Ye, Lin, & Li, 2021; Singh, Pal, Chalotra, & Brar, 2022; Yildiz et al., 2020). These MCDM methods provide frameworks for determining the weight of criteria and have been successfully applied across different industries to evaluate the factors influencing customer loyalty and satisfaction (Jenneboer, Herrando, & Constantinides, 2022; Molinillo, Aguilar-Illescas, Anaya-Sanchez, & Carvajal-Trujillo, 2022).

MCDM methods face a fundamental challenge when it comes to estimating the weights of criteria: relying on expert judgments for intangible data. Expert judgments, especially in assessing complex factors like customer loyalty, can be a sophisticated task. Moreover, these judgments may not be generalizable from a detailed social situation to a larger customer base. Therefore, it is often more reliable and advisable to utilize customer feedback polls in studies aimed at evaluating the factors influencing customer loyalty (Kanyama et al., 2022; Khan, Salamzadeh, Iqbal, & Yang, 2022; Molinillo et al., 2022).

To transform data from customer loyalty polls into actionable customer insights, a high-efficient technique for data collection and analysis is required. One commonly employed method for assessing customer loyalty in companies is the net promoter score (NPS). NPS is broadly used across various industries as a means to measure customer loyalty. The NPS asks a simple question: "How likely is it that you would recommend product X to a friend or colleague?" Customers provide their responses on a scale of 0-10, where 0 signifies "not at all likely" and 10 represents "extremely likely." Respondents are then classified into three groups: detractors (scores 0-6), passives (scores 7-8), and promoters (scores 9-10) (Haseli et al., 2023; Manyanga, Makanyeza, & Muranda, 2022; Rivaldo, Kamanda, & Yusman, 2022). However, as mentioned before, customer loyalty is multidimensional and dependent on multiple criteria. So, asking a general question about recommending the product does not provide a comprehensive understanding of the reasons underlying customer loyalty. To address this limitation, NPS can be tailored to assess the willingness to recommend based on each specific criterion that affects the product, enabling a more nuanced analysis of loyalty factors. While this approach may be logical, it may not detect potential Halo effect errors in customer feedback (Chen & Ming, 2020; Chiu et al., 2020; Jin & Lee, 2019).

One critical factor that influences customer feedback is the Halo effect. Coined by Thorndike, the Halo effect is a common cognitive bias that affects individuals in various aspects of life. It refers to the tendency to form a positive impression of a product, company, brand, or person based on a specific attribute or a general positive feeling, which then impacts other judgments and evaluations (Jin & Lee, 2019; Levitt, Taylor Jr, & Norris, 2023). According to the Halo effect, individuals tend to make directional judgments about other features and cognitive aspects based on previous judgments, often overlooking negative attributes. For instance, research involving senior military officers rating soldiers on intelligence, appearance, management, loyalty, and trustworthiness revealed a significant impact of appearance on other attributes. A good-looking soldier was more likely to be evaluated as loyal, intelligent, and trustworthy, demonstrating the influence of the Halo effect (Byun, Duhan, & Dass, 2020; Haseli et al., 2023).

Furthermore, unhappiness with one specific product feature can spill over and result in overall unhappiness with the product, potentially overshadowing other positive features. This phenomenon can be compared to the domino effect, where a failure in one product aspect can cascade into failures in other areas. This effect distorts a proper analysis of the subject, making it essential to be mindful of its influence when interpreting customer feedback and making decisions based on it Jin and Lee (2019) and Byun et al. (2020).

In addition to the previous discussions, it is crucial to recognize that dissatisfaction with a single product feature can have a cascading effect, leading to overall dissatisfaction with the entire product. When customers encounter weaknesses in one aspect, it can color their perceptions and significantly influence their decision-making process. This phenomenon is similar to a domino effect, where a failure in one product feature may trigger dissatisfaction in other related features. The interdependence of these features underscores the importance of thoroughly evaluating all aspects of a product to ensure customer satisfaction (Frank, Chrysochou, Mitkidis, & Ariely, 2019; Jafarzadeh Ghoushchi, Ab Rahman, Raeisi, Osgooei, & Jafarzadeh Ghoushji, 2020; Jafarzadeh Ghoushchi, Memarpour Ghiaci, Rahnamay Bonab, & Ranjbarzadeh, 2022).

This effect distorts the proper analysis of the subject, often leading to biased evaluations. In the context of customer decision-making, the Halo effect can cause customers to prioritize certain criteria, such as brand recognition, and overlook other important factors. For example, when purchasing a mobile phone, some customers may focus heavily on the brand or operating system, which becomes the primary basis for their purchase decision. It is essential to recognize that customers may not always be consciously aware of this bias, highlighting the need to address and mitigate the Halo effect (Byun et al., 2020; Jin & Lee, 2019; Levitt et al., 2023).

From a business standpoint, the decision to purchase products like clothing, mobile phones, or cars involves various criteria. Sometimes, the influence of a brand can overshadow other criteria, leading customers to neglect to evaluate other essential factors. This does not diminish the importance of those other criteria; rather, it highlights the influence of certain criteria in driving purchase decisions. For instance, customers may prioritize a particular brand or operating system when buying a mobile phone, basing their decision primarily on these two criteria. In some cases, the distinction between criteria may be subtle, and customers themselves may not consciously recognize it. In such instances, the Halo effect manifests as the customer's inability to discern and differentiate between different criteria (Jafarzadeh Ghoushchi et al., 2020; Jin & Lee, 2019). In business scenarios, identifying the Halo effect and understanding which criteria are most susceptible to its influence is crucial for accurate and reliable evaluation of product criteria. Given that the cost of acquiring new customers far exceeds that of retaining existing ones, customer loyalty becomes an essential focus for companies. Customers may face challenges in independently evaluating the impact of each criterion on their loyalty to a product. Therefore, to effectively assess the factors affecting customer loyalty, decision-makers must consider the Halo effect in customer thinking to ensure a comprehensive and accurate evaluation process (Byun et al., 2020; Hayati et al., 2020; Levitt et al., 2023).

By acknowledging the Halo effect and its potential influence on customer decision-making, businesses can make informed strategic decisions that enhance customer loyalty. Addressing this cognitive bias enables a more reliable evaluation of product criteria and ensures that companies are catering to customers' true needs and preferences. With a deeper understanding of how the Halo effect operates, organizations can develop targeted strategies to effectively manage customer perceptions and foster long-term loyalty (Chen & Ming, 2020; Gheibdoust et al., 2023; Jin & Lee, 2019).

2. LITERATURE REVIEW

In a study conducted by Utz et al. (2023), the authors examined the difficulties encountered by electricity suppliers as they strive to maintain customer trust and loyalty during the shift towards renewable energy sources. One of the primary concerns highlighted in the research is the failure of suppliers to deliver on promises regarding the inclusion of green electricity in their offerings, resulting in a loss of trust among customers. This issue is further compounded by information imbalances, which not only worsen the erosion of trust but also generate feelings of ambivalence among customers, potentially leading them to switch to other suppliers. To mitigate these challenges, the researchers propose the implementation of a customer loyalty program that utilizes blockchain technology. Through a Design Science Research approach, the loyalty program was refined over four iterations and evaluation cycles. The study's findings indicate that the customer loyalty program effectively restores trust, reduces distrust, and resolves customer ambivalence by incorporating key features such as increased customer agency, provision of sufficient and verifiable information, improved usability, and unrestricted data access. By adopting such a program, electricity suppliers can address the trust deficit and cultivate customer loyalty during the transition to green energy. Haseli et al. (2023) proposed an innovative approach called the Halo Effect using Convolutional Neural Networks (HECON) to evaluate the weight of product loyalty criteria while accounting for the halo effect in customer decision-making. HECON utilizes a Convolutional Neural Network (CNN) model as a deep learning framework to derive more precise weights for the criteria. By collecting feedback from a large sample of customers through the Net Promoter Score (NPS) scale, the study determines the impact of each criterion on product selection and loyalty, taking into consideration the halo effect. Unlike conventional methods, which often overlook the halo effect when evaluating factors contributing to customer loyalty, the HECON method overcomes this limitation by harnessing the power of deep neural networks. The research includes two case studies that demonstrate the effectiveness and superiority of the HECON method compared to other approaches. The findings underscore the significance of considering the halo effect to comprehend customer behavior and align product development with customer preferences. Khoa, Oanh, Uyen, and Dung (2022) investigated the impact of service quality, trust, customer ethnocentrism, and perceived risk on customer loyalty. Employing a mixed-method approach, the study aimed to achieve its research objectives. Leveraging the growing popularity of machine learning in research, the findings indicated that trust, ethnocentrism, and service quality had a positive influence on customer loyalty. However, perceived risk had a negative effect on customer loyalty toward domestic products within the e-marketplace during the Covid-19 pandemic. The study also suggested managerial implications derived from the research outcomes. Delved into the airline industry, where customer satisfaction hinges on aligning passenger expectations with the airline experience. Given the pivotal role of airline service quality in acquiring and retaining customers, airlines are employing diverse strategies to enhance physical and social servicescapes. Though data analysis techniques are frequently employed for marketing insights, their application in the airline sector has historically centered on surveys, overlooking deep learning methods rooted in survey findings. This study has dual objectives. Firstly, it aims to establish the correlation between various factors influencing customer churn risk and satisfaction by analyzing airline customer data. Deep learning techniques were employed on survey data from primarily Korean airline users, a pioneering effort in this context. Secondly, the study explores the impact of the social servicescape, encompassing perspectives from cabin crew and aircraft passengers, on customer tendencies. Experimental findings revealed that incorporating human services considerations bolstered predictive model accuracy by up to 10% for customer churn risk and 9% for satisfaction prediction.

