“Predicting future brand value: The role of machine learning monitoring”

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PREDICTING FUTURE BRAND VALUE: THE ROLE OF MACHINE LEARNING MONITORING

Abstract

Data-driven strategies have become essential for brand valuation optimization in today's rapidly evolving virtual economy, where organizations face increasing pressure to gain real-time, accurate insights to maintain a competitive edge. The purpose of the study examine the impact of machine learning in monitoring key market factors to predict future brand value, addressing the growing need among industry professionals for tools that enhance strategic decision-making. From April to September 2024, a purposive sample of 350 upper-level brand managers and sales marketing directors from various Jordanian companies targeted due to their direct involvement in brand evaluation and marketing strategy. 229 completed and valid responses were collected through a self-administered questionnaire. The data analyzed using AMOS software and Structural Equation Modeling (SEM) to test the research hypotheses. Results indicated that all proposed factors significantly influenced the prediction of future brand value, with purchase frequency ($\beta = 2.681$), industry trend monitoring ($\beta = 2.228$), consumer behavior ($\beta = 0.353$), and social media metrics ($\beta = 0.345$) showing statistically significant effects ($p < 0.05$). These findings demonstrate the effectiveness of machine learning in identifying predictive patterns relevant to brand performance and provide a practical framework for leveraging digital tools to enhance brand valuation strategies. The study concludes that integrating machine learning with key performance monitoring enables organizations to make more informed, timely, and impactful branding decisions in a dynamic digital landscape.

Keywords monitoring, digital tools, consumer behavior, brand sustainability, market trends, Jordan

JEL Classification M30, M31

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INTRODUCTION

For decades, brands have helped consumers differentiate products from specific manufacturers. Branding enables informed decision-making by creating mental frameworks to categorize and recall information about products and services (Fu, 2022). A brand, therefore, is more than a product; its distinct identity within the market that fulfills unique consumer needs. Trustworthy brands foster customer loyalty, as consumers tend to repeatedly choose products from brands they trust today businesses seek to deepen emotional connections with customers by cultivating brand loyalty, awareness, confidence, and recognition, which can enhance the overall customer experience (Chauhan, 2023). These factors contribute significantly to brand value, a complex construct influenced by brand trust, loyalty, and customer engagement. Brand equity consumer perception of a brand's value shaped by a company's market position and built on emotional investment, trust, and affinity (Syed & Jamim, 2022). Effective brand equity provides resilience against competitor strategies and aids in customer retention. As the digital landscape evolves, consumers increasingly engage with brands through digital channels such as social media, review sites, and weblogs, where brand value constantly reassessed based on consumer feedback (Faruk et al., 2021). In light of these dynamics, a pressing question arises for marketers: How can predictive analytics,

particularly machine learning (ML) models and social media, enhance the accuracy of brand value forecasts? The integration of AI and machine learning into brand evaluation offers transformative potential, especially in real time trend prediction and customer insights analysis (Ziakis & Vlachopoulou, 2023). By monitoring these key information sources, ML models can significantly improve the forecasting accuracy for brand value.

1. LITERATURE REVIEW

AI is a subset of computer-based intelligence that allows computers to learn from experience, improve upon past performance, and predict the future (Haleem et al., 2022). Supervised and unsupervised models are the two main ML categories. The requirement for marked information preparation is the main difference between supervised and unaided learning. While unaided learning encounters unlabeled or crude input, administered AI relies on significant and result-preparing information (Watson et al., 2023). Prediction in machine learning, also known as machine learning prediction, is the result of a machine learning algorithm being applied to a dataset of data from the past (Marcelino et al., 2019). After that, for each new data record, the algorithm will produce estimates for the information gaps (Ray, 2019). In machine learning, prediction is the process of generating a likely data set that connected to the original data. This is useful for forecasting brand value because it allows businesses to anticipate customer behavior and market shifts (Sheng et al., 2020). All data modelled into a shape as close to the data as possible, and predictions made. Machine learning predictions allow businesses to take preventative measures against user defection (Quasim et al., 2022). Organizations need the infrastructure to support the solutions and high-quality data to supply the algorithm for machine learning prediction to be successful (Ray, 2019). Forecasting the future and estimating the likelihood of an outcome are possible applications of prediction. In addition, it can do what-if analyses and demand forecasts for the future (Wexler et al., 2019). The analysis of trends and consumer behavior, necessary for predicting brand value, can aided by regression analysis, a method for determining the relationship between two or more variables (Shrestha, 2020). Data mining is the process of extracting meaningful information from vast volumes of data, and the term "predictive analytics" characterizes this particular kind of data mining. Predictive analytics involves looking at past data to make educated guesses about the future so that those guesses can then inform critical business decisions (Ruz et al., 2020). Future industry trends can identified, user behavior predicted, and new customers identified through social media monitoring using prediction. Machine learning's capacity for prediction helps businesses plan for the future based on what might have happened in the past. Because of these presumptions, management can make choices that improve the company's bottom line.

