SvedbergOpen
DISSEMINATION OF KNOWLEDGE
International Journal of Artificial Intelligence and Machine Learning
Publisher's Home Page: https://www.svedbergopen.com/
Research Paper
Open Access

Machine Learning For Real-Time Brand Health Tracking: A Framework For Ai-Augmented Brand Equity Management

Dr. Sunanda Jindal[1], Dr. Asita Ghewari[2], Dr. Mayank Tripathi[3], Dr. Ambar Beharay[4], Dr. Gaganpreet Kaur Ahluwalia[5], Dr. Priyanka Dhoot[6], Dr. Cyril Crasto[7]

[1]Academician and Researcher, sunandag22@gmail.com
[2]Associate Professor, Savitribai Phule Pune University, Pune. asita.sa@gmail.com
[3]Associate Professor, Pranveer Singh Institute of Technology (PSIT), Kanpur. tripathimayank2018@gmail.com
[4]Associate Professor, Management Department, Tilak Maharashtra Vidyapeeth, Pune. dr.ambar.beharay@gmail.com
[5]Professor and Area Chair- Marketing Management, School of Business (MBA), Indira University, Pune. higaganpreet@gmail.com ORCID ID 0000-0001-7955-6551
[6] Sr.Asst.Professor, D Y Patil International University Akurdi Pune. priyankazanvar29@gmail.com
[7]Associate Professor, Balaji Institute of Management & Human Resource Development, Sri Balaji University, Pune. cyril.crasto@bimhrdpune.edu.in

Abstract

This study develops and empirically validates a framework for integrating machine learning into real-time brand health tracking, advancing AI-augmented brand equity management. Recognizing the limitations of conventional periodic brand audits, the proposed framework leverages predictive analytics and continuous data streams to provide dynamic, actionable insights into brand performance. To assess the framework's practical relevance and perceived efficacy, a structured survey was administered to 289 brand and marketing professionals in Pune City, Maharashtra, India. The instrument utilized a five-point Likert scale to capture respondent evaluations of the framework's core components, including predictive accuracy, real-time responsiveness, and decision-support utility. The analysis employed one-sample t-tests to determine whether mean perceptions significantly exceeded a neutral baseline, and Pearson correlations to examine the interrelationships among key framework dimensions. The results robustly support the study's hypotheses. The aggregate mean for the primary hypothesis (H1) was approximately 3.66, indicating favorable professional endorsement of the framework's foundational principles. Furthermore, significant positive correlations, ranging from 0.603 to 0.712, were observed among the framework's constituent elements, confirming the internal consistency and convergent validity of the proposed model. Both H1 and H2 were supported, demonstrating that brand professionals recognize the value of machine learning for enhancing the timeliness and strategic depth of brand health monitoring. These findings suggest that the proposed framework offers a viable pathway for organizations to transition from reactive brand management to a proactive, data-driven approach, thereby strengthening long-term brand equity. The study contributes to the marketing literature by providing an evidence-based blueprint for AI integration in brand management practice (Joseph et al., 2025; Mannaru, 2025).

Keywords: machine learning; brand health; brand equity; real-time tracking; marketing analytics; AI-augmented management; brand metrics; sentiment analysis; India; predictive branding.

1. Introduction

The contemporary business environment is characterized by an unprecedented velocity of consumer feedback, social discourse, and competitive maneuvering, rendering traditional periodic brand audits increasingly insufficient. Brands are no longer static entities but dynamic constructs continuously shaped by real-time digital interactions across multiple platforms. In response, organizations are pivoting towards continuous monitoring systems capable of capturing and interpreting these ephemeral brand signals. The integration of machine learning into this domain offers a transformative capability, moving beyond simple sentiment analysis to predictive and prescriptive insights. This shift towards AI-augmented brand equity management represents a fundamental evolution in how marketing leaders perceive, measure, and steward their most valuable intangible assets, enabling a proactive rather than reactive strategic posture (Joseph et al., 2025; Mannaru, 2025).

Within the rapidly expanding Indian marketplace, the competitive intensity across sectors such as FMCG, automotive, financial services, and technology has created a pressing demand for granular, real-time brand intelligence. The proliferation of affordable smartphones and high-speed data networks has generated a vast and complex digital footprint of Indian consumers, offering a rich repository of behavioral and attitudinal data. However, the sheer volume and unstructured nature of this data overwhelm conventional analytical tools, creating a critical need for sophisticated machine learning frameworks. This necessity is particularly acute in emerging commercial hubs like Pune City, Maharashtra, a prominent center for corporate headquarters, IT parks, and a vibrant startup ecosystem, where brand managers must navigate a sophisticated and discerning consumer base (Paturi, 2025).

Despite the theoretical promise of machine learning in marketing analytics, a significant disconnect persists between algorithmic development and its practical application in managerial brand equity practice. The existing literature often addresses either the technical sophistication of predictive models or the conceptual dimensions of brand equity, but rarely integrates both within a coherent, actionable framework. Furthermore, empirical evidence from the Indian context, particularly at the city level, remains scarce, with most studies focusing on national aggregates or specific product categories. This gap is further compounded by a lack of research that specifically captures the perspectives of brand and marketing professionals, who are the ultimate end-users and decision-makers in this process, leaving a critical void in understanding the practical barriers and facilitators of AI adoption (Lodhi and Singh, 2025).

The purpose of this study is to address these identified gaps by proposing and empirically validating a comprehensive framework for AI-augmented brand equity management, specifically designed for real-time brand health tracking. The scope of this investigation is deliberately focused on the Indian context, with a concentrated geographical emphasis on Pune City, Maharashtra, a representative microcosm of the nation's evolving marketing landscape. To ensure the relevance and applicability of the findings, the study sample comprises exclusively brand and marketing professionals (N=289) who are actively engaged in brand strategy and management. Through this targeted approach, the research aims to develop a practical model that bridges the divide between machine learning capabilities and strategic brand stewardship, offering actionable insights for practitioners while contributing to the academic discourse on technology-enabled brand management.

2. Literature Review

Joseph et al. (2025) examine the integration of artificial intelligence into marketing frameworks, focusing on how AI-driven behavioural analytics enable hyper-personalised strategies. The study highlights the use of advanced machine learning techniques, natural language processing, and predictive modelling to refine consumer targeting. By analysing vast amounts of structured and unstructured data, AI uncovers nuanced patterns in consumer interactions, sentiment, and purchasing behaviour. The authors note that anticipating customer needs with high precision has driven adoption of AI-powered recommendation systems, generative AI models, and real-time data processing. These technologies enhance user experience and revenue growth. This work contributes to understanding AI-augmented brand management and its role in strengthening brand equity through more responsive consumer insights.

Mannaru (2025) examines the role of artificial intelligence-based sentiment analysis in real-time brand monitoring. The paper argues that traditional manual methods of tracking user-generated content are inadequate given the vast scale of digital platforms. The research discusses how machine learning algorithms process linguistic signals, contextual information, and affective indicators to categorize consumer sentiment. This approach enables firms to discern shifts in brand perception as they occur across social media, review sites, and digital news outlets. The abstract highlights practical benefits of automated monitoring for timely action. This work is relevant to brand equity and brand health tracking, demonstrating how AI-augmented brand management can provide faster and more precise insights.

Paturi (2025) examines the integration of artificial intelligence into marketing, specifically focusing on AI-driven sentiment analysis as a transformative tool for understanding consumer behavior. The paper explores how organizations extract and interpret emotional cues from diverse data sources, including social media, reviews, and customer service interactions. It addresses the implications of these systems for product positioning and real-time marketing decisions within dynamic consumer landscapes. The abstract highlights the role of natural language processing, machine learning, and big data analytics in decoding customer perceptions and market signals. This technological capability enables brands to transition from reactive marketing models toward proactive and predictive approaches. The findings are relevant to brand equity and health tracking, suggesting that AI-augmented brand management can enhance adaptive campaign optimization.

Lodhi and Singh (2025) examine the role of artificial intelligence in sentiment analysis and brand management within the context of digital transformation. The authors highlight the challenge posed by the surge in user-generated content across social media and review platforms, noting that traditional sentiment tracking methods struggle with scalability and linguistic nuance. They argue that AI offers sophisticated solutions through advanced data processing and pattern recognition, enabling organizations to understand public opinion and anticipate trends. The paper explores how these capabilities empower businesses to craft responsive brand strategies. This work is relevant to brand equity and health tracking, as AI-augmented management may enhance real-time consumer engagement.

Ojuade et al. (2024) examine the application of natural language processing for sentiment analysis within the banking sector, focusing on its role in reputation management. The work demonstrates that categorizing user-generated content as positive, negative, or neutral enables financial institutions to monitor, evaluate, and control their online perception more effectively. The authors reference the UniCredit case in Europe to illustrate how internet reviews influence brand equity and consumer loyalty. Furthermore, the paper highlights the utility of machine learning and predictive analytics for real-time monitoring, crisis prevention, and service enhancement. Challenges such as identifying irony, ensuring data privacy, and addressing moral dilemmas are acknowledged. This research underscores the growing importance of AI-augmented brand management for maintaining trust and resilience in the financial industry.

Khan et al. (2022) explore the role of artificial intelligence in enhancing social media analytics to improve business performance and understand customer behaviour. The paper highlights how technologies such as natural language processing, machine learning, deep learning, and computer vision enable automated and scalable analysis of vast data volumes. These AI capabilities facilitate real-time sentiment analysis, user behaviour prediction, and image and video recognition. The authors position AI as a transformative force in marketing and customer engagement, allowing organizations to extract actionable insights for strategic decision-making. This work is relevant to brand equity and brand health tracking, as AI-augmented brand management offers a data-driven approach to monitoring consumer perceptions.

Chowdhury (2024) explores the influence of sentiment analysis and social media analytics on brand management. Through a comprehensive review of literature and case studies, the research highlights the critical role of these techniques in assessing consumer sentiment and optimizing brand engagement. The study details how sentiment analysis, utilizing natural language processing and machine learning algorithms, provides insights into consumer attitudes and emotional responses, enabling brands to refine marketing strategies based on real-time feedback. Concurrently, social media analytics offers valuable data on consumer interactions across platforms. The findings underscore the importance of these tools for understanding consumer perceptions and shaping effective brand strategies. This work is relevant to advancing AI-augmented brand management and brand health tracking.

Verma and Fatma (2025) examine the transformative role of personalization and artificial intelligence in digital marketing campaigns. The paper details how AI-powered algorithms analyze consumer behavior, preferences, and purchasing patterns to deliver highly relevant content, product recommendations, and targeted advertisements in real time. The authors highlight the use of machine learning models, predictive analytics, and natural language processing to automate customer interactions through chatbots, virtual assistants, and AI-driven email marketing. The abstract indicates that this integration significantly impacts consumer experience, brand loyalty, and overall campaign effectiveness. This work is relevant to brand equity and health tracking, as AI-augmented brand management increasingly relies on such data-driven personalization to strengthen consumer relationships.

Ranaware (2025) proposes a scenario-driven framework for brand positioning that integrates real-time market intelligence from curated social media datasets with quantitative consumer insights from structured surveys. The study employs machine learning models and sentiment analysis to evaluate how brands can develop adaptive positioning strategies across diverse market scenarios. Findings indicate that scenario-based narratives enhance consumer resonance by up to 84%, and predictive models achieve 89% accuracy in forecasting preference shifts. This framework offers marketers a robust toolset for navigating uncertainty and optimizing brand equity. Consequently, the approach holds direct relevance for brand health tracking and AI-augmented brand management, enabling more responsive and data-informed strategic decisions.

Adwan et al. (2025) examined the role of machine learning in monitoring key market factors to predict future brand value, addressing the need for real-time insights in the virtual economy. The study targeted upper-level brand managers and sales marketing directors from Jordanian companies, collecting 229 valid responses via a self-administered questionnaire. Data were analyzed using AMOS software and Structural Equation Modeling to test the research hypotheses. The findings support the utility of machine learning monitoring for enhancing strategic decision-making in brand valuation. This research contributes to discussions on brand equity and health tracking by demonstrating the potential of AI-augmented approaches in brand management.

Khedekar (2025) addresses the limitations of traditional attribution models in measuring influencer marketing ROI within the FMCG sector, where short purchase cycles and impulsive buying complicate accurate assessment. The paper identifies three primary deficiencies in current methods: an inability to distinguish genuine campaign impact from random correlations, inadequate handling of fragmented cross-platform customer journeys, and a failure to balance short-term sales metrics with long-term brand equity development. To resolve these issues, the author proposes a five-layer artificial intelligence architecture combining LSTM neural networks with attention mechanisms for sequential journey modeling, alongside causal inference engines. This framework offers a relevant contribution to brand health tracking by enabling more precise, AI-augmented brand management decisions.

Dzreke and Dzreke (2025) developed and empirically validated the Social Brand Intelligence Framework (SBIF), an integrated architecture designed to convert dispersed social data into strategic intelligence for brand performance optimization. The framework addresses gaps in marketing analytics by unifying data collection, processing, and activation into four interconnected layers, rather than treating them as separate processes. The Input Layer resolves platform heterogeneity through middleware-enabled data harmonization, exemplified by a 65% latency reduction at Nestlé. The Processing Layer employs transformer-based natural language processing to measure causal relationships between sentiment and market outcomes, demonstrating that increases in anger intensity predict subsequent sales declines with high statistical significance. The output layer enhances existing brand equity models. This framework offers a relevant advancement for brand health tracking and AI-augmented brand management.

Sahu and Anjana (2025) explore the transformative role of artificial intelligence in personalized marketing within the digital ecosystem. The paper examines how AI-powered technologies, including machine learning algorithms, predictive modeling, and natural language processing, enable marketers to collect and interpret vast volumes of consumer data in real time. The authors investigate mechanisms by which AI identifies behavioral patterns, preferences, and purchasing intent across digital platforms, facilitating hyper-targeted content and recommendations. The study also addresses ethical implications and privacy concerns associated with personal data use. This research contributes to understanding AI-augmented brand management by highlighting how advanced analytics can inform brand health tracking and consumer engagement strategies.

Wang (2025) investigates the application of artificial intelligence technologies to optimize seasonal consumption forecasting and marketing resource allocation for luxury brands. The study proposes a comprehensive framework that integrates machine learning algorithms with cross-cultural consumer behavior analysis to enhance predictive accuracy. Advanced methodologies, including neural networks, ensemble learning, and real-time optimization algorithms, address complex seasonal patterns in luxury consumption. The system demonstrates improved forecasting accuracy through hybrid models and enables dynamic resource allocation strategies that adapt to cultural preferences and market fluctuations. Empirical validation across multiple luxury market segments reports a 41.9 percent improvement in return on investment and 89 percent accuracy. This work contributes to brand health tracking by illustrating how AI-augmented forecasting can inform strategic marketing decisions in luxury sectors.

3. Research Objectives and Hypotheses

Competitive brand environments increasingly demand continuous visibility into brand health rather than episodic tracking studies alone. Machine learning systems now enable firms to process social signals, search interest, sales proxies, and campaign responses in near real time, creating opportunities for AI-augmented brand equity management. Pune City, Maharashtra, as a major commercial and marketing hub, offers a concentrated setting in which brand and marketing professionals negotiate dashboards, predictive alerts, and multi-source brand metrics in everyday practice. Despite growing vendor claims and technical literature, empirical evidence remains limited regarding how managers perceive ML-enabled brand health tracking and how data quality, dashboard usefulness, analytics capability, alert responsiveness, and integration relate to brand performance outcomes. This study therefore examines these relationships among brand and marketing professionals in Pune City, Maharashtra, India.

Objectives

Objective 1: To examine whether machine learning enabled real-time brand health tracking correlates with improved brand equity management effectiveness among brand and marketing professionals in Pune City, Maharashtra, India.

Objective 2: To examine whether data quality, dashboard usefulness, analytics capability, alert responsiveness, and cross-functional data integration are significantly associated with brand performance and equity protection outcomes among brand and marketing professionals in Pune City, Maharashtra, India.

Hypotheses

H1o: Machine learning enabled real-time brand health tracking exhibits no statistically significant association with improved brand equity management effectiveness among brand and marketing professionals in Pune City, Maharashtra, India.

H1a: Machine learning enabled real-time brand health tracking demonstrates a statistically significant positive association with improved brand equity management effectiveness among brand and marketing professionals in Pune City, Maharashtra, India.

H2o: Data quality, dashboard usefulness, analytics capability, alert responsiveness, and cross-functional data integration show no statistically significant correlations with brand performance and equity protection outcomes among brand and marketing professionals in Pune City, Maharashtra, India.

H2a: Data quality, dashboard usefulness, analytics capability, alert responsiveness, and cross-functional data integration are significantly and positively correlated with brand performance and equity protection outcomes among brand and marketing professionals in Pune City, Maharashtra, India.

4. Research Methodology

The research adopted a quantitative, cross-sectional design to investigate the applicability of machine learning frameworks for real-time brand health tracking within an Indian metropolitan context. A structured survey methodology was deemed appropriate for capturing measurable perceptions and attitudes from industry practitioners regarding AI-augmented brand equity management. The design facilitated the systematic examination of relationships between constructs such as perceived utility, data-driven decision-making, and brand health monitoring effectiveness. This approach enabled the collection of standardized data amenable to statistical analysis, thereby allowing the study to test hypotheses concerning the adoption and perceived value of machine learning tools in brand management practice. The cross-sectional nature of the design provided a snapshot of professional opinions during a defined period, which was sufficient for establishing correlational evidence and assessing central tendencies within the target population.

The respondent class was deliberately restricted to brand and marketing professionals operating in Pune City, Maharashtra, India. This category exclusively comprised brand managers, marketing managers, marketing analytics and insights managers, brand equity or brand health specialists, and digital marketing managers whose roles involved brand tracking responsibilities. Students, general consumers, and information technology engineers without direct brand-related functions were excluded from the sample. This purposive restriction was essential to ensure that all participants possessed the requisite professional expertise and contextual familiarity to evaluate the proposed machine learning framework. The inclusion of only experienced practitioners enhanced the content validity of responses, as these individuals were directly accountable for brand performance metrics and were therefore best positioned to assess the practical implications of AI-augmented brand health monitoring systems.

Purposive stratified sampling was employed to select respondents across distinct role cadres within the brand and marketing professional class. This method ensured adequate representation of each functional designation, thereby capturing diverse perspectives on brand health tracking practices. The sample size of 289 respondents was determined based on considerations of statistical power for the planned analyses, including one-sample t-tests and Pearson correlation coefficients. This number exceeded the minimum threshold required for detecting moderate effect sizes at conventional significance levels, while remaining feasible given the six-month data collection window. The stratification by role cadre facilitated subgroup comparisons and enhanced the generalizability of findings across the professional categories of interest, thus strengthening the external validity of the study within the defined population of Pune-based brand practitioners.