De Lima Lemos, Silva, and Tabak (2022) conducted a study centered on customer churn prediction in the banking sector, utilizing an extensive customer-level dataset from a major Brazilian bank. The study's unique value lies in leveraging this dataset's comprehensive historical client behavior attributes, which yielded fresh insights into key factors predicting future client churn. By subjecting numerous supervised machine learning algorithms to the same cross-validation and evaluation framework, a balanced comparison across algorithms was achieved. The research revealed that the random forests technique outperformed logistic regression, elastic net, k-nearest neighbors, decision trees, and support vector machines across various metrics. Notably, the investigation highlighted that customers with stronger institutional relationships, higher product engagement, and greater borrowing tendencies were less inclined to close their checking accounts.

Khanal et al. (2023) conducted research spotlighting Nepal's burgeoning fintech landscape, primarily driven by various fintech firms. Despite each organization's push to expand service usage, a comparative analysis of customer satisfaction remains vital. While numerous studies have assessed factors impacting customer satisfaction, fewer have delved into the machine learning dimension. Their study, rooted in the Theory of Planned Behavior (TPB), loyalty, investigates customer satisfaction, and compatibility within F1 Soft, a Nepalese fintech firm. By employing Principal Component Analysis (PCA) and Explainable AI (XAI), eight pivotal factors (loyalty intention, customer service, technology perception, ease of use, assurance, speed, compatibility, and firm's innovativeness) were identified as individual influencers of customer satisfaction. Utilizing Logistic Regression (LR) and Support Vector Machine (SVM), local interpretable model-agnostic explanation (LIME) and Shapley additive explanations (SHAP) shed light on the primary contributors. SVM and LR achieve training accuracies of 89.13% and 87.88% respectively, both identifying compatibility as a central factor. With insights into fintech's multidimensional impact on customer satisfaction, this study suggests integrating these factors into fintech systems to drive further process development.

Kilimci (2022) introduced a pioneering approach for predicting customer loyalty in mobile applications, employing sentiment analysis grounded in word embeddings, deep learning algorithms, and deep contextualized word representations. This study stands as the first to assess customer loyalty by analyzing user sentiments from their comments through deep learning, word embeddings, and contextualized word representation models. Various models including RNNs (Recurrent Neural Network), BERT (Bidirectional Encoder Representations from Transformers), DistilBERT (compact version of the BERT), LSTMs (Long Short-Term Memory), CNNs (Convolutional Neural Network), MBERT (Multilingual BERT), and RoBERT (A Robustly Optimized BERT Pretraining Approach) are utilized for classification, while GloVe, Word2Vec, and FastText serve for text representation. Through extensive experiments across seven datasets, the research underscores that sentiment analysis within mobile applications holds substantial potential as a predictive factor for customer loyalty.

Oh, Ji, Kim, Park, and del Pobil (2022) innovatively merged deep learning methodologies with the expectation-confirmation theory to unravel customer satisfaction dynamics in the realm of hospitality services. By leveraging customer hotel reviews, hotel details, and images, the study aimed to forecast satisfaction with hotel services. The outcomes demonstrated that the developed amalgamated model attained an impressive accuracy rate of 83.54%. Notably, the model's ability to predict dissatisfaction, as indicated by the recall value, saw a significant enhancement from 16.46% to 33.41%. With these findings in mind, the study provides pertinent implications for both the academic and managerial facets of the hospitality industry. Matuszelański and Kopczewska (2022) presented a contemporary and extensive methodology for predicting customer churn using an e-commerce retail store in Brazil as a case study. Their approach encompasses three key stages, integrating three distinct datasets: numerical order data, post-purchase textual reviews, and socio-geo-demographic census data. In preprocessing, text reviews are analyzed using methods like Dirichlet Multinomial Mixture, Latent Dirichlet Allocation, and Gibbs sampling to extract topics. The spatial analysis involves DBSCAN to identify urban/rural locations and analyze customer neighborhoods via zip codes. In modeling, machine learning techniques like extreme gradient boosting and logistic regression are applied and validated using area-under-curve and lift metrics. Employing explainable AI, including permutation-based variable importance and partial dependence profiles, aids in unraveling churn determinants. Key findings reveal that churn propensity is influenced by factors such as payment value, item count, shipping cost, product categories, customer demographics, and location. In contrast, churn propensity is not affected by population density, urban/rural classification, quantitative first-purchase reviews, or qualitative topic summaries.

Wei, Zhang, and Ming (2023) delved into the role of cultural traits in shaping the impact of attribute-level experiences on tourist satisfaction. Leveraging a Deep Learning algorithm, they introduced the Attribute-Level Sentiment Analysis Model (ASAM) to extract attribute-level experiences from online reviews. With a dataset of nearly 50,000 TripAdvisor reviews, the study empirically revealed that positive attribute-level experiences significantly impact the satisfaction of individualistic American tourists, while negative experiences influence the satisfaction of collectivist Chinese tourists. Additionally, the study uncovered that the type of attribute moderates the effect of perceived experiences on overall satisfaction. Notably, positive experiences with vertical attributes hold greater sway over American tourists, while negative experiences with horizontal attributes more profoundly affect Chinese tourists. This research enriches hospitality literature by deepening insights into cross-cultural factors influencing tourist satisfaction and offers valuable implications for enhancing tourist contentment.

Nilashi et al. (2022) explored the factors driving consumer purchases of smart home security systems within the Internet of Things (IoT) consumer market, characterized by a diverse range of smart home devices. Their study involved the development of a novel model, using data collected from customer reviews on Amazon.com. A comprehensive dataset of 12,678 reviews was analyzed to discern customer preferences when purchasing smart home security systems. Employing a novel approach, the study combined text mining, unsupervised clustering, and a neuro-fuzzy system. Latent Dirichlet Allocation (LDA) was utilized to extract factors from textual reviews, while the Expectation-Maximization (EM) technique was employed to segment customer preferences. The Adaptive Neuro-Fuzzy Inference System (ANFIS) was then utilized to establish the relationship between factors and customers' purchase intentions. The study demonstrated the efficacy of text mining in analyzing customer preferences via online reviews. Pal, Biswas, Gupta, Kumar, and Gupta (2023) focused on the rising demand for mobile health (mHealth) platforms, accelerated by the COVID-19 pandemic and the preference for contactless services. Despite this surge, the factors influencing user experiences and satisfaction on these platforms, as reflected in customer reviews, remain understudied. To address this gap, the researchers presented an empirical framework that delved into unmonitored user comments across prominent mHealth platforms.

Aldunate, Maldonado, Vairetti, and Armelini (2022) address a critical concern for both marketing scholars and service industry professionals—understanding the pivotal factors influencing customer satisfaction. Introducing an innovative approach, the study presents a unique framework designed to automatically analyze open-ended survey data and extract the drivers that underlie customer satisfaction. This is achieved using deep learning models tailored for natural language processing. Building on 11 well-established drivers recognized within marketing literature to shape customer experiences, the collected data is transformed into a multi-label classification challenge. This expert system not only facilitates the automated analysis of fresh data but also ranks the drivers based on their significance across diverse service industries. Furthermore, it delivers essential insights for practical applications. Experimenting with a dataset encompassing 25,943 customer survey responses, spanning 39 service companies across 13 distinct economic sectors, the study demonstrates the accurate identification of these drivers.