User churn predicted with the help of predictive analytics. In light of this understanding, businesses will be in a stronger position to maintain consumer satisfaction. Customers and retailers alike can benefit from price predictions. Users are more likely to interact with a brand or carefully consider deals when they have access to a price prediction tool (Montaguti et al., 2022). Predictive pricing allows companies to set prices to encourage repeat business and brand loyalty. Machine learning (ML) uses regression analysis, a statistical method for estimating the connection between a dependent (target) variable and one or more independent (interdependent) variables, to solve the price prediction problem (Manasa et al., 2020). Numeric variables used as the end goal in regression.

How much is an organization's brand worth is the most important question asked by business managers (Swaminathan et al., 2022). Trying to put a price on intangible assets as brand equity is a significant problem (He & Calder, 2020). In contrast, Professor Natalie Mizik of Columbia Business School and her colleague Robert Jacobson found proof that including brand equity in financial analysis can better predict the entire worth of a corporation (Mizik & Pavlov, 2021). Using market and consumer data, trend forecasters attempt to anticipate changes in consumer behavior and purchase patterns. Businesses can gain an advantage over their rivals during transition periods by anticipating future market trends (Gupta et al., 2021;

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Sharabati et al., 2024). The most future-ready businesses are the ones that monitor crucial metrics and make reliable predictions about the direction of their industry. Predicting the brand's future success and value requires an analysis of the impact and opportunities presented by emerging technologies, shifting demographics, and other market factors (Swaminathan et al., 2020).

The ability accurately predict production and sales requires managers to grasp the extent to which their products will welcomed by the market and ultimately purchased. Recognizing market developments that may have long-term implications for the company. They will be able to discover and analyze market trends and predict future trends by analyzing historical data from both their own and a competitor's business (Verma et al., 2021). Businesses may better estimate the future worth of their brands and plan for any upswings or dips in activity if they have a warning of these changes (Ball, 2022; Al Adwan, 2024). The prospective market for a product or service is a significant consideration for businesses. Past sales data analyzed statistically to forecast future business. To help business managers choose the best strategies for marketing their products, Vernon Research compiles information about their competitors' prices, sales, and distribution channels ("B2B Data-Driven and Value-Based Pricing Strategies, Price Setting, and Price Execution," 2022). The company would benefit significantly from adopting a machine learning system to utilize AI for trend forecasting. This method designed to evaluate historical data for recurring tendencies and patterns. Once these regularities are established, the algorithm may look forward and make educated guesses about future trends and, in turn, brand value.

All the mental associations with a brand connected to a specific node collectively known as "brand associations." According to studies cited by Qazzafi (2020), brand associations are the additional memory nodes linked to the brand node that convey the brand's significance to consumers. An association could be anything from a simple word picture to a detailed description of the product's features and benefits (Alzate et al., 2022). The more time a consumer spends considering product details and drawing connections to their prior experience with the brand, the more favorable that detail will remembered. Relevance and consistency in presentation throughout time are two characteristics that boost brand connection with any content (Šerić et al., 2020). Brand associations include product features, designs, social programs, quality, user imagination, worldwide product range, innovations, system solutions, brands' personalities, and symbols (Keller & Brexendorf, 2019). Everything a consumer encounters while interacting with a brand. Relationships with customers, sales, user satisfaction, and brand allegiance may all built on them (Edlom, 2020).