The survey instrument comprised a structured questionnaire designed to measure key constructs related to machine learning adoption and brand health tracking. All items were rated on a five-point Likert scale, ranging from one for strongly disagree to five for strongly agree. The questionnaire was developed based on established literature in brand equity management and technology acceptance, with items tailored to the specific context of real-time brand monitoring. The instrument captured perceptions regarding the accuracy, timeliness, and decision-making utility of AI-based tracking systems, as well as attitudes toward integrating such tools into existing brand management workflows. Prior to full deployment, the questionnaire was reviewed for clarity and relevance, and the Likert format was selected to facilitate quantitative analysis of professional attitudes while maintaining respondent ease of completion.

Data collection was conducted over a six-month period from July 2023 to December 2023. Responses were gathered through multiple modes, including face-to-face interviews, online surveys, and telephone administration, to maximize reach and accommodate respondent preferences. Informed consent was obtained from all participants prior to their involvement, and confidentiality of individual responses was assured. The collected data were analyzed using SPSS version 26. Descriptive statistics were computed to summarize respondent profiles and item distributions. Inferential analysis employed one-sample t-tests with a test value of three to determine whether mean responses differed significantly from the neutral midpoint, thereby assessing the direction and strength of professional agreement with study propositions. Additionally, Pearson correlation analysis was conducted to examine the relationships among key variables, providing evidence regarding the interconnections between machine learning perceptions and brand health tracking outcomes.

5. Data Analysis and Interpretation

Table 1: Age Profile of Respondents

Particulars	Frequency	Percentage	Cumulative Percentage
25-34 years	67	23.18	23.18
35-44 years	84	29.07	52.25
45-54 years	73	25.26	77.51
55-64 years	41	14.19	91.70
65 years and above	24	8.30	100.00
Total	**289**	**100.00**	**100.00**

The age distribution of the 289 brand and marketing professionals reveals a concentration in the middle career brackets, with the 35 to 44 years cohort representing the largest segment at 29.07 percent. This group, followed closely by the 45 to 54 years category at 25.26 percent, suggests that brand equity decisions in Pune are predominantly managed by experienced mid-career professionals. The relatively smaller proportions in the younger 25 to 34 years cohort (23.18 percent) and the senior 55 years and above categories indicate a workforce that is seasoned yet not overly aged. For Indian brand equity management practice, this demographic skew implies that adoption of machine learning tools will depend on the digital fluency and change readiness of professionals who have substantial conventional marketing experience.

Table 2: Gender Distribution of Respondents

Particulars	Frequency	Percentage	Cumulative Percentage
Male	151	52.25	52.25
Female	138	47.75	100.00
Total	**289**	**100.00**	**100.00**

The gender composition of the sample is nearly balanced, with male respondents comprising 52.25 percent and female respondents 47.75 percent. This near parity is notable for the Indian marketing profession, which has historically exhibited wider gender gaps in senior roles. The balanced representation strengthens the generalizability of the study findings across gender perspectives in brand health tracking and equity management. It also suggests that organizational cultures in Pune's brand and marketing functions have progressed toward inclusive hiring and retention practices. For practitioners, this equilibrium implies that AI-augmented brand equity frameworks must be designed and communicated in ways that resonate with diverse professional viewpoints, avoiding gender-biased assumptions in user interface design or algorithmic training data.

Table 3: Role Cadre Profile of Brand and Marketing Professionals

Particulars	Frequency	Percentage	Cumulative Percentage
Brand Managers	71	24.57	24.57
Marketing Managers	68	23.53	48.10
Marketing Analytics and Insights Managers	58	20.07	68.17
Brand Equity and Brand Health Specialists	49	16.96	85.12
Digital Marketing Managers (Brand Tracking)	43	14.88	100.00
Total	**289**	**100.00**	**100.00**

The occupational breakdown shows Brand Managers as the largest single cadre at 24.57 percent, followed closely by Marketing Managers at 23.53 percent and Marketing Analytics and Insights Managers at 20.07 percent. The presence of specialized roles such as Brand Equity and Brand Health Specialists (16.96 percent) and Digital Marketing Managers focused on brand tracking (14.88 percent) indicates that Pune's brand management ecosystem has matured beyond generic marketing functions. The distribution suggests that real-time brand health tracking is not solely the domain of analytics teams but is embedded across managerial hierarchies. For Indian firms, this diversity in occupational roles implies that machine learning dashboards must cater to varying levels of technical sophistication, from strategic brand managers to data-centric insights professionals, requiring customizable interfaces and role-specific training.

Table 4: ML-Based Real-Time Brand Health Dashboards Improving Decision Speed (Statement 1)

Particulars	Frequency	Percentage	Cumulative Percentage
Strongly Agree	98	33.91	33.91
Agree	86	29.76	63.67
Neutral	52	17.99	81.66
Disagree	34	11.76	93.43
Strongly Disagree	19	6.57	100.00
Total	**289**	**100.00**	**100.00**

The first statement on machine learning based real-time brand health dashboards improving decision speed received strong endorsement, with a combined agreement of 63.67 percent. The modal response was strongly agree at 33.91 percent, indicating that a substantial proportion of professionals perceive tangible acceleration in decision making from such dashboards. The neutral category captured 17.99 percent, while dissent remained modest at 18.34 percent. This pattern suggests that while the majority recognize the value of real-time dashboards, a meaningful minority remains unconvinced, possibly due to concerns about data latency or interface complexity. For Indian brand equity management, this finding underscores the need for organizations to demonstrate clear time-to-insight improvements through pilot implementations before full-scale deployment.

Table 5: AI Sentiment and Social Listening Strengthening Brand Equity Signals (Statement 2)

Particulars	Frequency	Percentage	Cumulative Percentage
Strongly Agree	101	34.95	34.95
Agree	88	30.45	65.40
Neutral	47	16.26	81.66
Disagree	32	11.07	92.73
Strongly Disagree	21	7.27	100.00
Total	**289**	**100.00**	**100.00**

The statement on AI sentiment and social listening strengthening brand equity signals recorded the highest combined agreement among the H1 items at 65.4 percent. Strong agreement alone accounted for 34.95 percent of responses, the highest across all five statements. This robust endorsement reflects the growing acceptance of social media analytics as a legitimate source of brand health intelligence in the Indian market, where digital consumption is rapidly expanding. The relatively lower neutral and disagreement proportions, at 16.26 percent and 18.34 percent respectively, indicate that skepticism is limited. Practitioners in Pune appear ready to integrate unstructured social data into brand equity frameworks, though the presence of dissent suggests that concerns about noise, fake engagement, and platform biases must be addressed through rigorous validation protocols.

Table 6: Predictive Brand Risk Alerts Enabling Proactive Equity Protection (Statement 3)

Particulars	Frequency	Percentage	Cumulative Percentage
Strongly Agree	94	32.53	32.53
Agree	91	31.49	64.01
Neutral	53	18.34	82.35
Disagree	31	10.73	93.08
Strongly Disagree	20	6.92	100.00
Total	**289**	**100.00**	**100.00**

Predictive brand risk alerts enabling proactive equity protection received a combined agreement of 64.01 percent, with strong agreement at 32.53 percent and agreement at 31.49 percent. The near parity between these two response categories indicates that professionals are broadly convinced of the value of predictive alerts, though with slightly less intensity than for sentiment analysis. The neutral proportion of 18.34 percent and total disagreement of 17.65 percent suggest that a considerable segment remains cautious about the reliability of predictive models in anticipating brand crises. For Indian brand managers, this finding implies that predictive risk alerts should be positioned as decision support tools rather than autonomous warning systems, with human oversight retained to interpret alerts in the context of local market dynamics and cultural sensitivities.

Table 7: Integrated Multi-Source Brand Metrics Improving Measurement Accuracy (Statement 4)

Particulars	Frequency	Percentage	Cumulative Percentage
Strongly Agree	83	28.72	28.72
Agree	89	30.80	59.52
Neutral	56	19.38	78.89
Disagree	37	12.80	91.70
Strongly Disagree	24	8.30	100.00
Total	**289**	**100.00**	**100.00**

The statement on integrated multi-source brand metrics improving measurement accuracy received a combined agreement of 59.52 percent, the lowest among the H1 items. Strong agreement fell to 28.72 percent, while the neutral category rose to 19.38 percent and disagreement reached 21.11 percent. This comparatively weaker endorsement suggests that professionals in Pune harbor reservations about the practical feasibility of integrating disparate data sources such as sales, social media, customer surveys, and distribution metrics into a unified brand health score. Concerns may stem from data silos, inconsistent taxonomies, and the absence of standardized integration protocols in Indian firms. The finding indicates that while the conceptual appeal of multi-source integration is acknowledged, implementation challenges remain a significant barrier that organizations must overcome through investments in data governance and interoperability standards.

Table 8: AI-Augmented Brand Equity Frameworks Supporting Strategic Allocation (Statement 5)

Particulars	Frequency	Percentage	Cumulative Percentage
Strongly Agree	78	26.99	26.99
Agree	84	29.07	56.06
Neutral	61	21.11	77.16
Disagree	39	13.49	90.66

Strongly Disagree	27	9.34	100.00
Total	**289**	**100.00**	**100.00**

AI-augmented brand equity frameworks supporting strategic allocation recorded the lowest combined agreement among all H1 statements at 56.06 percent, with strong agreement at 26.99 percent. The neutral proportion was the highest across the set at 21.11 percent, and total disagreement reached 22.84 percent. This pattern reveals considerable ambivalence about whether AI frameworks can genuinely guide resource allocation decisions such as media spend, distribution expansion, or brand portfolio rationalization. Indian brand managers may perceive strategic allocation as inherently judgment-driven, requiring qualitative insights that algorithms cannot fully capture. The finding suggests that AI-augmented frameworks should be presented as complementary to managerial intuition rather than replacements, with clear explanations of how model outputs translate into actionable allocation recommendations.

Table 9: Data Quality and Reliability of Real-Time Brand Health Models (Statement 1 for H2)

Particulars	Frequency	Percentage	Cumulative Percentage
Strongly Agree	96	33.22	33.22
Agree	89	30.80	64.01
Neutral	49	16.96	80.97
Disagree	34	11.76	92.73
Strongly Disagree	21	7.27	100.00
Total	**289**	**100.00**	**100.00**

The statement on data quality and reliability of real-time brand health models received a combined agreement of 64.01 percent, with strong agreement at 33.22 percent. This high endorsement indicates that professionals recognize data quality as a critical enabler for the effectiveness of machine learning models in brand tracking. The neutral proportion of 16.96 percent and disagreement of 19.03 percent suggest that while confidence is substantial, a segment of respondents has experienced or anticipates issues with incomplete, outdated, or inconsistent data in their organizations. For Indian brand equity practice, this finding emphasizes that investments in data infrastructure, cleansing routines, and validation protocols are prerequisites for realizing the benefits of real-time brand health monitoring. Firms must prioritize data governance before scaling AI tools across brand portfolios.

Table 10: ML Dashboard Usefulness and Brand Manager Decision Confidence (Statement 2 for H2)

Particulars	Frequency	Percentage	Cumulative Percentage
Strongly Agree	81	28.03	28.03
Agree	93	32.18	60.21
Neutral	54	18.69	78.89
Disagree	37	12.80	91.70
Strongly Disagree	24	8.30	100.00
Total	**289**	**100.00**	**100.00**

The statement on ML dashboard usefulness and brand manager decision confidence recorded a combined agreement of 60.21 percent, with strong agreement at 28.03 percent and agreement at 32.18 percent. The distribution indicates that a majority of professionals believe that well-designed dashboards enhance their confidence in making brand decisions, though the intensity of endorsement is moderate. The neutral category at 18.69 percent and disagreement at 21.11 percent reveal that dashboard usefulness is contingent on factors such as user interface design, training adequacy, and the relevance of displayed metrics to specific decision contexts. For Indian organizations, this finding suggests that dashboard adoption strategies must include user-centric design processes, iterative feedback loops, and role-based customization to ensure that brand managers perceive tangible improvements in their decision confidence.

Table 11: Organizational Analytics Capability and AI Brand Tool Adoption (Statement 3 for H2)

Particulars	Frequency	Percentage	Cumulative Percentage
Strongly Agree	74	25.61	25.61
Agree	88	30.45	56.06
Neutral	59	20.42	76.47
Disagree	41	14.19	90.66
Strongly Disagree	27	9.34	100.00
Total	**289**	**100.00**	**100.00**

The statement on organizational analytics capability and AI brand tool adoption received a combined agreement of 56.06 percent, the lowest among the H2 items, with strong agreement at 25.61 percent. The neutral proportion was elevated at 20.42 percent, and total disagreement reached 23.53 percent. This pattern indicates that professionals perceive organizational readiness, including technical skills, data literacy, and leadership support, as a significant constraint on the adoption of AI-based brand tools. The relatively high dissent suggests that many firms in Pune lack the internal capabilities to deploy and sustain advanced analytics systems. For Indian brand equity management, this finding underscores the necessity of capability building programs, including training for existing staff and recruitment of specialized data talent, before expecting successful AI tool integration into brand health workflows.

Table 12: Real-Time Alert Responsiveness and Brand Equity Protection (Statement 4 for H2)

Particulars	Frequency	Percentage	Cumulative Percentage
Strongly Agree	86	29.76	29.76
Agree	91	31.49	61.25
Neutral	51	17.65	78.89
Disagree	36	12.46	91.35
Strongly Disagree	25	8.65	100.00
Total	**289**	**100.00**	**100.00**

The statement on real-time alert responsiveness and brand equity protection received a combined agreement of 61.25 percent, with strong agreement at 29.76 percent and agreement at 31.49 percent. This endorsement indicates that professionals value the ability to respond swiftly to emerging brand threats, such as negative viral content or competitor actions, through real-time alerts. The neutral proportion of 17.65 percent and disagreement of 21.11 percent suggest that some respondents doubt whether alert systems can consistently distinguish genuine threats from false positives. For Indian practitioners, this finding implies that alert mechanisms must be calibrated to local market contexts, with clear escalation protocols and human verification steps to prevent alert fatigue and ensure that responses are proportionate to the actual risk level.

Table 13: Cross-Functional Data Integration and Brand Performance Outcomes (Statement 5 for H2)

Particulars	Frequency	Percentage	Cumulative Percentage
Strongly Agree	90	31.14	31.14
Agree	84	29.07	60.21
Neutral	54	18.69	78.89
Disagree	35	12.11	91.00
Strongly Disagree	26	9.00	100.00
Total	**289**	**100.00**	**100.00**

The statement on cross-functional data integration and brand performance outcomes recorded a combined agreement of 60.21 percent, with strong agreement at 31.14 percent and agreement at 29.07 percent. The distribution indicates that professionals recognize the value of integrating data across functions such as sales, customer service, supply chain, and finance for improving brand performance. The neutral category at 18.69 percent and disagreement at 21.11 percent reveal that cross-functional integration is often hampered by departmental silos, conflicting data ownership, and divergent performance metrics. For Indian firms, this finding suggests that successful brand equity management requires organizational structures that incentivize data sharing and collaborative analytics, rather than isolated departmental dashboards, to achieve a holistic view of brand health.

Table 14: One-Sample t-Test Results for H1

Particulars	Test Value	t-Statistic	df	Sig. (2-tailed)	Mean	Std. Deviation
ML Real-Time Brand Health Dashboards Improving Decision Speed	3	12.791	288	0.000	3.73	0.968
AI Sentiment and Social Listening Strengthening Brand Equity Signals	3	13.318	288	0.000	3.75	0.954
Predictive Brand Risk Alerts Enabling Proactive Equity Protection	3	12.698	288	0.000	3.72	0.961
Integrated Multi-Source Brand Metrics Improving Measurement Accuracy	3	9.801	288	0.000	3.59	1.021
AI-Augmented Brand Equity Frameworks Supporting Strategic Allocation	3	8.031	288	0.000	3.51	1.078
H1 Summary (Aggregate Mean Across Statements)	**3**	**14.231**	**288**	**0.000**	**3.66**	**0.788**

The one-sample t-test results provide robust statistical support for the first hypothesis, with an aggregate mean of 3.66 across all H1 statements and a t-value of 14.231 at 288 degrees of freedom. All individual statement means exceeded the neutral midpoint of 3, and all p-values were below 0.001, indicating that the observed agreement levels are highly unlikely to have occurred by chance. This finding confirms that brand and marketing professionals in Pune perceive machine learning based real-time brand health tracking as significantly beneficial for improving decision speed, strengthening equity signals, enabling proactive risk management, enhancing measurement accuracy, and supporting strategic allocation. For Indian brand equity practice, the statistical significance reinforces the strategic imperative for firms to invest in AI-augmented brand health monitoring systems as a competitive necessity.

Table 15: Correlation Analysis Results for H2

Particulars	Pearson r	Sig. (2-tailed)	N	Result
Data Quality and Model Reliability	0.684	0.000	289	Significant
Dashboard Usefulness and Decision Confidence	0.647	0.000	289	Significant
Analytics Capability and AI Tool Adoption	0.603	0.000	289	Significant
Alert Responsiveness and Equity Protection	0.669	0.000	289	Significant
Data Integration and Brand Performance Outcomes	0.712	0.000	289	Significant
H2 Summary (Mean Correlation Across Relationships)	**0.663**	**0.000**	**289**	**Significant**

The Pearson correlation analysis for the second hypothesis revealed significant positive relationships between organizational and technological factors and brand performance outcomes, with correlation coefficients ranging from 0.603 to 0.712 and a mean correlation of 0.663. All correlations were statistically significant at the sample size of 289, indicating robust associations between constructs such as data quality, dashboard usefulness, organizational analytics capability, alert responsiveness, cross-functional integration, and brand equity outcomes. The moderate to strong magnitude of these correlations suggests that improvements in these enabling factors are consistently associated with better brand health and equity management results. For Indian practitioners, this finding implies that investments in data infrastructure, user-centric tool design, organizational capability building, and cross-functional collaboration will yield measurable improvements in brand equity protection and performance.

6. Key Findings

The demographic profile of the surveyed brand and marketing professionals in Pune City, Maharashtra, India (N=289) reveals a predominantly middle-aged, marginally male-skewed cohort, with the largest age segment being 35 to 44 years (29.07%) and a gender split of 52.25% male and 47.75% female. Brand managers constituted the largest professional cadre (24.57%), followed by other senior marketing roles. Regarding technology adoption, a substantial majority expressed high agreement on the utility of machine learning dashboards, AI-driven sentiment analysis and social listening tools, and predictive risk alerts for brand health monitoring. The combined agreement rates for these AI-enabled features consistently exceeded 60%, indicating strong professional receptivity to real-time, data-driven brand management systems within the regional corporate landscape. Hypothesis testing via one-sample t-tests rejected the null hypothesis H1o, yielding a significant aggregate t-statistic of 14.231 (p=0.000) with a mean score of 3.66, confirming that professionals perceive AI-augmented tools as critical for effective brand equity management. Furthermore, Pearson correlation analyses supported the alternative hypothesis H2a, revealing robust positive relationships between real-time ML tracking and brand equity outcomes, with correlation coefficients ranging from 0.603 to 0.712 and a mean r of 0.663; all correlations were statistically significant. These findings imply that integrating AI-driven predictive analytics and continuous brand health dashboards can substantially enhance proactive brand equity stewardship in Indian markets, enabling faster response to sentiment shifts and more agile resource allocation for brand managers.

7. Conclusion

The study establishes that machine learning enabled real-time brand health tracking significantly enhances brand equity management effectiveness among brand and marketing professionals in Pune. The findings demonstrate that the integration of predictive analytics and continuous sentiment monitoring into brand management workflows facilitates more agile responses to market shifts and improves the diagnostic precision of brand equity assessments. By moving beyond periodic, retrospective surveys, the framework enables professionals to identify emerging brand perception threats and opportunities as they occur, thereby strengthening the alignment between brand strategy and dynamic consumer realities. Consequently, the research confirms that AI augmented brand health systems function not merely as measurement tools but as strategic decision support mechanisms that elevate the overall responsiveness and efficacy of brand equity management practices. For brand teams, chief marketing officers, and analytics units in India, the practical implications are substantial. The framework offers a scalable blueprint for transitioning from static brand tracking to a continuous, data driven operational model, which is particularly valuable in heterogeneous and rapidly evolving urban markets. Marketing technology vendors can leverage these insights to design localized solutions that account for linguistic diversity, regional cultural nuances, and tier two city consumption patterns. Furthermore, the adoption of such systems necessitates investment in analytical talent and change management to ensure that algorithmic outputs are effectively interpreted and translated into actionable brand strategies. For practitioners, the study underscores that real time intelligence is a competitive necessity, enabling proactive brand stewardship rather than reactive crisis management in the Indian marketplace. Future research should extend this investigation to other Indian cities to assess the generalizability of the findings across different market maturities and cultural contexts. Longitudinal designs are essential to capture the dynamic relationship between real time tracking and brand equity outcomes over extended periods, thereby establishing causal inference beyond the current cross sectional approach. Category wise comparisons across fast moving consumer goods, services, and durables would illuminate sector specific sensitivities to AI augmented tracking. Additionally, multi stakeholder designs incorporating consumers, retailers, and channel partners are warranted, as the present study relied exclusively on brand and marketing professionals, whose perspectives may differ from those of other ecosystem actors. Such expansions would enrich the theoretical and practical understanding of AI augmented brand equity management in emerging economies.

8. Suggestions

1. Establish a unified brand data architecture that integrates structured sales, unstructured social media, and real-time point-of-sale feeds from Pune retail clusters and national e-commerce channels. Standardize entity resolution for brand mentions across Marathi, Hindi, and English. This single source of truth reduces latency in signal detection and enables consistent equity measurement across regions.

2. Implement a model governance framework with documented versioning, drift monitoring, and periodic retraining protocols for ML algorithms tracking brand health. Assign ownership to a data steward in Pune and a national review board. Define clear rollback procedures when model performance degrades, ensuring that equity indices remain reliable and auditable for leadership decisions.
3. Design real-time dashboards that prioritize actionable alerts over raw metrics. Use tiered visual hierarchies for brand awareness, sentiment, and share of voice, with drill-downs to Pune-specific and national views. Include anomaly flags with contextual explanations, such as competitor launches or festival season shifts, to help brand managers interpret changes without data science support.
4. Develop alert playbooks that prescribe pre-approved response protocols for negative sentiment spikes, influencer controversies, or sudden competitor promotions. Each playbook should specify trigger thresholds, responsible roles, communication templates, and escalation paths within 24 hours. Test these playbooks quarterly with simulated scenarios in Pune and national markets to ensure speed and consistency.
5. Create cross-functional brand-analytics teams that include marketing, IT, sales, and customer service representatives from Pune and headquarters. Hold weekly stand-ups to review ML outputs, align on corrective actions, and share local market insights. This structure prevents siloed interpretations and ensures that real-time signals translate into coordinated brand management actions.
6. Link measurement frameworks to brand equity pillars such as awareness, associations, perceived quality, and loyalty. Map each ML-derived metric, like sentiment polarity or engagement velocity, to these pillars with clear definitions. Validate the mapping annually through consumer surveys in Pune and national samples, ensuring that algorithmic indicators remain conceptually grounded and managerially meaningful.
7. Upskill brand managers in applied ML literacy through structured workshops covering model inputs, output interpretation, and limitations. Focus on practical exercises using Pune market data and national case studies. Certify completion and integrate analytics proficiency into performance reviews, enabling teams to question model outputs intelligently and communicate findings to senior leadership effectively.
8. Adopt ethical guidelines for consumer and social data usage, including consent protocols, anonymization standards, and bias audits for ML models. Publish a transparency statement for Pune and national stakeholders, detailing data sources and algorithmic decision boundaries. Regularly review compliance with Indian data protection laws, ensuring that brand tracking builds trust rather than eroding consumer confidence.

References

1. Abbas, H. (2025). Sentiment Analysis of Product Reviews. International Scientific Journal of Engineering and Management. https://doi.org/10.55041/isjem03416
2. Adwan, A. A., Altrjman, G., Al-Mu'ani, L. (2025). Predicting future brand value: The role of machine learning monitoring. Innovative Marketing. https://doi.org/10.21511/im.21(2).2025.15
3. Ballı, A. (2024). The Effect of Product Personalization on Consumer Purchasing Intention, Customer Satisfaction, Brand Loyalty and Artificial Intelligence Applications with Machine Learning. Fiscaoeconomia. https://doi.org/10.25295/fsecon.1449755
4. Carter, E. (2024). Understanding Consumer Sentiment with Social Media Data Analytics. American journal of data science and analysis. https://doi.org/10.71465/ajdsa1222
5. Chowdhury, R. H. (2024). Sentiment analysis and social media analytics in brand management: Techniques, trends, and implications. World Journal of Advanced Research and Reviews. https://doi.org/10.30574/wjarr.2024.23.2.2369
6. Dahake, P., Pathan, A. R. A. K., Dahake, N., Wadhwani, K. (2025). A Predictive Analytics Approach to Brand Equity Optimization: Unveiling Consumer Insights for Masstige Marketing. 2025 International Conference on Data Science and Business Systems (ICDSBS). https://doi.org/10.1109/ICDSBS63635.2025.11031946
7. Dzreke, S., Dzreke, S. (2025). The Social Intelligence Nexus - Leveraging Social Media Analytics for Comprehensive Brand Performance Optimization. International Journal For Multidisciplinary Research. https://doi.org/10.36948/ijfmr.2025.v07i04.50402
8. Gaikwad, A., Rao, G. S., Goud, M. (2025). Beyond Likes and Shares: Gamification and Machine Learning as Drivers of Enhanced Social Media Brand Engagement on Gen Z. 2025 2nd International Conference on Innovations in Engineering, Science and Technology for Sustainable Development (ICEST). https://doi.org/10.1109/ICEST65883.2025.11428466
9. Jaiswal, S. (2025). The Role of Artificial Intelligence in Personalizing Digital Marketing Strategies. International Scientific Journal of Engineering and Management. https://doi.org/10.55041/isjem04415

10. Jeswani, R. (2023). The Role and Importance of Social Media Marketing in Brand Building. Irish Interdisciplinary Journal of Science & Research. https://doi.org/10.46759/iijsr.2023.7401
11. Joseph, O. O., Akintola, A. S., Offiong, E., Olajuwon, O. O., Offia, U. I., Faniyan, A. A. (2025). AI-Enhanced Consumer Insights: Leveraging Behavioural Analytics for Hyper-Personalised Marketing Strategies. Journal of Artificial Intelligence, Machine Learning and Data Science. https://doi.org/10.51219/jaimld/omotoso-oluwayomi-joseph/511
12. Khan, M. S. A., Syed, M. M., Mohammed, M. H. S. (2022). Utilizing Artificial Intelligence in Social Media Analytics to Enhance Business Performance and Understand Customer Behaviour. Journal of Business, IT, and Social Science. https://doi.org/10.51470/bits.2022.01.01.09
13. Khedekar, P. (2025). Bridging Performance and Brand Equity: An AI-Driven Framework for FMCG Influencer Marketing ROI Measurement. The American Journal of Interdisciplinary Innovations and Research. https://doi.org/10.37547/tajiir/volume07issue10-07
14. Kothari, B., Mani, A. P. (2024). Machine Learning Based study on Relationship of Brand Image and Purchase Intentions towards the Herbal Cosmetic with Practical Implementation. 2024 OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 4.0. https://doi.org/10.1109/OTCON60325.2024.10687953
15. Li, Y., You, C. (2021). Brand Loyalty Measurement Model Based on Machine Learning Clustering Algorithm. Journal of Physics, Conference Series. https://doi.org/10.1088/1742-6596/1982/1/012089
16. Limbore, N., Lahoti, Y., Kalshetti, P., Anute, N. (2025). Machine Learning Models for Sentiment Analysis in Brand Management and Consumer Engagement. 2025 International Conference on Innovations in Intelligent Systems: Advancements in Computing, Communication, and Cybersecurity (ISAC3). https://doi.org/10.1109/ISAC364032.2025.11156276
17. Lodhi, S. S., Singh, D. (2025). Harnessing Artificial Intelligence for Sentiment Analysis and Brand Management: Transforming Consumer Engagement in the Digital Age. International Journal of Innovative Science and Research Technology. https://doi.org/10.38124/ijisrt/25jul615
18. Mannaru, S. (2025). AI-Powered Sentiment Analysis in Real-Time Brand Monitoring. International Journal of Integrated Research and Practice. https://doi.org/10.65579/31075037.093
19. Miglani, T. (2025). AI-Powered Sports Marketing: Predictive Insights, Consumer Behavior, and Global Brand Strategy. International Journal For Multidisciplinary Research. https://doi.org/10.36948/ijfmr.2025.v07i06.62891
20. Ojuade, S., Adepeju, A. S., Idowu, K., Berko, S. N., Olisa, A., Aniebonam, E. (2024). Social Media Sentiment Analysis and Banking Reputation Management. International Journal of Multidisciplinary Research and Growth Evaluation. https://doi.org/10.54660/.ijmrge.2024.5.6.1701-1708
21. Pamuksuz, U., Yun, J. T., Humphreys, A. (2021). A Brand-New Look at You: Predicting Brand Personality in Social Media Networks with Machine Learning. Journal of Interactive Marketing. https://doi.org/10.1016/j.intmar.2021.05.001
22. Paturi, M. (2025). AI-Driven Sentiment Analysis for Real-Time Product Positioning and Adaptive Marketing Campaign Optimization. International Journal of Research Publication and Reviews. https://doi.org/10.55248/gengpi.6.0625.21104
23. Ranaware, H. (2025). Scenario-Driven Brand Positioning Strategies Informed by Real-Time Market Intelligence and Quantitative Consumer Insights. International Journal For Multidisciplinary Research. https://doi.org/10.36948/ijfmr.2025.v07i04.51867
24. Ranganathan, C. (2024). Hootsuite for Cloud-Based Monitoring of Consumer Social Media in Business. International Journal of Modern Computation, Information and Communication Technology. https://doi.org/10.65000/5kgc4g20
25. Rayimdjanova, G., Ismanov, I., Yakubov, V., Kunduzova, K., Ablazov, N., Jakhbarov, J. (2025). Leveraging Real-Time Insights: AI's Impact on Competitive Marketing Strategies. 2025 3rd International Conference on IoT, Communication and Automation Technology (ICICAT). https://doi.org/10.1109/ICICAT68430.2025.11414650
26. Sahu, J. K., Anjana, D. S. D. C. (2025). Personalized Marketing in the Digital Age: The Role of AI in Consumer Behavior Analytics. European Economic Letters (EEL). https://doi.org/10.52783/eel.v15i3.3415
27. Samanta, P., Amir, M., Bagga, S., Dubey, B., Khulbe, M., Gupta, R. (2025). Influencer Marketing in the Age of AI: Improving Brand Loyalty Through Advanced Analytics. International Conference on Contemporary Computing. https://doi.org/10.1109/IC363308.2025.10956901

28. Sinha, Y. K., Sharma, S. (2025). Sentiment, reach, and quality: A machine learning approach to social media analytics in food and beverage industry. World Journal of Advanced Engineering Technology and Sciences. https://doi.org/10.30574/wjaets.2025.15.2.0833
29. Susanti, L. (2025). Product Marketing Strategy Using Digital Marketing Technology. Journal of Social Science and Business Studies. https://doi.org/10.61487/jssbs.v3i1.128
30. Verma, S., Fatma, D. (2025). How Personalization and AI Are Transforming Digital Marketing Campaigns. INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT. https://doi.org/10.55041/ijsrem42751
31. Wagh, V., Ramesh, G. (2024). A Study on The Role of AI in Hyper-Personalization Marketing of FMCG Products. Economic Sciences. https://doi.org/10.69889/kpr5pr58
32. Wang, J. (2025). Artificial Intelligence-Driven Seasonal Consumption Forecasting and Resource Allocation Optimization in Luxury Brand Marketing. Proceedings of the 2025 2nd International Conference on Digital Economy and Computer Science. https://doi.org/10.1145/3785706.3785882