Rajesh et al. (2022) highlight the substantial advantages that digital social networking has brought to the tourism and hotel industries. By utilizing social big data and deep learning, these sectors have harnessed effective marketing strategies and improved customer preference estimation. Digital technology and social media have notably leveraged insights into human psychology, crucial for industrial success. The emergence of the Internet of Things (IoT) has opened doors for the hotel sector to elevate customer experiences while optimizing operational costs. Ratings are influenced by key factors including Value, Apartment, Location, Hygiene, Front Office, Facilities, Professional Service, Internet, and Parking. Traditional methods of predicting hotel ratings with limited accuracy have added complexity to rating assessments. Hence, this study employs efficient deep learning algorithms to analyze reviews, aiding customers in selecting optimal hotels. Multiple classification techniques, such as Convolutional Neural Network-based Deep Learning (CNN-DL) and Support Vector Machine Network-based Deep Learning, were employed to predict attributes. Drawing data from TripAdvisor, a prominent American database, the study reveals that the CNN-DL approach surpasses other methods in terms of classification accuracy and failure rates. The visual results generated can enhance the proposed model's efficacy and offer insights into response strategies, underscoring the academic and conceptual accomplishments of the study. While the research highlights the potential of IoT in the hotel industry, it suggests that there is untapped potential yet to be fully explored, as many researchers speculate about IoT's swift relevance to the hotel sector without fully acknowledging its expansive market implications. In this study, a novel attention-based deep learning (DL) method is proposed for assessing the weights of product loyalty criteria while taking into account the Halo effect in customer decision-making. With the increasing availability of big customer data, marketing departments are seeking effective approaches to extract hidden and unknown customer information. The objective of this research is to introduce a DL-based method that can identify the criteria with the greatest impact on customer loyalty for various segments of customers. The proposed method introduces an innovative approach to determine the influence level of each product criterion on customers' selection and loyalty, leveraging feedback from a large volume of customers and considering the Halo effect in their decision-making process. Recognizing the presence of the Halo effect in customers' thinking is crucial, as it shapes their perceptions and preferences. By integrating this understanding into the DL model, the method aims to provide insights into the criteria that play a significant role in driving customer loyalty. Assessing and identifying the factors and criteria that impact customer loyalty is a complex task that cannot be easily accomplished through a few simple questions posed to experts or customers, as traditionally done. Human thinking is intricate, and the Halo effect suggests that certain product criteria exert a subtle influence on customers' opinions. Analyzing these hidden dynamics requires the use of deep neural networks capable of uncovering and understanding the intricate relationships between criteria and customer loyalty.

By applying this attention-based DL method, companies can gain a deeper understanding of the underlying dynamics of customer loyalty and make data-driven decisions. This approach harnesses the power of big customer data and takes into account the Halo effect, offering a more comprehensive analysis of the factors influencing customer preferences. Ultimately, this research contributes to the development of advanced methodologies for understanding customer behavior and devising effective strategies to enhance customer loyalty.

The utilization of an attention-based deep learning method to evaluate product criteria and understand customer behavior holds significant potential for companies. This approach enables businesses to accurately identify and address customers' desires, thereby enhancing product development and driving customer satisfaction and loyalty. The main objective of this paper is to introduce a novel attention-based deep learning (DL) method that provides insights into the impact weights of individual product criteria on customer loyalty.

The proposed DL model takes into account the Halo effect, an important aspect of customer decision-making, to capture the subtle influences that shape customers' preferences. By incorporating an attention mechanism block, the model emphasizes the crucial parts of the input features that contribute to the Halo effect. This attention mechanism enables a more focused analysis of the factors that play a significant role in influencing customer decisions. This study makes several key contributions. Firstly, it introduces an attention-based deep learning method that enables the determination of the impact weights of each product criterion on customer loyalty. This provides valuable insights into the relative importance of different criteria in shaping customer preferences and behavior. Secondly, the model incorporates the Halo effect, which is crucial for understanding the hidden dynamics that influence customers' decisions. By considering this cognitive bias, the proposed method offers a more comprehensive analysis of customer behavior.

Moreover, the attention mechanism employed in the DL model enhances the accuracy of the analysis by focusing on the most important parts of the input features that contribute to the Halo effect. This attention mechanism enables a more precise evaluation of the factors that influence customer loyalty. Lastly, the paper includes a comprehensive comparison of the proposed model with existing analysis methods, demonstrating the accuracy and advantages of the suggested approach. This comparative analysis highlights the effectiveness and reliability of the attention-based deep learning method in capturing and understanding customer behavior.

This paper is structured as follows: Section 1 provides an introduction and overview of the research. Section 3 explains the framework and outlines the steps of the suggested method. In Section 4, a real-life case study is presented, focusing on the application of the suggested method to analyze customer feedback regarding mobile phone criteria and considering the impact of the Halo effect on customer loyalty. Section 5 conducts a comprehensive analysis of the outcomes achieved from the suggested method, comparing them with the results of the Net Promoter Score (NPS) index and five Multiple Criteria Decision Making (MCDM) methods. Finally, Section 6 concludes the paper by summarizing the findings and proposing directions for future research.

3. MATERIAL AND METHOD

This section provides a detailed explanation of the framework and the step-by-step process of our suggested method.

3.1. Suggested Attention-Based Deep Learning Model

Deep learning models have revolutionized the field of artificial intelligence and machine learning by enabling computers to learn and make decisions from complex and large-scale datasets (Ranjbarzadeh, Caputo, Tirkolaee, Ghoushchi, & Bendechache, 2022; Ranjbarzadeh, Zarbakhsh, Caputo, Tirkolaee, & Bendechache, 2022; Safavi & Jalali, 2022; Singh, Ranjbarzadeh, Raj, Kumar, & Roy, 2023). These models are designed to mimic the structure and function of the human brain, utilizing multiple layers of interconnected artificial neurons to process and extract meaningful representations from raw data. By automatically learning hierarchical features, deep learning models have achieved remarkable success in various domains, including computer vision, natural language processing, and speech recognition (Kasgari et al., 2023; Ranjbarzadeh, Bagherian Kasgari, et al., 2021; Ranjbarzadeh, Jafarzadeh Ghoushchi, et al., 2022; Ranjbarzadeh, Sadeghi, et al., 2023; Saadi et al., 2022; Tataei Sarshar et al., 2021).

Deep learning models have become increasingly important due to their ability to handle and extract insights from vast amounts of data. With the exponential growth of data in today's digital world, traditional machine learning models often struggle to capture intricate patterns and dependencies. Deep learning models, on the other hand, excel at handling complex data and discovering hidden patterns, leading to more accurate predictions and decision-making (Ranjbarzadeh, Jafarzadeh Ghoushchi, et al., 2023; Ranjbarzadeh, Tataei Sarshar, et al., 2022; Saadi et al., 2021; Safavi & Jalali, 2021).

In the context of our CNN-based model, we have developed a framework that accepts 12 input features related to mobile phone selection and loyalty. The model employs three convolutional layers, which are responsible for extracting relevant features from the input data. Each convolutional layer applies filters to the input features, capturing local patterns and spatial relationships.

The model architecture consists of three convolutional layers that are responsible for extracting key features from the input data. Convolutional layers utilize filters to scan and capture local patterns and spatial relationships within the input features. This allows the model to identify important characteristics and differentiate between different aspects of mobile-phone selection criteria.

After the first and second convolutional layers, we introduce an attention block. The attention mechanism serves as a crucial component in the model, as it allows the model to focus more on the relevant parts of the input features. By assigning different weights to different parts of the input, the attention block highlights the most significant information and helps the model capture the Halo effect and its influence on customer loyalty.

Following the attention block, two fully connected layers are employed to enable the model to learn complex relationships between the extracted features. These layers connect all the neurons from the previous layers and allow the model to analyze the interdependencies among the extracted features. The fully connected layers serve as a bridge between the convolutional layers and the final output layer.

The output layer of our model consists of 12 neurons, each corresponding to one of the input features. These neurons provide a quantitative measure of the importance of each input feature in influencing customer loyalty. The output values indicate the relative significance of each feature, allowing companies to prioritize their efforts and resources based on the most impactful criteria. The suggested Attention-Based deep learning model is demonstrated in Figure 1.