The textual components of internet-based reviews have increased the significance of text mining to research company orientation and reputation how people relate to a product or necessity (Li et al., 2022). Businesses today must focus on both product and non-product-related qualities of the brand products in a modern world where online shopping platforms becoming more prominent and every product ire viewed and discussed online (Saulīte et al., 2022). Symbols, price, and ads are product characteristics that allow customers to associate their personalities with the brand. For the public to perceive the brand as trustworthy and affiliated with it, other social aspects, such as CSR and celebrity endorsements in product advertisements, must considered (Cinar, 2021). These actions can strengthen brand associations, enhancing the frequency of purchases.

How often a customer purchases over some specified period measured by what known as the purchase frequency (PF). The more frequently a consumer buys from you, excellent your opportunity to provide the remarkable service that will win them over as devoted patrons. One of the most critical KPIs for the firm to monitor to assess the brand's value is the frequency with which its products purchased (Liu et al., 2020). It can see as a barometer of long-term economic health. A higher frequency value indicates a greater likelihood of client retention, suggesting a more significant potential for continued expansion. The retention rate, purchasing patterns, and level of customer satisfaction may all be better-understood thanks to this data, which is invaluable to business leaders (Bag et al., 2021). All of these factors are crucial for estimating a brand's worth. Only two methods are available for maximizing earnings from current

clientele. Two methods are increasing the average order value and encouraging customers to submit frequent orders (He et al., 2020). Businesses can use data on consumer spending habits to project the brand's future profitability. Data like this can also inform strategic decision-making for future marketing initiatives. One way a company can increase the effectiveness of its marketing efforts is by collecting and analyzing data on the purchase frequency values of its most loyal customers (Ting et al., 2020).

One of the most critical factors in determining a brand's worth is the regularity with which its customers make purchases, alongside the amount spent and the length of time since the last transaction (Saraf et al., 2022). Using RFM (Recency, Frequency, and Monetary value) segmentation, managers can divide customers into groups defined by their past purchases and then tailor their strategies to each group (Chattopadhyay et al., 2022). RFM displaying can help advertisers and business owners choose their target market to make the best use of their budget (Sabuncu et al., 2020). This method assigns clients ratings based on values linked to recency, recurrence, and money and helps a business target them as per the category they fall in. Consistent customer demand significantly contributes to the company's successful financial performance. The worth of a company's brand can be predicted using a machine learning model that attempts to establish whether or not customers will make another purchase within a short time frame following their most recent one (Sophia, 2018). An appealing aspect of purchase frequency is that it is one of the few metrics that influenced directly and rapidly by a company. Instead of enticing new and existing consumers to spend more money by offering discounts and bulk discounts, a firm can win over its repeat customers by rewarding them for how often they shop with them (Gielens et al., 2021). This is the primary way the predict brand's future value. A company's bottom line can benefit from accurate brand value forecasting through its increased ability to retain existing customers (Xu et al., 2022). Businesses can tell when a customer is overdue by looking at how often they have ordered, giving them a heads up on when to contact them about placing an order.

The term "customer behavior" describes a buyer's actions, thoughts, and motivations concerning a product or service (Miah et al., 2022). In order to better appeal to their demographic, businesses constantly study client habits to learn more about them and design products that are more appealing and services and their value (Kevin et al., 2020). An analysis of customer behavior is a systematic investigation, from both a qualitative and quantitative perspective, of how customers engage with the business (Hesham et al., 2021). First, companies identify commonalities among their customers and create "buyer personas" better serve those groups. Then, track each set of personas as they progress through the various stages of the customer lifecycle to see how they respond to the business at each point. This analysis delivers insight into the aspects influencing the audiences and the reasons, priorities, and decision-making procedures clients consider during their trips (Lynch & Barnes, 2020). By surveying customers, business leaders can learn if the public's image of their organization is consistent with their beliefs. Knowing your market what drives and motivates them to buy is crucial to the success of your business (Alzghoul et al., 2022). Any strategy for predicting the value of a brand must include creating a system for proactively assessing consumer behavior (Zhao et al., 2022). Leading firms use Experience Management to understand customer behavior, predict it, and handle problems before they occur (Baran & Woznyj, 2020).

Understanding the client is always ongoing: expectations, platforms, and demands constantly change. Predicting a brand's future value requires analyzing its current health (Pauwels & van Ewijk, 2020). By monitoring the brand, business managers have a constant standard against which to gauge their performance in volatile markets and prepare for potential problems. The company will be able to measure how customers' interactions have affected its reputation, thanks to this.

With the help of AI and ML, "big data" transformed into "useful data" (Neethirajan, 2020), (Adwan & Aladwan, 2022). If the company wants to see outcomes from predictive ML, it needs to hear a straightforward narrative. Rather than becoming lost in numbers, the brand needs to take action by emphasizing critical and creative think-

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ing. AI and machine learning is the life raft (Butner, 2019). Research automation allows for quick operational decisions, allowing business managers to stop problems in their tracks before they spread.

Because of rising competition in the businesses, companies are re-evaluating their marketing communication tactics to increase consumer relevance, foster two-way interaction, and forge lasting bonds with clients to boost their brands' value (Teshager, 2021). Social networking is a more adaptable instrument for enhancing communication between businesses and their customers across various sectors (Klein & Todesco, 2021). There are advantages and disadvantages to managing a company's brand image in the social media era because of the shift in power from marketers to customers (Dwivedi et al., 2021). Customers are more likely to trust the recommendations of their peers in their social networks than they are to trust the monologues of companies' advertisements. Nonetheless, consumers' valuations influenced by their expertise level and commitment to the business. Therefore, to attract and retain consumers over the long run, banks must effectively convey the value they provide. Acceptance of social media as a new online knowledge source originated, shared, and used by customers to educate one another about brands amongst the general public (Nazir et al., 2020). Social networking refers to a series of apps collectively known as "Web 2.0." These applications enable users to produce and share their unique content online (Kaplan & Haenlein, 2019). Brand equity is the intangible value consumers assign to a product because of its association with a particular name or logo (Lang et al., 2022).

Consumers' positive associations with the results of using a brand and the features of that brand are the foundation of consumer brand equity. According to Keller (2001), brand equity created when businesses develop intense bonds of loyalty and trust with their target audience. According to Lang et al. (2022), a strong customer relationship is essential to establishing a solid brand's credibility and value. As a result, more and more businesses are using social media to strengthen their relationships with customers by handling complaints and answering queries from a wide range of stakeholders. Two studies that look at the connection between social media and brand equity (Yu & Yuan, 2019; Dabbous & Barakat, 2020) reach the same favorable conclusion: social media has a significant impact on brand recognition. As a result, keeping an eye on the brand's mentions on social media might be a good indicator of its future success.

This study aims to investigate the influence of machine learning in monitoring critical factors, including industry trends, purchase frequency, consumer behavior, and social media dynamics, on the predictive accuracy of future brand value.

The formulated hypotheses based on the literature review are as follows:

H1: Industry trend monitoring has a significant impact on predicting brand value.

H2: Purchase frequency monitoring has a significant impact on predicting brand value.

H3: Customer behavior monitoring has a significant impact on predicting brand value.

H4: Social media monitoring has a significant impact on predicting brand value.

2. METHODOLOGY

The survey constructed based on an extensive literature review to capture the factors managers consider in brand value assessment. Key topics included industry trends, purchase frequency, customer behavior, and social media monitoring. A purposive sampling technique employed to select 350 upper-level brand managers and sales marketing directors from various companies in Jordan, chosen for their specialized expertise in brand evaluation. Data collection conducted between April and September 2024 using a self-administered questionnaire. The instrument developed based on an extensive review of the relevant literature to ensure alignment with established theoretical frameworks and to prioritize variables critical to the study's objectives. The questionnaire underwent both face and content validation by a panel of five experts in marketing and branding. All participants provided informed

consent before participation. Anonymity maintained throughout the study, with no personally identifiable information collected. Participants also informed of their right to withdraw from the study at any stage without any consequences. This research conducted by ethical standards and received formal approval from the Ethical Committee of the Business School, Al-Ahliyya Amman University. Research Ethics Committee (Approval No, SR-F17-14-001-Eng, Rev. a) (March 2024). