Journal of Optimization in Industrial Engineering
Vol.18, Issue 1, Winter & Spring 2025, 361-373

Research Article

A machine learning–enabled framework for measuring and evaluating brand equity in the telecommunications sector

Mohammadjavad Sadoughi [1], Taher Roushandel Arabtani [2,*]

1. College of Management, University of Tehran, Tehran, Iran
2. College of Management, University of Tehran, Tehran, Iran

https://doi.org/10.71720/joie.2025. 1226977

Received: 04 December 2025
Revised: 25 December 2025
Accepted: 27 December 2025

Abstract

This study was conducted with the aim of developing a data-driven model for assessing and analyzing brand equity in the telecommunications industry. In the first stage, the factors influencing brand equity were identified through a literature review and expert surveys, and then weighted using the Fuzzy Best–Worst Method (FBWM) to determine the relative importance of each dimension. Subsequently, data collected from a structured questionnaire consisting of 75 indicators and 1,980 valid records were used to develop the machine learning model. At this stage, a multinomial logistic regression algorithm was employed to classify brand equity into three levels: "weak," "moderate," and "strong." The analysis results revealed that the dimensions of conformity and loyalty, brand image, brand performance, and brand trust played the most significant roles in shaping overall brand equity. The final model achieved an accuracy rate of 81 percent, demonstrating strong performance in distinguishing the two extreme classes (weak and strong). The findings indicate that in the digital services sector, brand equity is not solely dependent on technical quality but emerges from the interaction among trust, emotional experience, behavioral loyalty, and a positive brand image. By integrating a multi-criteria decision-making approach with machine learning techniques, the proposed model provides an effective analytical tool for brand data evaluation and supports decision-making in marketing strategy and customer experience management.

Keywords:
Brand Equity;
Machine Learning;
Fuzzy Best–Worst Method (FBWM);
Logistic Regression;
Telecommunications Industry

Citation:
Sadoughi, M. & Roushandel Arabtani, T.(2025) "A machine learning–enabled framework for measuring and evaluating brand equity in the telecommunications sector ." *Journal of Optimization in Industrial Engineering*, vol. 18, no. 1, 2025, pp. 361-373. https://doi.org/10.71720/joie.2025. 1226977

* **Corresponding Author:**
Taher Roushandel Arabtani
College of Management,University of Tehran, Tehran, Iran
E-Mail: **arbatani@ut.ac.ir**

1. Introduction

In an era of intense competition and saturated markets, brands are recognized as one of the most important strategic assets of organizations. The role of a brand is no longer limited to a trademark or a marketing tool; rather, it has become the primary driver of economic value creation, competitive differentiation, and emotional connection with customers (Agu et al., 2024; Piriyakul et al., 2024; Tavakoli et al., 2023). In this context, the concept of brand equity has emerged as a key indicator for assessing a brand's position, its level of mental penetration among customers, and its ability to maintain consumer loyalty. Organizations with higher brand equity typically possess greater capabilities in pricing, attracting investors, expanding markets, and sustaining operations during crises (Mandarić et al., 2022; Zeynali et al., 2024). Therefore, identifying and accurately measuring this concept is of vital importance for brand managers and marketing decision-makers.

Previous studies on brand equity assessment have generally focused on conceptual and perceptual models. Well-known frameworks such as Aaker's model and Keller's model have provided theoretical structures for understanding the dimensions of brand equity, including awareness, association, loyalty, and perceived quality. However, most of these models rely heavily on subjective judgments and questionnaire-based evaluations, while failing to incorporate real customer behavior data or organizational operational information. This approach makes brand evaluation largely dependent on respondents' perceptions and, in today's dynamic and data-driven environment, limits its precision and decision-making utility (Mashhadi et al., 2025; Park & Kim, 2023). This limitation is particularly significant in service industries such as telecommunications, where vast amounts of behavioral and transactional customer data are available, resulting in a clear gap between actual data and traditional evaluation models.

Recent advances in data analytics and artificial intelligence have created new opportunities for more accurate and scientific measurement of brand equity. The use of data-driven models enables the integration of customer data, behavioral indicators, brand perceptions, and organizational variables, shifting brand assessment from a subjective domain toward a quantitative and analytical one (Molaei et al., 2025; Park & Kim, 2023; ZhianVamarzani et al., 2025). By employing machine learning algorithms, it becomes possible to identify nonlinear and complex relationships among indicators, dynamically calculate their relative weights, and ultimately develop a model capable of predicting and analyzing brand equity trends over time (Chi et al., 2024; Tavakoli et al., 2024). This paradigm shift has directed the trajectory of marketing research from descriptive and qualitative analyses toward data-driven and machine learning–based decision-making.

Despite these potentials, a review of existing literature indicates that the integration of multi-criteria decision-making (MCDM) methods with machine learning algorithms in the context of brand equity evaluation has received limited attention. While decision-making methods such as AHP, ANP, or BWM can be used to weight brand indicators, most of them operate within deterministic frameworks and cannot effectively incorporate the ambiguity and uncertainty inherent in human judgment. Conversely, machine learning models generally function without theoretical weighting of variables and remain structurally disconnected from managerial decision-making frameworks. Therefore, this study aims to fill this research gap by proposing a hybrid model based on the Fuzzy Best–Worst Method (FBWM) and machine learning classification algorithms, designed to integrate theoretical rigor with data-driven precision in evaluating brand equity.

The FBWM, as an advanced extension of multi-criteria decision-making models, provides strong capability in extracting optimal and consistent weights. In this method, the decision-maker identifies the "best" and "worst" criteria and expresses relative judgments between them in fuzzy terms. This approach not only reduces the complexity of human judgment but also accounts for the inherent uncertainty in expert opinions, thereby calculating the final weights with higher precision and realism. Since brand evaluation typically involves a wide range of indicators—such as brand awareness, brand image, perceived quality, satisfaction, loyalty, and digital engagement—using FBWM ensures that the relative importance of each factor is determined in a consistent and transparent framework. These calculated weights are then used as inputs for the data-driven modeling phase through machine learning algorithms.