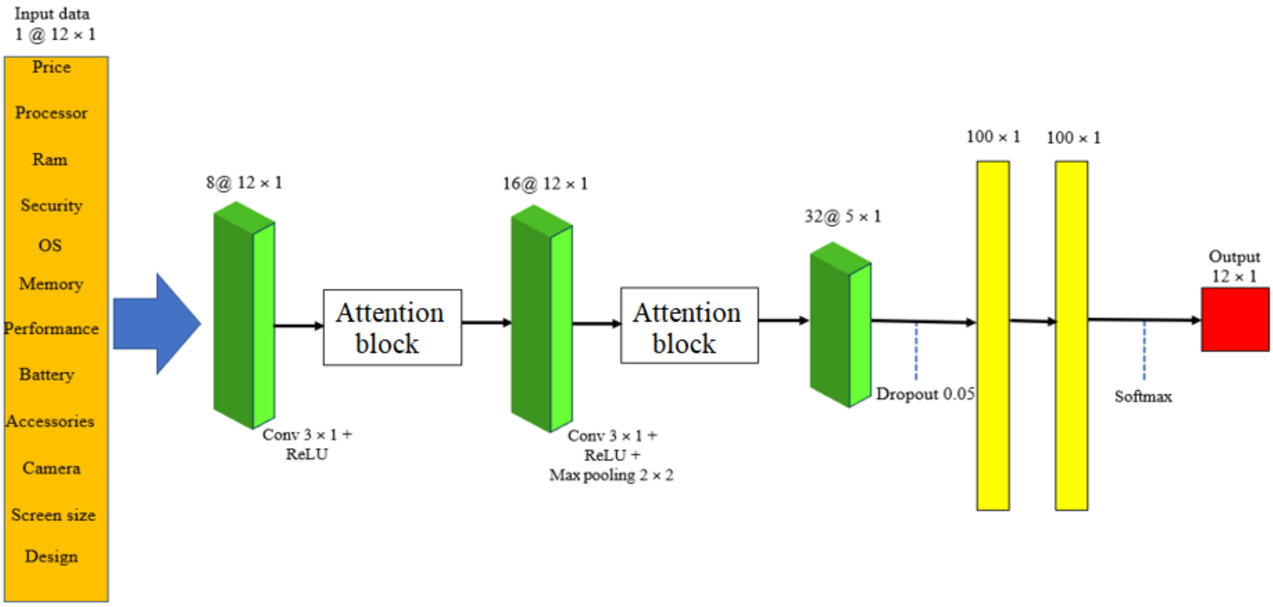

Figure 1. Illustration of the attention-based deep learning model to evaluate the loyalty of mobile attributes.

In addition to the previously mentioned architecture, we employ specific strategies and layer configurations to further optimize the model's capabilities.

Firstly, we utilize 3x1 kernels in the convolutional layers. These kernels have a narrow width but span the entire height of the input features. This configuration allows the model to capture local patterns and dependencies along the vertical axis of the features, which are particularly relevant in the context of mobile-phone selection criteria. To further downsample and summarize the extracted features, we apply max pooling after the second and third convolutional layers. Max pooling selects the maximum value within a predefined region, effectively reducing the spatial dimensions of the features while retaining the most important information. This pooling operation helps to capture the most salient features and discard irrelevant or redundant information (Ranjbarzadeh, Dorosti, et al., 2022; Ranjbarzadeh, Jafarzadeh Ghoushchi, et al., 2023; Ranjbarzadeh, Tataei Sarshar, et al., 2022).

In order to prevent overfitting and improve the model's generalization capabilities, we incorporate dropout regularization with a rate of 0.05 before the fully connected layer. The dropout randomly deactivates a fraction of the neurons during training, forcing the model to rely on a more robust representation of the input features. This regularization technique helps to prevent the model from relying too heavily on specific features and encourages a more diverse and reliable representation (Hu & Razmjooy, 2021; Razmjooy, Razmjooy, Vahedi, Estrela, & de Oliveira, 2021). Finally, the fully connected layer serves as the bridge between the convolutional layers and the output layer. It connects all the neurons from the previous layers and enables the model to capture complex relationships and interactions among the extracted features. The fully connected layer consolidates the learned representations and prepares them for the final prediction (Akhtar & Ragavendran, 2020; Shahzadi, Meriadeau, Tang, & Quyyum, 2019). A 3x1 kernel has a width of three and a height of one. It means that during the convolution operation, the kernel slides over the input features with a width of three and processes a vertical column of values at a time. This configuration allows the model to capture local patterns and relationships along the vertical axis of the input features.

Using a 3x1 kernel can be particularly effective when dealing with features that exhibit vertical dependencies or when there are specific patterns that are relevant to the task at hand. In the context of mobile-phone selection criteria, certain features may have vertical patterns or dependencies that are indicative of customer loyalty. By using a 3x1 kernel, our model can focus on these specific patterns and capture the relevant information. It's important to note that the kernel size can vary depending on the nature of the data and the specific task. Larger kernel sizes, such as 5x1 or 7x1, capture more global information and can be useful for detecting larger patterns or structures in the input. On the other hand, smaller kernel sizes, like the 3x1 used in our model, allow for more localized and fine-grained analysis (Alotaibi, Asghar, & Ahmad, 2021; Gore, Sinha, & Deshpande, 2022; Ranjbarzadeh, Tataei Sarshar, et al., 2022). By employing 3x1 kernels in our model, we aim to capture important patterns and dependencies within the input features related to customer loyalty. This choice of kernel size allows the model to extract meaningful information from the data and provide a comprehensive evaluation of the impact of each input feature.

The stochastic gradient descent technique is applied with the cross-entropy loss function for training the model. In the output layer of the model, 12 logistic units are utilized to calculate the probabilities of the given samples belonging to each of the 12 classes. The cross-entropy loss function is formulated as follows (Ho & Wookey, 2019; Hu et al., 2018; Li, Zhang, Huang, & Wang, 2020):

$$loss_i = -log\left(\frac{e^{U_p}}{\sum_{d=1}^{Q} e^{U_d}}\right) \quad (1)$$

Where $loss_i$ implies the loss for the i[th] samples, U_p is the unnormalized score for the true label (ground-truth) class P. The unnormalized score for each class is calculated based on the logits output by the model. The cross-entropy loss function compares the predicted probabilities with the true labels to measure the dissimilarity between them. By minimizing this loss function during the training process, the model learns to make more accurate predictions and improve its performance.

The learning process of our framework involves the utilization of various parameters to train the model effectively. These parameters play a crucial role in determining the performance and behavior of the framework. The following parameters are employed in the learning process (He et al., 2020; Li, He, & Jing, 2019; Mullissa, Marcos, Tuia, Herold, & Reiche, 2020; Novotna, Vicar, Hejc, & Ronzhina, 2021; Safavi & Jalali, 2021, 2022):

1. Learning rate: The learning rate determines the step size at which the model adjusts its weights during training. It controls the speed at which the model learns and converges to an optimal solution. A high learning rate may lead to overshooting, while a low learning rate may result in slow convergence. Finding an appropriate learning rate is essential for efficient training.
2. Number of epochs: An epoch refers to a single pass of the entire training dataset through the model. The number of epochs defines how many times the training process iterates over the entire dataset. Setting an appropriate number of epochs ensures that the model has sufficient iterations to learn the underlying patterns in the data without overfitting or underfitting.
3. Batch size: The batch size determines the number of training examples processed in each iteration before updating the model's parameters. A smaller batch size consumes less memory but may result in slower training, while a larger batch size accelerates the training process but requires more memory. Balancing the batch size is crucial for efficient training and memory utilization.
4. Loss function: The choice of loss function is crucial in guiding the learning process by quantifying the difference between the predicted and actual values. The selection of an appropriate loss function depends on the specific task and the nature of the data. Common loss functions include mean squared error (MSE), categorical cross-entropy, and binary cross-entropy.
5. Optimization algorithm: The optimization algorithm determines how the model's parameters are updated during training to minimize the loss function. Popular optimization algorithms include stochastic gradient descent (SGD), Adam, and RMSprop. Each algorithm has its own advantages and may perform differently depending on the specific problem.

6. Regularization techniques: Regularization techniques such as L1 and L2 regularization can be employed to prevent overfitting and improve the generalization ability of the model. Regularization adds a penalty term to the loss function, encouraging the model to learn simpler and more robust representations.

These parameters need to be carefully tuned to strike a balance between model performance, convergence speed, and generalization ability. Optimizing these parameters can significantly impact the effectiveness and efficiency of the learning process, resulting in a well-trained and accurate model. Table 1 presents the parameters utilized in the learning process of our framework.

Table 1. Parameters utilized to learn using our model.

Parameters	Value
Input (Case study)	12 Criteria
Output	12 Classes
Max epochs	120
Learning rate drop factor	0.05
Optimizer	Adam
Learning rate	0.001

3.2. Spatial Attention Block

In recent years, attention mechanisms have gained significant attention in the field of deep learning due to their ability to enhance model performance by focusing on important features or regions of the input. Attention mechanisms enable the model to selectively attend to relevant parts of the input and allocate more attention to informative features, while downplaying or ignoring less relevant information. This allows the model to prioritize and extract meaningful patterns, leading to improved accuracy and interpretability (Guo et al., 2022; Jain, Jain, Upadhyay, Kathuria, & Lan, 2020; Qu, Baghbaderani, Qi, & Kwan, 2020).

One of the key advantages of attention mechanisms is their ability to capture both local and global dependencies within the data. By attending to specific parts of the input, the model can learn to focus on fine-grained details, such as specific words in a sentence or individual pixels in an image, while still considering the broader context. This makes attention mechanisms particularly effective in tasks that require understanding and interpretation of complex relationships (Niu, Zhong, & Yu, 2021; Qu et al., 2020).

In our proposed model, we incorporate an attention spatial block that takes advantage of the attention mechanism. This block aims to further enhance the model's ability to focus on important features related to customer loyalty. Within this attention spatial block, we employ two pooling approaches: median pooling and max pooling. The median pooling is a method that calculates the median value of a set of numbers. It is a robust pooling technique that reduces the influence of outliers and extreme values, resulting in a more stable representation. By using the median pooling within the attention spatial block, our model can extract representative information from the input features while mitigating the impact of potential noise or outliers (Sun, Song, Jiang, Pan, & Pang, 2017; Zhou, Qu, & Cao, 2021). On the other hand, max pooling selects the maximum value from a set of numbers. It helps capture the most salient features within a given region, allowing the model to emphasize the most relevant information. By incorporating a max pooling within the attention spatial block, our model can identify the most important features related to customer loyalty (Chang et al., 2019; Yu, Wang, Chen, & Wei, 2014; Zhang, Zhang, Zhang, Wang, & Shi, 2019).

By combining both median pooling and max pooling approaches within the attention spatial block, our model can effectively attend to important features while considering the robustness of the data. This enhances the model's ability to capture the key patterns and relationships that influence customer loyalty, leading to more accurate evaluations of the impact of each input feature. The suggested Attention Spatial Block is demonstrated in Figure 2.

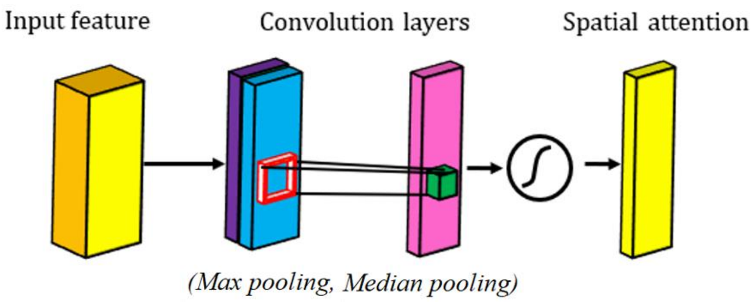

Figure 2. The suggested attention spatial block with median and max pooling.

3.3. Steps of the Suggested Technique

To determine the weight and impact of criteria on product selection and loyalty using our method, the following sequential steps need to be undertaken:

Step 1: Identify the target product(s) and relevant influencing criteria. In order to evaluate product selection and loyalty, it is essential for companies to identify the specific product(s) under consideration and the criteria that have an effect on customer decision-making. For instance, criteria like quality, price, and services are often influential factors in product selection and loyalty.

Step 2: Gather customer feedback on loyalty using the Net Promoter Score (NPS) scale for both the product and each criterion. To assess the weight and extent of the impact of criteria, it is necessary to collect customer feedback using the Net Promoter Score (NPS) scale. This scale allows customers to express their level of loyalty and likelihood of recommending both the product and each individual criterion.

Customers are asked to rate their likelihood of recommending the product and each criterion on a scale ranging from zero to 10. A score of zero signifies "not at all likely," while a score of 10 indicates "extremely likely." Gathering customer feedback through the NPS scale provides valuable insights into the perceived importance of each criterion and its influence on customer decision-making.

By actively seeking and analyzing customer feedback, companies can gain a comprehensive understanding of the weight and impact of criteria on product selection and loyalty. This information enables informed decision-making and empowers companies to enhance their products, improve customer satisfaction, and drive loyalty.

The NPS is a metric introduced to assess the level of customer loyalty. It measures customers' willingness to recommend a company or its products/services to others. The NPS is based on a simple question: "On a scale of zero to 10, how likely are you to recommend our company/product/service to a friend or colleague?" Customers are then categorized into three groups: Promoters (score 9-10), Passives (score 7-8), and Detractors (score 0-6). The NPS is calculated by subtracting the percentage of Detractors from the percentage of Promoters. This metric provides a concise and standardized way for organizations to gauge customer loyalty and identify areas for improvement, making it a valuable tool in assessing customer satisfaction and loyalty levels (Chiu et al., 2020; Haseli et al., 2023; Hayati et al., 2020; Liang et al., 2021).

To accurately assess the impact of criteria on customer loyalty, it is crucial for companies to collect customer feedback. One effective approach is to utilize the Net Promoter Score (NPS) scale, as shown in Figure 3, for evaluating each criterion and product.

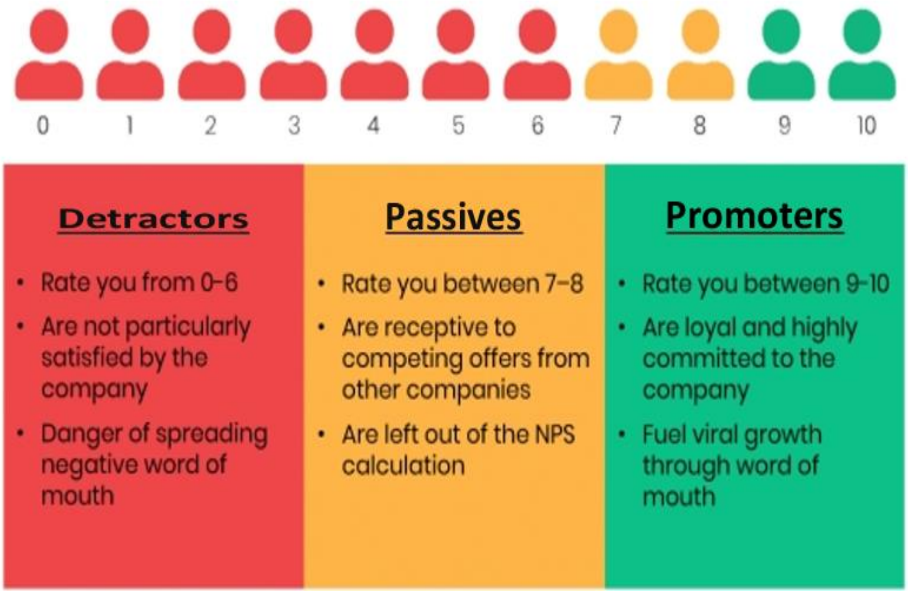

Figure 3. Net promoter scores.

Note: Haseli et al. (2023).

The NPS is defined as follows:

$$NPS = \left(\frac{\sum Promoters\ (rating \geq 9)}{Sample\ size} \times 100\right) - \left(\frac{\sum Detractors\ (rating \leq 6)}{Sample\ size} \times 100\right) \quad (2)$$

The NPS value can range from -100% to +100%. To calculate the NPS, respondents are grouped into three categories based on their rating (Haseli et al., 2023):

1. Promoters: These are customers who give a rating of nine or 10, indicating high satisfaction and a strong likelihood of recommending the product. Promoters are considered loyal customers and advocates for the brand.
2. Passives: These are customers who give a rating of seven or eight. They are generally satisfied but not enthusiastic enough to actively promote the product. Passives have a neutral impact on the NPS.
3. Detractors: These are customers who give a rating of zero to six, indicating low satisfaction and a low likelihood of recommending the product. Detractors are at risk of churning and may have negative word-of-mouth impact.

Step 3: Implement a attention-based deep learning model based on the number of product criteria.

To construct a Convolutional Neural Network (CNN) model that accommodates the number of product criteria, you need to tailor the architecture and input dimensions accordingly. The specific steps involved in building this model are as follows:

1. Determine the number of product criteria: Identify the total number of criteria that need to be considered for the evaluation. For instance, if there are 10 product criteria, the CNN model will be designed to process these 10 features.
2. Design the CNN architecture: Construct the architecture of the CNN model by incorporating appropriate layers and parameters. This may include convolutional layers, pooling layers, and fully connected layers, tailored to handle the input data and capture relevant patterns.
3. Define the input and output dimensions: Set the input dimensions of the CNN model based on the number of product criteria. This defines the shape of the input data that will be fed into the model.

4. Configure the model: Specify the configuration of the CNN model, such as the choice of activation functions, loss functions, and optimization algorithms. These choices will impact the learning process and performance of the model.
5. Train the model: Train the CNN model using suitable training data, adjusting the weights and biases to optimize its performance. This involves feeding the input data through the model, computing the loss, and updating the model parameters through backpropagation.
6. Evaluate and fine-tune the model: Assess the performance of the trained model by evaluating its predictions on validation or test data. If necessary, fine-tune the model by adjusting hyperparameters or modifying the architecture to enhance its accuracy and generalization capabilities.

By following these steps, you can construct a customized CNN model that accommodates the specific number of product criteria, enabling effective analysis and decision-making in your application.

The proposed attention-based deep learning model is utilized to determine the key factors for evaluating criteria that contribute to product loyalty. Through data mining techniques, the CNN-based model generates an output that assigns weights to each criterion based on its impact on product loyalty. The output layer of the model consists of 12 logistic units, which compute the probabilities of the input samples belonging to each of the 12 classes, representing different criteria. In contrast to 2D input samples, such as images, the dataset used in this research consists of 1D samples, which significantly reduces training and testing time. This is advantageous because traditional CNN models are typically memory-intensive and computationally expensive when trained on 2D input samples. By leveraging the 1D nature of the dataset, the suggested model achieves acceptable performance while mitigating the computational complexity associated with 2D CNN models.

4. DATA ANALYSIS

To demonstrate the practical application of the suggested framework, a real-world case study focusing on a large-scale decision-making problem is conducted. Specifically, this case study investigates the impact of various criteria on the selection and loyalty of customers towards a mobile-phone product.

This study presents a method that addresses various questions related to product loyalty evaluations. Specifically, the method aims to shed light on why customers exhibit loyalty towards certain products and which specific product criteria contribute to this loyalty. Additionally, it seeks to identify the product criteria that hold the greatest influence on customer loyalty. Furthermore, the study delves into understanding the role of the Halo effect in shaping customer loyalty. By employing our method, businesses can gain valuable insights into the factors that drive customer loyalty. The method allows for a thorough analysis of the underlying reasons behind customer loyalty, enabling companies to identify the specific product criteria that play a significant role in fostering customer loyalty. This information can be instrumental in guiding product development strategies and enhancing customer satisfaction and retention. Moreover, the method offers a means to assess the impact of various product criteria on customer loyalty. By quantifying the influence of different criteria, businesses can prioritize their efforts and resources towards the aspects that have the greatest potential to drive customer loyalty. This targeted approach helps optimize decision-making and resource allocation, leading to more effective strategies for customer retention and business growth. Furthermore, the study recognizes the importance of considering the Halo effect in customer loyalty evaluations. The Halo effect refers to the cognitive bias where customers' opinions and perceptions are influenced by specific attributes or general impressions of a product. By acknowledging and accounting for the Halo effect, our method provides a more comprehensive understanding of how customer loyalty is shaped and affected by various factors. This enables companies to make more accurate assessments and predictions regarding customer behavior and loyalty.

4.1. Case Study

In the real world, making a purchasing decision for a product, like a mobile phone can be a complex process influenced by various criteria. Understanding the factors that impact customer decisions and loyalty are crucial for companies. Once the key criteria affecting the selection of a mobile phone are identified, evaluating the impact of each criterion becomes essential. This knowledge enables companies to make informed strategic decisions regarding the development of their future products. It is important to consider the Halo effect, as it significantly affects human decision-making and evaluations. In this section, the application of the suggested method is demonstrated by measuring the effective criteria for mobile-phone selection while considering the Halo effect (Haseli et al., 2023).

The first step in the process involves identifying twelve criteria that have a significant influence on the selection and loyalty of a mobile phone. These criteria are carefully chosen based on their relevance and impact indicated in Figure 4. To determine the importance and impact of each criterion on the selection and loyalty of a mobile phone with a specific brand, customer feedback is gathered. Customers are asked to express their opinions and rate each criterion using the Net Promoter Score (NPS) scale.

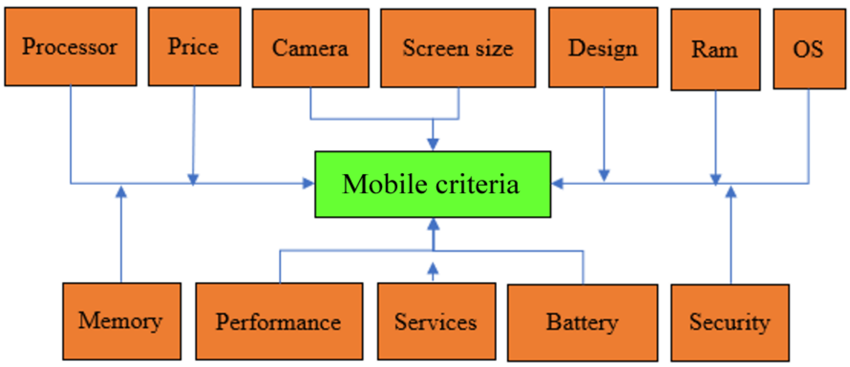

Figure 4. Different criteria for mobile phones.

In the subsequent step, customers were requested to provide feedback on the mobile phone and its associated criteria using the NPS scale framework. A total of 1,500 customers participated in the evaluation, with their responses collected using the NPS scale. The selection of these 1,500 customers was conducted randomly to ensure representativeness (Haseli et al., 2023). Detailed characteristics of the customers involved in this study can be found in Table 2.

Table 2. Profile of mobile customers.

Title	Category	Number
Gender	Female	637
	Male	863
Academic degree	Ph.D.	139
	M.Sc.	371
	B.Sc.	615
	Diploma	327
	Illiterate	48
Age	45 and up	168
	35-45	365
	25-35	521
	18-25	446

The summarized results of the data collected from customers based on the Net Promoter Score (NPS) scale for the mobile phone and its affecting criteria are presented in Table 3. This table provides an overview of the feedback and evaluations provided by the customers regarding the mobile phone and the specific criteria considered. The NPS scores indicate the customers' level of satisfaction and loyalty towards the mobile phone and its associated criteria. By analyzing the data in Table 3, insights can be gained into the customers' perceptions and preferences, which can further inform decision-making processes and product improvements.

Table 3. Attained values of NPS for mobile loyalty.

Attributes	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	…	C_{1500}
Memory	5	3	2	6	6	7	8	5	6	6	…	8
Camera	3	4	5	7	6	8	9	7	7	8	…	8
Design	8	7	9	9	10	10	9	7	10	9	…	9
Security	7	6	2	8	5	9	7	2	7	6	…	7
Performance	9	10	7	9	9	10	9	8	10	9	…	9
Processor	6	5	4	7	7	8	8	6	7	8	…	9
Ram	6	7	4	8	5	7	7	5	7	7	…	9
Battery	2	3	5	7	6	7	8	6	8	4	…	7
OS	8	7	5	9	7	9	8	6	8	6	…	8
Screen size	10	8	5	10	9	10	10	9	10	9	…	9
services	9	7	8	9	10	9	8	9	9	8	…	8
Price	7	5	2	7	7	9	7	4	9	7	…	9
Mobile phone	9	7	5	10	10	10	9	7	9	8	…	9

Note: *** indicates that attributes are in the range of [1-1500].

In the third step, our proposed model was utilized to determine the most significant factors for evaluating the criteria that drive product (Mobile phone) loyalty. The output of the data mining process, based on our suggested model, provided the weight assigned to each criterion that influences product loyalty.

To assess the performance of our pipeline, we employed three evaluation measures: Sensitivity, Accuracy, and Specificity. These measures are defined as follows (Mohammed, Hassaan, Amin, & Ebied, 2021; Ranjbarzadeh, Jafarzadeh Ghoushchi, et al., 2021; Ranjbarzadeh, Jafarzadeh Ghoushchi, et al., 2023; Rezaei, 2021):

1. Sensitivity: Sensitivity, also known as the true positive rate, measures the proportion of actual positive cases that are correctly identified by the model. It represents the model's ability to correctly detect and classify positive instances.
2. Accuracy: Accuracy refers to the overall correctness of the model's predictions. It calculates the proportion of correctly classified instances, regardless of whether they are positive or negative. A higher accuracy indicates a better-performing model.
3. Specificity: Specificity, also known as the true negative rate, measures the proportion of actual negative cases that are correctly identified as negative by the model. It represents the model's ability to correctly identify and classify negative instances.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100 \qquad (3)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \times 100 \qquad (4)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100 \qquad (5)$$

By utilizing these evaluation measures, we can assess the effectiveness and performance of our suggested pipeline in determining the importance of criteria for product loyalty.

According to the results presented in Table 4, the performance, memory, design, and operating system (OS) criteria have the highest impact on the selection and loyalty of customers towards the mobile phone studied in this case. These four criteria are considered crucial factors that significantly influence customers' decisions and perceptions of the product. The weight assigned to these criteria indicates that customers attach great importance to aspects such as performance, memory capacity, design aesthetics, and the quality of the operating system. These criteria play a significant role in shaping customers' opinions and determining their level of satisfaction and loyalty towards the mobile phone. For companies aiming to enhance customer loyalty to their products, it is essential to prioritize and focus on these high-weight criteria identified through our method. By paying close attention to the performance, memory, design, and OS aspects, companies can effectively meet customer expectations and requirements, thereby increasing customer satisfaction and fostering long-term loyalty. Understanding the significance of these criteria empowers companies to allocate resources and efforts to continuously improve and innovate in these areas. By consistently delivering excellent performance, optimal memory capabilities, attractive designs, and a user-friendly operating system, companies can strengthen their competitive position in the market and build strong relationships with their customers. The performance evaluation of our proposed CNN model is presented in Tables 4 and Table 5, showcasing the results obtained from its implementation.

Table 4. The results of the criteria weight obtained from our method. The important factors are demonstrated with *.

Mobile phone	Weight	Rank	Leads to loyalty
Battery	0.066	11	
Design	0.112	3	*
Processor	0.079	6	
Ram	0.062	12	
Security	0.070	8	
Camera	0.068	10	
Price	0.073	7	
Screen size	0.067	9	
Performance	0.116	1	*
OS	0.092	4	*
Services	0.081	5	
Memory	0.114	2	*
Sum	1.00		

Note: The most important factors are demonstrated by *.

Table 5. The results of the evaluation measures (Specificity, Accuracy, and Sensitivity) obtained from our database.

Technique	Specificity	Sensitivity	Accuracy
The proposed method	0.94	0.97	0.97

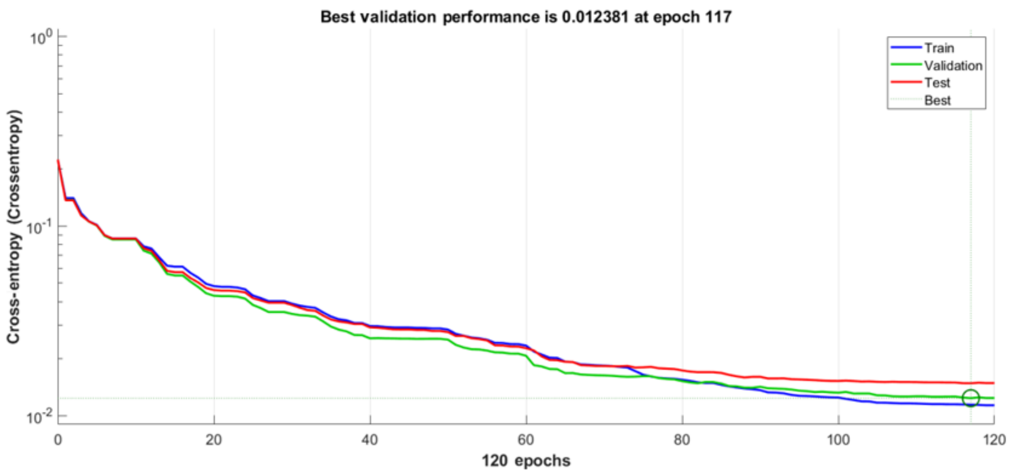

Figure 5. Evaluation of our method by epoch versus loss.

Figure 5 illustrates the evaluation of our proposed method using the epoch versus loss graph. This graph displays the loss achieved after each epoch during the training process, which was conducted over a total of 120 epochs.

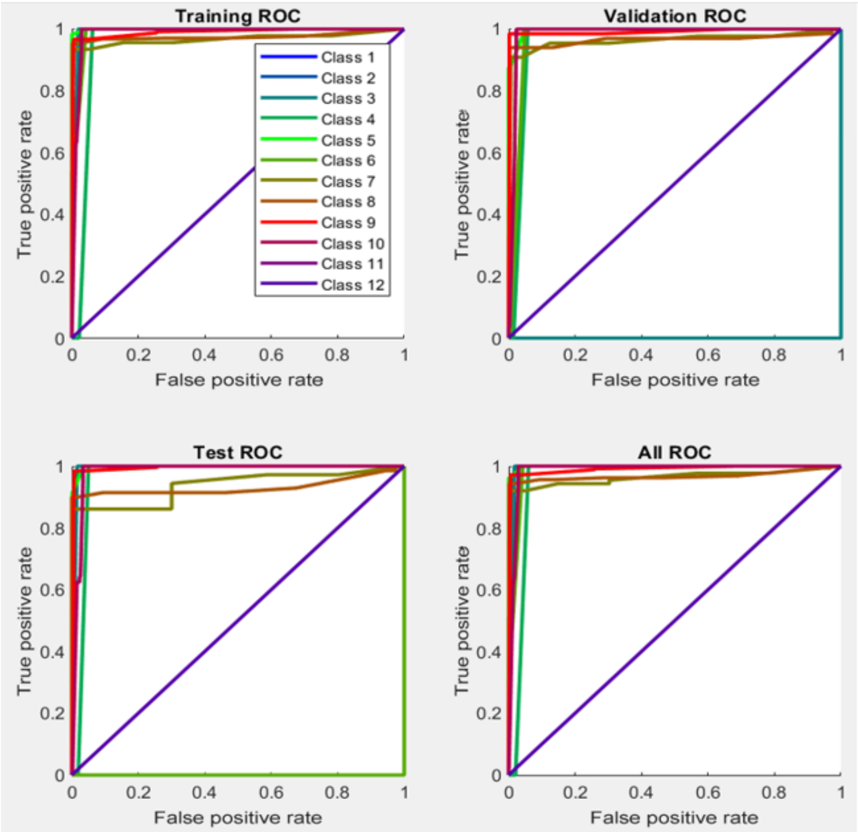

Figure 6. The ROC region for training, validation, and testing dataset.

Figure 6 showcases the receiver operating characteristic (ROC) curve, which visually represents the trade-off between true positives and false negatives on the y-axis, and the trade-off between false positives and true negatives on the x-axis. A higher position on the y-axis indicates a higher number of true positives compared to false negatives, while a higher position on the x-axis signifies a higher number of false positives compared to true negatives.

5. COMPARATIVE ANALYSIS

To demonstrate the effectiveness of the suggested method, a comparison is made between the results obtained from the case study and other existing methods used for determining the importance of criteria. Initially, the collected data for the case study is processed using the Net Promoter Score (NPS) index, and the obtained results are contrasted with the outcomes derived from our method. Subsequently, experts are involved in evaluating the weight and significance of the criteria using Multi-Criteria Decision Making (MCDM) methods instead of relying solely on customer feedback. Finally, a comprehensive comparison is conducted, juxtaposing the results obtained from our method with the outcomes generated by the other aforementioned methods. In contrast to methods that derive the weight of criteria through data mining of extensive customer data, Multi-Criteria Decision Making (MCDM) methods determine the weight and importance of criteria by soliciting judgments from decision-makers or experts. Various methods have been developed in recent years to obtain criteria weights, including Analytic

Hierarchy Process (AHP), Step-wise Weight Assessment Ratio Analysis (SWARA), Best Worst Method (BWM), and Benefit-Cost Analysis (BCM), among others. Some of these methods, such as AHP, BWM, and BCM, rely on pairwise comparisons, where decision-makers are asked to assess and compare the criteria against each other in terms of their relative importance. To obtain the weight of criteria using MCDM methods, expert judgments were utilized instead of relying on a large number of customer data. The weight of criteria was evaluated using MCDM frameworks, specifically the SWARA, AHP, BWM, and BCM methods. These methods involve gathering expert opinions and utilizing pairwise comparisons or other mathematical techniques to determine the relative importance of the criteria. Table 6 presents the calculated results of the criteria weight based on the MCDM methods, namely SWARA, AHP, BWM, HECON, and BCM. These results showcase the weight assigned to each criterion according to the respective method. By comparing the weight values obtained from these methods, the applicability and efficiency of our method can be assessed.

6. DISCUSSION

In the past, expert judgments were commonly used to analyze the criteria that affect product selection and loyalty. However, over time, the focus shifted towards customer feedback as companies recognized its importance. It was found that evaluating feedback from a large number of customers often yields better results compared to relying solely on expert opinions. One critical aspect to consider is the presence of the Halo effect in customers' decision-making process. This effect can cause customers to overlook certain product features and prioritize others. Therefore, evaluating criteria individually may not provide a comprehensive understanding of the reasons behind customer selection and loyalty. Comparing the results of our suggested method with other approaches highlights this point. The Halo effect in customer decisions can manifest in different ways. For instance, in our case study on mobile-phone selection and loyalty, customers remained loyal to the product despite not rating the memory criterion highly. This suggests that the impact of other criteria, such as performance, screen size, and design, was so significant that decision-makers chose the product based on those important criteria, disregarding the memory criterion. The NPS index logic argues that only specific criteria play a key role in product loyalty, based on customer promotions. However, when comparing the NPS index results with our method, this argument is refuted. In the mobile-phone criteria, the criteria with the greatest impact on selection and loyalty were often those that received negative feedback from customers. This discrepancy can be attributed to the influence of the Halo effect on customers' thinking. CEOs and companies should focus on the criteria that customers prioritize to increase product loyalty. In other words, attention should be given to criteria that trigger the Halo effect in customers' decisions, as other criteria might be considered insignificant or overlooked.

Table 6. Comparison of the final outcomes between the proposed technique and five MCDM methods for mobile phone criteria.

Criteria / Product	Ours		BCM		AHP		SWARA		BWM		HECON	
	Weight	Rank	Weight	Rank	Weight	Rank	Weight	Rank	Weight	Rank	Weight	Rank
Performance	0.116	1	0.262	1	0.255	1	0.260	1	0.240	1	0.120	1
Design	0.112	3	0.029	11	0.017	10	0.004	11	0.024	11	0.108	3
Services	0.081	5	0.029	11	0.015	11	0.002	12	0.024	11	0.081	5
Processor	0.079	6	0.131	2	0.174	2	0.218	2	0.114	3	0.079	6
Ram	0.062	12	0.131	2	0.134	3	0.175	3	0.114	3	0.062	12
Security	0.070	8	0.066	6	0.067	5	0.055	6	0.080	6	0.070	8
OS	0.092	4	0.044	8	0.030	8	0.013	9	0.048	8	0.092	4
Memory	0.114	2	0.037	10	0.023	9	0.007	10	0.039	10	0.069	9
Screen size	0.067	9	0.044	8	0.040	7	0.022	8	0.048	8	0.112	2
Battery	0.066	11	0.052	7	0.053	6	0.036	7	0.059	7	0.066	11
Camera	0.068	10	0.087	4	0.096	4	0.083	5	0.089	5	0.068	10
Price	0.073	7	0.087	4	0.096	4	0.125	4	0.120	2	0.073	7
Sum	1.00		1.000		1.000		0.260	1	1.000		1.00	

Investing in criteria that have minimal impact on customer choice and loyalty can result in wasted resources and the failure of new products in the market. Therefore, it is crucial for companies to identify the criteria that significantly contribute to product loyalty. This requires assessing the relationship between product loyalty and loyalty to each criterion. While some companies rely on expert evaluations to determine criteria weights, MCDM methods are often used for this purpose. However, comparing the results of our method with four different MCDM methods revealed that the other methods fail to consider the Halo effect in the relationship between criteria and product loyalty. Additionally, the inability of MCDM methods to incorporate feedback from a large number of customers makes them less recommended. Our method, on the other hand, can serve as an analytical tool for researchers, managers, experts, and other stakeholders in marketing, product design, and development to make informed decisions based on data analysis.

By leveraging the power of deep learning, the model can effectively analyze and extract meaningful insights from a large amount of customer feedback data. This allows for a comprehensive evaluation of the criteria that influence product selection and loyalty. The attention mechanism incorporated in the model enables it to focus on the most important factors and weigh them accordingly, thereby capturing the nuances and complexities of customer preferences.

Furthermore, the attention-based deep learning model has the capability to address the Halo effect and account for its impact on customer decision-making. By considering the interplay between different criteria and their relative importance, the model can provide a more accurate representation of the factors that truly drive product loyalty. This ensures that decision-makers and companies are well-informed about the criteria that customers prioritize, enabling them to make strategic decisions in product design, marketing, and development. Overall, our proposed model enhances the understanding of the intricate relationship between criteria and product loyalty, empowering companies to align their strategies with customer expectations and improve customer satisfaction.

7. CONCLUSION AND FUTURE WORKS

This study introduces a novel approach for assessing the weight of product loyalty criteria by incorporating the customer decision's Halo effect through an attention-based deep learning model. By collecting feedback from a large number of customers using the NPS scale, the proposed method accurately evaluates the impact of criteria on product loyalty, considering the potential biases introduced by the Halo effect. This allows for a more comprehensive and reliable assessment of the criteria weights, providing valuable insights for decision-making.

To validate the effectiveness of the proposed method, a real-world case study focusing on mobile phone loyalty is conducted. The results of the proposed method are compared with the NPS index, which is widely used for evaluating customer loyalty. The comparison reveals that the proposed method outperforms the NPS index by effectively capturing the influence of the Halo effect on customer decisions and delivering more accurate criteria weights.

Furthermore, the proposed method's performance is benchmarked against four commonly used Multiple Criteria Decision Making (MCDM) methods: SWARA, AHP, BWM, and BCM. The comparison highlights significant differences between the results obtained from the proposed method and the MCDM methods, which rely on expert judgments rather than customer feedback. The proposed method's ability to leverage a large volume of customer feedback provides a more comprehensive and representative view of the criteria's impact on loyalty. Additionally, it is worth noting that the proposed method exhibits a minor difference when compared to the HECON method, which also incorporates the Halo effect and employs a deep learning model. However, the inclusion of an attention block within the proposed CNN model enhances its performance, setting it apart from the HECON method.

Accordingly, the proposed attention-based deep learning model offers a powerful and reliable tool for assessing criteria weights in the context of product loyalty. By considering the Halo effect and leveraging customer feedback, the method provides valuable insights that can assist researchers, managers, and other stakeholders in making informed decisions regarding marketing, product design, and development strategies.

The suggested method offers several outstanding features that make it an interesting and attractive approach for assessing criteria weights in the context of product loyalty.

Firstly, the method leverages the power of deep learning and attention mechanisms. By utilizing an attention-based deep learning model, the proposed method can effectively capture the intricate relationships between criteria and product loyalty. The attention mechanism allows the model to focus on the most relevant criteria and weigh their impact accordingly, enhancing the accuracy and robustness of the results.

Secondly, the method takes into account the Halo effect in customer decision-making. The Halo effect is a cognitive bias that can significantly influence customers' perceptions and choices. By explicitly considering the Halo effect, the proposed method provides a more realistic and comprehensive evaluation of the criteria's impact on product loyalty. This valuable insight helps companies understand the hidden biases that may shape customer preferences and make more informed decisions in their product development and marketing strategies.

Thirdly, the proposed method incorporates a large volume of customer feedback. Instead of relying solely on expert judgments or limited samples, the method gathers feedback from a substantial number of customers using the NPS scale. This approach allows for a more representative and diverse range of perspectives, leading to more accurate and reliable criteria weights. The inclusion of a wide customer base ensures that the results reflect the preferences and behaviors of the target market more effectively.

The suggested method also has some limitations that should be considered:

1. Dependence on customer feedback: The proposed method heavily relies on customer feedback collected through the NPS scale. While this approach provides valuable insights, it is subject to potential biases and limitations associated with self-reported data. Factors such as response bias, subjective interpretations, and varying degrees of customer engagement can impact the accuracy and reliability of the obtained criteria weights.
2. Limited generalizability: The suggested method's performance is contingent upon the specific context and dataset used for evaluation. The weights assigned to criteria may vary across different industries, products, or customer segments. Thus, the generalizability of the method's results might be limited, and its applicability should be assessed carefully before implementation in diverse scenarios.

Two ideas for future work in this area could be:

1. Integration of additional data sources: To enhance the robustness and reliability of the suggested method, future research could explore incorporating other data sources, such as social media sentiment analysis, online reviews, or user behavior tracking. By integrating multiple data streams, a more comprehensive and dynamic understanding of customer preferences and their impact on product loyalty could be achieved.
2. Investigation of dynamic and temporal factors: Customer preferences and product loyalty can change over time due to various factors, such as technological advancements, market trends, or shifting consumer behaviors. Future work could focus on developing models that consider the temporal dynamics of criteria weights and product loyalty, enabling companies to adapt their strategies and decision-making processes to evolving customer needs.

By addressing these limitations and exploring new avenues of research, the proposed method can be further refined and expanded, leading to more accurate and insightful assessments of criteria weights and their impact on product loyalty.

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