In the next stage, machine learning classification algorithms are applied to analyze behavioral data and predict brand equity levels. Algorithms such as Random Forest, Logistic Regression, and Support Vector Machine are among those employed in this research. These algorithms are capable of uncovering complex patterns between brand indicators and customer-related outcomes such as loyalty or satisfaction, enabling the development of a model that not only reflects the weighted importance of factors but also predicts future brand performance. The choice of algorithms was based on three main criteria: predictive accuracy, interpretability, and robustness to nonlinear and noisy data. The results obtained from these algorithms were evaluated using performance metrics such as Accuracy, Precision, Recall, and F1-score, and the model with the highest performance was selected as the proposed framework.

The distinguishing feature of this study, compared with previous research, lies in its systematic integration of multi-criteria decision-making and machine learning. Within this hybrid structure, FBWM serves as a theoretical layer for determining the importance of indicators, while classification algorithms act as the data-driven layer that interprets and predicts outcomes. This combination not only enhances evaluation accuracy but also enables dynamic sensitivity analysis and factor prioritization. Furthermore, unlike purely statistical or survey-based approaches, the proposed model utilizes real customer data and behavioral indicators extracted from organizational systems, thereby significantly increasing the validity and practical applicability of the findings.

From an applied perspective, the telecommunications industry—one of the most competitive service sectors—provides an ideal environment for testing such a model. Due to the diversity of services, the vast volume of transactional data, and the high sensitivity of customers toward brand experience, telecom companies require precise tools for continuous monitoring of their brand equity. In the present study, data from the case company were employed to test the proposed model in a real-world setting. The results demonstrate that combining FBWM with machine learning algorithms significantly improved evaluation accuracy compared with traditional models, identifying indicators such as perceived quality, cognitive engagement, user experience in digital services, and brand image in social media as the most influential factors affecting brand equity.

Overall, this research aims to bridge the gap between subjective and data-driven approaches in brand equity assessment. By employing the dual framework of FBWM and machine learning, it presents a comprehensive, transparent, and interpretable model for analyzing brand value. The outcomes of this study can serve as a foundation for developing innovative decision-making frameworks in data-driven marketing and for improving brand management processes in the competitive landscape of the digital era.

2. Literature review

This section presents a review of previous studies conducted in the field of brand equity evaluation. Various researchers have examined this topic from different perspectives and methodological approaches. For instance, (Stukalina & Pavlyuk, 2021) conducted a study aimed at simulating the current version of a university brand using the Customer-Based Brand Equity (CBBE) model. Data were collected through a multidimensional questionnaire administered to both local and international students of the Transport and Telecommunication Institute in Latvia and analyzed using structural equation modeling (SEM). The results showed that the dimensions of performance, imagery, judgments, feelings, and resonance constituted the core components of university brand equity. A significant difference was observed between the perceptions of domestic and international students—local students focused more on brand imagery, while foreign students emphasized brand resonance. These findings highlighted the importance of applying the CBBE model in educational contexts for designing competitive brand strategies. (Polat & Çetinsöz, 2021) examined the mediating role of brand love in the relationship between customer-based brand equity and brand loyalty among Starbucks customers in Turkey. Data were collected from 384 customers and analyzed using SEM. The findings revealed that the dimensions of physical service quality and lifestyle congruence fully mediated the effect of brand love on loyalty, whereas staff behavior, ideal self-congruence, and brand identification did not exhibit such mediation. The study concluded that a strong emotional bond with the brand is formed through service quality and alignment with customers' lifestyles, which plays a decisive role in long-term loyalty. Similarly, (Shanti & Joshi, 2022) investigated the impact of environmentally sustainable practices on hotel brand equity in Bangalore, India. The research used a structured questionnaire distributed among 400 guests of green hotels and analyzed the data using the PLS-SEM method. Results indicated that green brand image, green brand awareness, and green perceived value had significant positive effects on green brand equity. The authors emphasized that implementing sustainable practices in the hospitality industry strengthens brand image, enhances competitive differentiation, and increases customer loyalty, in addition to fulfilling social responsibility goals.

In another study, (Malarvizhi et al., 2022) examined the influence of social media marketing activities (SMMAs) on brand equity and consumers' willingness to pay premium prices for portable tech gadgets in Malaysia. Using a sample of 1,332 young users and employing the S-O-R model with SEM, the study found that trendiness, customization, and electronic word-of-mouth positively affected brand awareness and brand image, while interactivity had no significant impact. Moreover, brand awareness and brand image acted as mediators between digital marketing activities and willingness to pay a premium. The research underscored the importance of tailoring social media marketing strategies to the behavioral characteristics of digital consumers. (Cruz-Milán, 2023) explored the moderating effect of venturesomeness in a destination consumer-based brand equity model. Data were gathered from 210 visitors to the Corpus Christi seaside destination in Texas via an online survey and analyzed using PLS-SEM. Findings demonstrated that destination image and satisfaction had significant effects on destination brand equity, which in turn strongly predicted revisit intention. Venturesomeness moderated the relationship between satisfaction and revisit intention. These results highlighted the importance of incorporating psychological and lifestyle variables in developing brand equity models for tourism destinations.

(Chavadi et al., 2023) developed a model examining the effects of social media–based brand communities (SMBBC) on brand trust, brand equity, and consumer responses. Data from 384 respondents across various brands were analyzed using EFA, CFA, and SEM. Results indicated that online brand communities positively influenced brand trust and the core dimensions of brand equity—including awareness, perceived quality, association, and loyalty—which subsequently led to more favorable consumer behaviors such as purchase intention and willingness to pay a premium. The study emphasized that strengthening online brand communities can serve as an effective tool for enhancing brand equity. (Kara et al., 2024) introduced the T2NN-WENSLO-ARLON multi-criteria decision-making model to measure sustainable brand equity. The model, based on Type-2 Neutrosophic Numbers (T2NN), simultaneously performs criteria weighting and brand ranking. A case study in the Turkish cosmetics industry showed that "green product leadership" was the most influential criterion in shaping sustainable brand equity, while Misbahçe Inc. was identified as the brand with the highest sustainable brand value. Sensitivity analysis confirmed the robustness of the results and demonstrated the practical applicability of the model in sustainable brand decision-making.

(Chi et al., 2024) investigated the festival brand co-creation mechanism by extending the CBBE model. Combining quantitative and qualitative methods, the research was conducted in the context of the Qingdao International Beer Festival in China, incorporating variables such as product and destination familiarity, perceived value, and community involvement. The results revealed that festival brand co-creation was significantly influenced by familiarity, association, brand image, and emotional attachment, with perceived value and community involvement serving as reinforcing factors. The study emphasized the critical role of customer participation in co-creating brand value. (Piriyakul et al., 2024) proposed an innovative combination of customer journey analysis and text mining to assess brand equity in the hospitality industry. A case study conducted at the Amari Hotel in Phuket utilized customer reviews from social media as data inputs. Findings showed that location and community value were the most influential factors affecting hotel brand equity, and that the hotel room represented the dominant brand touchpoint (81%). The model demonstrated that integrating textual data with customer journey mapping provides a dynamic and cost-efficient approach to brand evaluation.

(Almaiman et al., 2024) analyzed the effects of sports sponsorship on brand equity using the Best–Worst Discrete Choice Experiment (BWDCE) method compared with a traditional purchase intention scale. Data were collected from 409 fans of three football teams sponsored by Nike, Adidas, and Puma. Results showed that sponsored brands enjoyed a higher willingness to pay among fans, and the Best–Worst scaling method achieved 35% greater predictive accuracy than the purchase intention scale. This study illustrated that quantitative choice-based methods can more precisely evaluate sponsorship return on investment. (Etumnu & Volpe, 2024) used actual sales data from Amazon.com to estimate the price and sales rank premiums of Starbucks ground coffee compared with competing brands. The results revealed that Starbucks commanded a price premium of 13–42% and a sales rank premium of 52–64%, outperforming major competitors such as Dunkin' Donuts, Folgers, and Lavazza. The study quantified brand equity using real market data expressed through financial and sales indicators. Finally, (France et al., 2025) conducted a conceptual study redefining digital brand equity in the era of digital transformation. By integrating academic and practitioner perspectives, the authors argued that measuring digital brand equity should go beyond social media metrics and incorporate constructs such as digital awareness, share of search, and digital brand sentiment. They emphasized that future measurement frameworks should capture both the human aspect of brands and the technology–consumer interaction. The paper concluded with a research agenda outlining key directions for theoretical and practical development of the digital brand equity concept. Table 1 presents a summary of the reviewed studies.

Table 1
Summary of the Literature Review

Author (Year)	Brand Equity Model Design	Weighting of Evaluation Indicators	Development of Quantitative Evaluation Model	Methodology (Summary)	Case Study (Summary)
Stukalina & Pavlyuk (2021)	*		*	CBBE + SEM	University (Latvia)
Polat et al. (2021)	*		*	SEM	Starbucks – Turkey
Shanti & Joshi (2022)	*		*	PLS-SEM	Hotels in Bangalore
Malarvizhi et al. (2022)	*		*	SEM – S-O-R Model	Portable Tech Gadgets – Malaysia
Cruz-Milán (2023)	*		*	PLS-SEM	Corpus Christi Destination
Chavadi et al. (2023)	*		*	SEM	Social Media Brand Communities
Kara et al. (2024)	*	*	*	T2NN-WENSLO-ARLON	Cosmetics Industry – Turkey
Chi et al. (2024)	*		*	Extended CBBE Model	Qingdao Beer Festival
Piriyakul et al. (2024)	*		*	Customer Journey + Text Mining	Amari Hotel – Phuket
Almaiman et al. (2024)	*	*	*	Best–Worst (BWDCE)	Sports Brands (Nike/Adidas/Puma)
Etumnu et al. (2024)			*	Market Data Mining	Starbucks Coffee on Amazon
France et al. (2025)	*			Conceptual Analysis	—

The review of literature indicates that although the concept of brand equity has been extended across various industries such as education, tourism, hospitality, and technology, most studies remain confined to survey-based methods and structural equation modeling frameworks. In these studies, brand evaluation is predominantly subjective and grounded in consumer perceptions, with limited utilization of real customer data or operational indicators. Moreover, only a few studies—such as those by Kara and Almaiman—have attempted to integrate multi-criteria decision-making methods or indicator weighting approaches. However, none of these efforts demonstrate a systematic linkage between indicator weighting and data-driven predictive modeling. In addition, the application of hybrid models in data-intensive service industries such as telecommunications—characterized by their digital and complex nature—has been largely neglected. Overall, the existing literature reveals a clear gap between conceptual, perception-based models and practical, data-driven models for evaluating brand equity.

To bridge this gap, the present study develops a hybrid framework combining the Fuzzy Best–Worst Method (FBWM) and machine learning classification algorithms. This framework enables the consistent and fuzzy-based calculation of brand equity indicator weights, followed by data-driven prediction of brand equity using real customer data from the telecommunications industry. By integrating the logic of multi-criteria decision-making with the analytical power of machine learning algorithms, this approach enhances both the accuracy and interpretability of brand evaluation. The proposed model not only determines the relative weights of indicators but also employs feature importance analysis within classification models to extract managerial insights—thus creating a bridge between perceptual marketing approaches and real data analytics. The use of real customer data within the telecom context, the application of fuzzy logic to manage uncertainty in expert judgments, and the design of an interpretable machine learning model constitute the main innovations of this research.

3. Methodology

This study employs a hybrid and data-driven approach to evaluate brand equity, consisting of two main stages: a multi-criteria decision-making phase using the Fuzzy Best–Worst Method (FBWM) for weighting indicators, and a machine learning modeling phase for predicting and analyzing the importance of these indicators. The purpose of this integration is to combine the precision of human judgment in determining the relative importance of criteria with the computational power of data-driven algorithms in analyzing complex relationships among variables. This approach enables the final model to embody both theoretical decision-making logic and data-driven explanatory and predictive strength.

The overall research process consists of three main components. First, identifying the indicators related to brand equity through a systematic literature review and expert consultation. Second, weighting these indicators using FBWM to determine the relative significance of each factor. Third, developing a machine learning classification model based on real customer data from the telecommunications industry to predict brand equity levels and extract managerial insights. This hybrid structure not only enhances analytical accuracy but also provides greater interpretability for decision-makers.

3.1. Fuzzy Best–Worst Method (FBWM)

The Fuzzy Best–Worst Method (FBWM) is one of the most advanced multi-criteria decision-making techniques, designed to derive optimal criterion weights based on pairwise comparisons. Compared with traditional models such as AHP, FBWM requires fewer comparisons, ensures higher consistency, and incorporates uncertainty in human judgments (Rostami et al., 2023; Sazvar et al., 2022). In this study, FBWM was applied to weight the indicators used for evaluating brand equity.

In the first step, a set of key indicators was extracted from the literature and through interviews with marketing experts. Decision-makers then identified the best (most important) and worst (least important) criteria. Next, fuzzy comparisons were made between the best criterion and all others (best–others vector) as well as between all other criteria and the worst one (others–worst vector). These values were defined using triangular fuzzy scales to capture a range of expert judgments.

Subsequently, an optimization model was solved to determine the final weights of the indicators by minimizing the inconsistency of the comparisons. The key advantage of FBWM lies in its ability to produce consistent and accurate weights using a limited number of comparisons, while simultaneously accounting for the inherent ambiguity of human reasoning through fuzzy logic. In this research, the resulting FBWM weights served as inputs to the machine learning models in the next phase, allowing an examination of the relationship between the theoretical importance of indicators and their data-driven predictive influence.

3.2. Machine learning classification algorithms

In the second phase of the study, a set of machine learning classification algorithms was employed to assess and predict the level of brand equity. These algorithms were developed using real customer data from the telecommunications industry and complemented the multi-criteria decision-making stage.

Four main algorithms were applied: Logistic Regression, Random Forest, XGBoost, and Support Vector Machine (SVM). These algorithms were selected for their ability to model nonlinear relationships, handle noisy data, and produce interpretable results. Each model received as input a set of brand-related indicators—such as awareness, perceived quality, brand image, digital experience, satisfaction, loyalty, and online engagement—and generated as output a predicted brand equity level for each customer or customer segment.

Model performance was evaluated using the metrics Accuracy, Precision, Recall, and F1-score. In addition, feature importance analysis was applied to interpret the influence of variables in tree-based models such as Random Forest and XGBoost. Results indicated that the

XGBoost algorithm outperformed the others, achieving the highest accuracy and balance across evaluation metrics. At this stage, the relationship between theoretical indicator weights (from FBWM) and their empirical importance within the machine learning models was also examined, enabling comparison and alignment between expert judgment and data-driven findings.

3.3. Research steps and hybrid approach

The present research followed a step-by-step hybrid process, summarized as follows:
Step 1 – Identification of Brand Equity Indicators:
In this stage, the indicators influencing brand equity were identified through an extensive literature review and semi-structured interviews with experts in marketing and brand management. The indicators were categorized into key dimensions such as brand awareness, perceived quality, brand associations, customer loyalty, satisfaction, digital experience, and online interactions.
Step 2 – Weighting of Indicators Using FBWM:
Experts conducted fuzzy pairwise comparisons between the best and worst indicators to determine their relative importance. Using the FBWM optimization model, final consistent weights were calculated. The output of this phase was a set of valid fuzzy weights reflecting expert judgment and domain knowledge.
Step 3 – Development of the Machine Learning Model for Brand Equity Evaluation:
Data related to brand indicators and customer behavioral variables in the telecom industry were collected, and the selected machine learning algorithms were trained on this dataset. The objective was to predict the level of brand equity and analyze the contribution of each indicator to this variable. The FBWM-derived weights were also employed as reference parameters during feature importance analysis.
Step 4 – Sensitivity Analysis and Extraction of Managerial Insights:
Finally, the sensitivity of the model to variations in indicator values was examined to identify the factors with the greatest impact on brand equity levels. The results of the FBWM and machine learning models were then integrated to provide a comprehensive understanding of the key drivers of brand success in the telecommunications sector. Based on this analysis, managerial recommendations were formulated to improve brand strategy and enhance the most influential dimensions.
Figure 1 illustrates the step-by-step hybrid research framework adopted in this study. The process integrates fuzzy multi-criteria decision-making (FBWM) with machine learning techniques to systematically identify, weight, and analyze brand equity indicators, ultimately supporting data-driven managerial decision-making in the telecommunications industry.

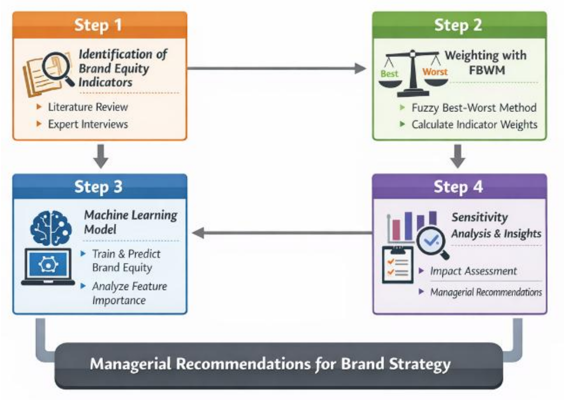

Fig. 1. Research steps and hybrid approach

In summary, the research methodology combines fuzzy multi-criteria analysis with machine learning modeling, offering an innovative, data-driven approach to evaluating brand equity. This framework not only determines the relative importance of indicators based on expert judgment but also empirically demonstrates the relationship between brand dimensions and market performance through real data analysis. The outcome is a theoretically grounded yet practically reliable decision-support model for brand managers in the telecommunications industry.

4. Findings

This section presents the results obtained from implementing the hybrid research model, which includes the weighting of brand equity indicators using the Fuzzy Best–Worst Method (FBWM) and the development of machine learning models for evaluating and predicting brand equity levels. The findings are derived from data collected in the telecommunications industry through multi-stage analyses, aiming to explain the relative importance of factors influencing brand equity and to assess the accuracy of the proposed model in analyzing real-world data.
The analytical process in this study began with the identification and validation of brand equity evaluation indicators. After an initial screening and comparison with theoretical frameworks, these indicators were used as inputs to the FBWM method to calculate the final weights of each factor. The results of this weighting phase were then utilized as the basis for data-driven modeling in the machine learning classification algorithms, which examined both the predictive ability and the interrelationships among the various indicators and brand equity levels.
The findings are presented in four sequential parts. First, the set of brand equity indicators and their main dimensions are introduced. Next, the final weights and relative importance of each indicator obtained through FBWM are reported. In the third part, the performance of the machine learning algorithms in modeling and predicting brand equity levels is analyzed and compared. Finally, the last section extracts managerial insights from the model results, outlining the practical implications of the study for marketing and brand management decision-makers.

4.1. Brand equity evaluation indicators

To achieve a comprehensive and multidimensional assessment of brand equity in the telecommunications industry, a set of indicators was developed based on an extensive literature review(Kara et al., 2024; Malarvizhi et al., 2022; Piriyakul et al., 2024; Stukalina & Pavlyuk, 2021), expert interviews, and empirical data analysis. These indicators cover various dimensions of consumer cognition, emotion, trust, image, loyalty, and perception toward brands and are structurally grouped into several major categories. Each category represents a key conceptual dimension of brand experience, shaped through real user interactions with digital payment applications.

The categorization of indicators was designed according to the interconnection among cognitive, emotional, and behavioral components of brand equity. This structure enables both researchers and brand managers to not only assess overall brand performance but also identify specific strengths and weaknesses within each dimension. The precise weighting of indicators through FBWM is described in the following subsection, while the complete list of indicators and their corresponding weights is provided in Appendix A.

- Brand Awareness: This dimension refers to the level of recognition and familiarity users have with a brand and indicates the extent to which consumers can identify and prefer it among competing alternatives. Indicators in this category include past and current experience with payment applications, intention to use the brand in the future, and recognition of active brands in users' minds. These factors are directly linked to brand choice probability and its positioning in the consumer's mind.
- Feelings Toward the Brand: Consumer emotions and affective experiences play a central role in shaping attitudes and loyalty. Indicators in this group include the sense of safety and trust while using the brand, emotional experiences such as friendliness or excitement, and perceived enhancement of social credibility through brand interaction. These affective elements are particularly critical in digital service industries, where human contact is limited and user experience is the primary determinant of brand attachment.
- Brand Trust: Trust is one of the cornerstones of long-term customer–brand relationships. Indicators in this dimension measure the perceived reliability, honesty, and overall confidence of users in the brand. A high level of trust increases customer willingness to continue using the service and reduces vulnerability to competitors.
- Brand Image: This dimension reflects the overall perception and mental associations customers have with a brand. Indicators include social admiration, perceived success, attractiveness and prestige, modernity and reliability, distinctiveness of experience, and identification with other brand users. Brand image determines how strongly and positively the brand is positioned in consumers' minds and the extent to which it translates into perceived value.
- Brand Engagement and Participation: This category measures the level of consumer involvement with the brand, such as seeking additional information, discussing the brand with others, and following brand-related content. High engagement typically indicates that the brand has become internalized within the consumer's lifestyle and is directly correlated with increased awareness and loyalty.
- Brand Salience (Mental Presence): This dimension captures the visibility and accessibility of the brand. Indicators include advertising intensity, ease of access and installation, and frequency of exposure across various channels—all of which determine how active and salient the brand is in consumers' minds.
- Brand Performance: The performance dimension reflects the quality of the actual customer experience. Indicators include service quality, speed, variety, usability, innovation, pricing, and responsiveness to customer needs. Superior performance not only leads to customer satisfaction but also plays a decisive role in sustaining loyalty.
- Brand Competitive Advantage: This dimension represents the brand's relative position compared with its competitors. Indicators include the brand's superiority over alternatives and the tangible benefits perceived by customers. From a strategic perspective, this component serves as a measure of brand competitiveness and differentiation.
- Social Acceptance of the Brand: Social acceptance reflects the positive perception of the brand within consumers' social circles. Indicators include social approval by family and friends, confidence in one's choice of brand, and minimal negative attitudes toward it.
- Brand Heritage: Brand heritage refers to the historical continuity and long-term use of the brand over time. Indicators such as positive historical experiences, intergenerational usage, and brand longevity contribute to enhanced customer trust and a sense of stability.
- Cognitive and Perceptual Understanding of the Brand: This dimension focuses on customers' cognitive evaluations of the brand, including perceived value, visual design, perceived security, compliance with standards, and personal preference among available brands. These indicators express the perceived quality and the degree of alignment between the brand's offerings and customer expectations.
- Overall Attitude Toward the Brand: This dimension captures the consumer's overall judgment of the brand, including emotional preference or disinterest and evaluative judgment (good/bad or favorable/unfavorable). A positive overall attitude serves as a foundation for future loyalty behaviors.
- Brand Conformity and Loyalty: Indicators in this group represent the depth of emotional and behavioral connection between customer and brand. Frequent use, time and energy commitment, sense of belonging, willingness to talk about the brand, and

perceiving it as more than a mere product are among the defining elements. These indicators reflect the true depth of customer–brand relationships.

- Behavioral Stability Toward the Brand: Behavioral stability reflects the customer's resilience to negative experiences or temporary brand weaknesses. Indicators such as continued usage despite dissatisfaction or consistent perception of the brand represent stable and enduring loyalty.
- Brand Extension Potential: This dimension assesses the brand's capacity for expansion into new products and services. Customer willingness to purchase new offerings, adopt new services, and believe in the brand's ability to succeed in other domains are key indicators.
- Emotional Bond With the Brand: The emotional bond reflects the degree of value alignment and emotional closeness between customer and brand. Indicators such as value congruence and deep trust in the brand capture this connection, which has a direct impact on long-term loyalty.
- Perceived Quality: The final dimension describes the overall perceived quality of the brand from the customer's viewpoint. Indicators include overall satisfaction, service quality, and perceived performance of the brand—all of which are directly associated with the brand's mental value in the market.

In summary, the presented multidimensional structure offers a comprehensive view of the cognitive, emotional, behavioral, and functional aspects of brand equity in the telecommunications industry. Detailed information on each indicator and its final FBWM-derived weight is provided in Appendix A, ensuring transparency and reproducibility of the study's results.

4.2. Weighting of identified brand equity indicators

To determine the relative importance of the various dimensions of brand equity, the Fuzzy Best–Worst Method (FBWM) was employed. This method enables researchers to derive consistent and accurate final weights through pairwise comparisons among selected indicators. In this phase, marketing experts identified the "best" (most important) and "worst" (least important) indicators within each category and conducted fuzzy comparisons between them to determine both local (intra-category) and global (overall model) weights. The results, after aggregating expert judgments and normalization, are summarized in Table 2, while the detailed fuzzy weights of sub-indicators are provided in Appendix B.

The findings indicate that, among the main categories, the brand conformity and loyalty dimension carries the highest weight (0.1366). This suggests that in the telecommunications industry, the emotional and behavioral attachment of users to a brand has the strongest impact on its overall equity. Indicators such as emotional attachment, perceived difference in the absence of the brand, and sustained loyalty account for the largest share within this dimension. Following this, the dimensions of brand image (0.0781) and brand performance (0.0781) rank next in importance, highlighting the key role of real user experience and mental positioning in shaping brand value.

The dimensions of brand trust (0.0683) and brand salience (0.0674) also emerge as influential factors, demonstrating that users' sense of confidence and ease of access to the brand play a vital role in sustaining loyalty. In contrast, dimensions such as brand heritage (0.0357) and overall attitude toward the brand (0.0355) hold lower weights, indicating that consumers in today's digital markets focus more on present performance and immediate experience than on a brand's historical legacy. Table 2 presents the final weights of the main brand equity dimensions.

Table 1
Final Weights of Main Brand Equity Dimensions

No.	Main Category of Indicators	Final Weight
1	Brand Conformity and Loyalty	0.1366
2	Brand Image	0.0781
3	Brand Performance	0.0781
4	Brand Trust	0.0683
5	Brand Salience	0.0674
6	Perceptual Understanding of the Brand	0.0625
7	Brand Competitive Advantage	0.0594
8	Social Acceptance	0.0585
9	Perceived Quality	0.0568
10	Behavioral Stability Toward the Brand	0.0554
11	Feelings Toward the Brand	0.0390
12	Emotional Bond	0.0402
13	Brand Extension Potential	0.0424
14	Brand Awareness	0.0413
15	Brand Engagement and Participation	0.0449
16	Overall Attitude Toward the Brand	0.0355
17	Brand Heritage	0.0357

The above results reveal that the structure of brand equity in the telecommunications sector is primarily driven by emotional and behavioral loyalty. Such loyalty is not only the outcome of brand performance satisfaction but also emerges from the combination of user experience, trust, and a positive brand image in the customer's mind. At the same time, functional, perceptual, and social acceptance dimensions interact with loyalty to form a cohesive and integrated construct of brand value.

From a managerial standpoint, these findings suggest that brand strategies should focus on maintaining emotional connection, enhancing user experience, and strengthening perceived trust and service quality. These three components yield the highest return in increasing perceived brand value and achieving a sustainable competitive advantage.

Comprehensive details of the sub-indicator weights—including both local and global values (as calculated in the complete FBWM table)—are provided in Appendix B, enabling researchers and practitioners to conduct a more in-depth exploration of the underlying dimensions of brand equity.

4.3. Development of the machine learning model for brand equity evaluation

4.3.1. Data and descriptive statistics

To develop the data-driven model, a structured questionnaire was designed based on the qualitative dimensions identified in Chapter Four and distributed online across several provinces. The final dataset included 1,980 valid records and 75 features representing various dimensions such as brand awareness, trust, loyalty, experience, emotions, satisfaction, and perceived quality. The target variable (label) was categorized into three levels: weak, moderate, and strong. The class distribution is presented in Table 3.

Table 2
Distribution of Labels and Respondents' Age

Label	Count	Mean Age	Standard Deviation
Weak	639	40.68	13.35
Moderate	607	40.18	13.24
Strong	734	40.86	13.17

The age distribution across the three classes is relatively homogeneous, indicating that age is not a decisive factor in differentiating brand equity levels. Instead, variations are primarily driven by factors such as user experience, trust, and service performance. The percentage distribution of labels across provinces, gender, and age groups (provided in Appendix C) reveals meaningful regional differences—such as a higher share of strong labels in the provinces of Fars and Alborz—as well as mild gender-based variations. These insights are valuable for regional and personalized campaign planning.

4.3.2. Data preprocessing

The data preparation process followed a structured pipeline consisting of the following steps:
(i) Data cleaning – Records with more than 20% missing values were removed; remaining missing values were imputed using the mean (for numeric variables) or mode (for categorical variables); outliers were handled using the interquartile range (IQR) method.
(ii) Categorical encoding – Gender was binary encoded (e.g., male = 0, female = 1); province was ordinally encoded; and the target label was encoded as 0, 1, and 2 for weak, moderate, and strong, respectively.
(iii) Feature scaling – All numeric features were standardized using StandardScaler to ensure equal scaling and prevent bias toward variables with larger numerical ranges.
(iv) Correlation analysis – Highly correlated features ($\rho > 0.90$) were examined for redundancy and removed when necessary. Sample correlation coefficients are presented in Table 10, while the full list is provided in Appendix C.
(v) Train/test split – The dataset was divided into 80% training and 20% testing subsets using Stratified Sampling with random_state=42 to preserve class proportions.
Class imbalance was minimal; therefore, model evaluations were reported per class, and class weighting was applied only when required. Logarithmic and Box–Cox transformations were used for a few skewed features. All preprocessing steps were fully documented, and separate training and testing files were stored for replication and future analysis.

4.3.3. Model training and ROC evaluation

Given the need for interpretability and model stability, the baseline classifier was developed using Logistic Regression with a multinomial configuration (multi_class='multinomial', solver='lbfgs', penalty='l2', C=1.0, max_iter=1000). The model outputs the probability of each class, which was then used under a One-vs-Rest scheme to plot the Receiver Operating Characteristic (ROC) curves for each category (weak, moderate, strong).

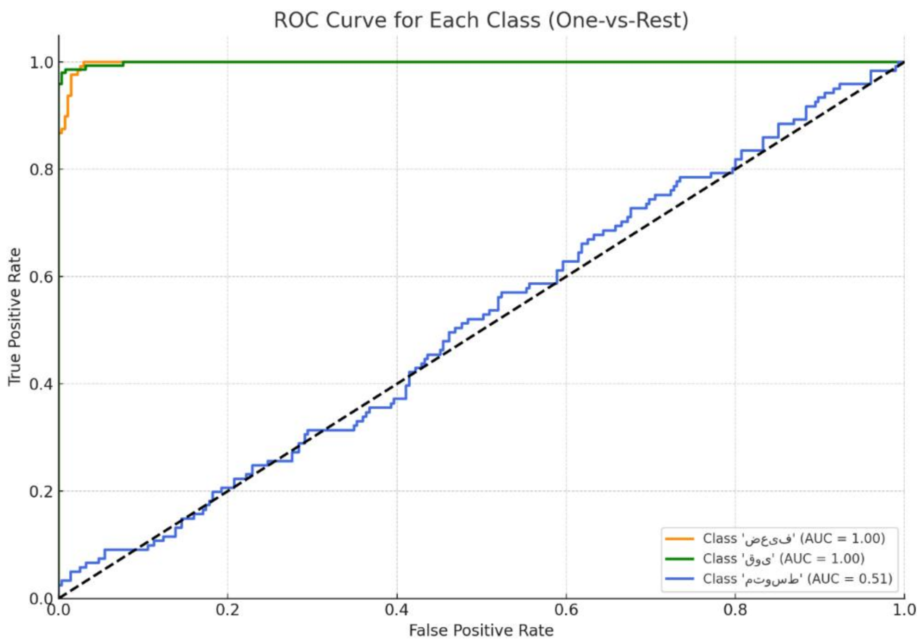

Figure 2. ROC Curve (One-vs-Rest Approach) for the Three Classes

In Figure 2, the ROC curves of two classes approach the upper-left region (AUC ≈ 1.00), while one class yields an AUC of about 0.51—close to the random-chance line. This heterogeneity may stem from probability calibration issues, boundary overlap among features, or uneven difficulty distribution of samples within that class. As discussed later in the validation and improvement section, this condition does not necessarily align with hard predictions—as the confusion matrix demonstrates, the model performs very well at the label-level classification stage.

4.3.4. Model comparison and confusion matrix

To ensure a rational model selection, five algorithms were compared: Logistic Regression, Decision Tree, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest. The results on the test dataset are summarized in Table 4.

Table 3
Performance Comparison of Classification Algorithms

Model	Accuracy	Precision	Recall	F1
Logistic Regression	0.8116	0.8086	0.8131	0.8084
SVM	0.6920	0.6905	0.6889	0.6890
Decision Tree	0.6734	0.6715	0.6742	0.6700
KNN	0.6641	0.6623	0.6637	0.6604
Random Forest	0.6086	0.5917	0.5889	0.5682

As shown above, Logistic Regression outperforms the other models across all four evaluation metrics, maintaining a strong balance among accuracy, recall, and F1-score; hence, it was selected as the final model.
Figure 3 illustrates the distribution of predicted decision scores for the three brand equity classes. The weak and strong classes show clearly separated probability distributions near the lower and upper ends of the decision space, while the moderate class exhibits overlap with both extremes. This overlap explains most misclassifications observed in the confusion matrix and reflects the inherent boundary nature of the moderate category.

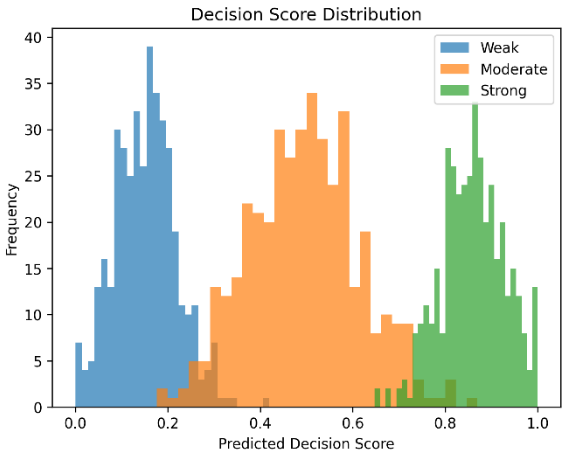

Fig. 3.. Decision score distribution for brand equity classification

4.4. Managerial insights

The results of the hybrid model provide a comprehensive picture of the key factors shaping brand equity in the telecommunications industry. Based on the FBWM weighting stage, conformity and loyalty emerged as the most influential dimension of brand equity, followed by brand image, brand performance, brand trust, and brand salience. This finding suggests that continued use, emotional attachment, and the sense of irreplaceability play central roles in generating perceived brand value among users. In essence, customer loyalty is not merely the outcome of functional satisfaction, but rather the product of a positive experience, social belonging, and mutual trust between the brand and its consumers. Therefore, brands that can maintain lasting emotional connections with users while delivering reliable and transparent performance are the most likely to move customers from a “moderate” to a “strong” brand value tier.
From another perspective, the data-driven machine learning model demonstrates that both functional and emotional factors jointly structure brand value prediction. The Logistic Regression model achieved an accuracy of 81%, successfully classifying brands into “weak,” “moderate,” and “strong” categories. The confusion matrix revealed that the model performs with high precision for the two extreme levels (weak and strong), while tending to assign borderline cases to the “moderate” class. This aligns with real user behavior, as customers who experience a mix of satisfaction and dissatisfaction across different interactions typically fall into a moderate perception level. Thus, effectively managing this middle group could be a turning point for brand growth. Managerial actions should focus on identifying and converting these users through personalized experiences, trust-building messages, and targeted rewards—increasing their likelihood of repeated usage and migration from moderate to strong brand equity.
Furthermore, the data analysis confirmed that trust and brand image play complementary roles in sustaining loyalty and enhancing brand value. Users evaluating payment service brands consider a blend of security perception, service quality, and social admiration. Therefore, brands should not only focus on technical performance but also design marketing communications that foster a sense of safety, transparency, and honesty. Indicators such as social admiration, aesthetic appeal, and modernity have shown significant influence in building a positive perception. Accordingly, maintaining an active and purposeful presence on social media, sharing user success stories, and continuously upgrading digital services can strengthen a brand’s mental presence and desirability in consumers’ minds.
Finally, the analytical results highlight that regional, demographic, and gender-based differences in perceived brand value are substantial and should inform managerial decisions. Provinces such as Fars and Alborz showed higher proportions of users with strong brand perceptions, while Isfahan and Khuzestan exhibited weaker evaluations. These discrepancies indicate that local cultural and economic traits significantly shape user perceptions. Moreover, gender analysis revealed that female users tend to associate more strongly with the “strong” label, likely due to higher sensitivity to trust and emotional engagement. Consequently, data-driven marketing strategies should be designed with attention to

demographic and geographic segmentation, tailoring messages, benefits, and user experiences to the expectations of each target group. Overall, the integration of FBWM and machine learning findings suggests that the future of brand management in the telecom industry depends on balancing emotional experience and functional performance, where trust, loyalty, and seamless user experience form the three core pillars of sustainable brand equity.

4.5. Theoretical implications

This study contributes to the theoretical development of brand equity research by advancing the methodological integration of multi-criteria decision-making (MCDM) and machine learning within a unified analytical framework. Traditional brand equity models, such as Aaker’s and Keller’s frameworks, have predominantly relied on perceptual and survey-based approaches, treating brand equity as a latent construct inferred from subjective judgments. By incorporating the Fuzzy Best–Worst Method (FBWM) as a formal weighting mechanism, this research theoretically strengthens brand equity measurement by embedding expert-based prioritization within a mathematically consistent and uncertainty-aware structure. This integration enriches the theoretical foundation of brand equity by demonstrating how qualitative managerial judgments can be systematically translated into quantitative inputs for predictive modeling.

From a data-driven theory perspective, this research extends the conceptual boundaries of brand equity by positioning it as a classifiable and predictable outcome rather than a purely descriptive construct. The application of machine learning classification—particularly multinomial logistic regression—demonstrates that brand equity levels (weak, moderate, and strong) can be empirically distinguished based on observable brand-related indicators. This finding supports the theoretical shift from static, perception-only models toward dynamic and outcome-oriented frameworks, where brand equity is treated as an emergent property of behavioral, emotional, and perceptual interactions. Moreover, the observed overlap of decision scores for the moderate class provides theoretical evidence that brand equity is not a binary phenomenon but a continuous and fuzzy construct, reinforcing the need for probabilistic and hybrid modeling approaches in brand theory.

Finally, the proposed hybrid framework contributes to theory by bridging the long-standing gap between normative decision-making models and empirical predictive analytics in marketing research. While MCDM methods offer strong theoretical grounding for criterion importance, they often lack empirical validation through real data. Conversely, machine learning models typically prioritize predictive accuracy without explicit theoretical justification for variable importance. By combining FBWM-derived weights with machine learning feature analysis, this study offers a theoretically coherent model that aligns expert judgment with data-driven insights. This alignment provides a robust theoretical basis for future research aiming to develop interpretable, explainable, and generalizable brand equity models across data-intensive service industries, thereby advancing both brand management theory and decision science literature.

5. Conclusion

This study was conducted with the aim of developing a data-driven model for measuring and analyzing brand equity in the telecommunications industry. In the first stage, key indicators influencing brand equity were identified through a systematic literature review and qualitative analyses, then weighted using the Fuzzy Best–Worst Method (FBWM) to determine the relative importance of each main dimension. In the next stage, machine learning algorithms were employed to validate and predict the levels of brand equity, and ultimately, Logistic Regression was selected as the most accurate and stable algorithm. The research data were collected via a comprehensive structured questionnaire encompassing 75 key indicators, and after preprocessing, analyses were performed on 1,980 valid records. This methodological integration made it possible to combine expert judgment with quantitative modeling accuracy, thereby enhancing the precision of customer perception assessment toward brands.

The results indicate that the dimensions of conformity and loyalty, brand image, brand performance, and brand trust exert the greatest influence on the formation of brand equity. These findings reveal that brand value, in customers’ minds, is not only based on service efficiency and quality but is also deeply linked to emotional attachment, trust, and social perception. Furthermore, the machine learning analysis demonstrated that brand equity can, in practice, be effectively predicted and classified; the final model achieved 81% accuracy in distinguishing between the three levels of “weak,” “moderate,” and “strong.” The confusion matrix showed that the main challenge lies in delineating the boundaries between the moderate group and other levels—a pattern consistent with actual customer behavior. Overall, the findings confirm the importance of behavioral loyalty, trust, and positive user experience as critical components for creating sustainable competitive advantage among digital payment service brands.

Overall, the findings of the present study are largely consistent with, yet extend beyond, prior research on brand equity evaluation. Similar to earlier studies based on CBBE and SEM frameworks (e.g., Stukalina & Pavlyuk, 2021; Polat & Çetinsöz, 2021; Shanti & Joshi, 2022), the results confirm the central role of emotional attachment, brand image, trust, and loyalty in shaping brand equity. However, unlike these studies, which primarily rely on perceptual and structural models, the current research empirically demonstrates that brand equity can be effectively classified and predicted using a data-driven approach. The strong influence of conformity and loyalty observed in this study aligns with findings reported by Chavadi et al. (2023) and Cruz-Milán (2023), yet the present work advances the literature by quantifying this influence through FBWM-derived weights and validating it via machine learning classification. Moreover, while recent studies have begun incorporating advanced decision-making or data-based techniques (e.g., Kara et al., 2024; Almaiman et al., 2024; Piriyakul et al., 2024), they often focus on either indicator weighting or alternative data sources in isolation. In contrast, the hybrid framework proposed in this study provides a systematic linkage between expert-based weighting and predictive analytics using real customer data. This integration responds directly to the research agenda suggested by France et al. (2025), offering a more holistic and operationalizable perspective on digital brand equity measurement in data-intensive service industries such as telecommunications.

Based on these findings, several directions are suggested for future research and managerial development. First, the model can be extended to other service industries such as insurance, banking, or online retail to assess its generalizability and comparative performance. Second, employing more advanced machine learning algorithms—such as XGBoost, CatBoost, or hybrid neural network models—could enhance the model's precision and class separability. Third, integrating actual behavioral data (e.g., transactions, usage time, or return rates) alongside perceptual survey data could provide deeper insights into the dynamics of brand equity over time. Finally, it is recommended that brand managers adopt similar data-driven frameworks to shift decision-making in marketing, customer experience, and loyalty improvement from intuition-based approaches toward analytical, evidence-based strategies, thereby guiding the enhancement of brand value with greater accuracy and efficiency.

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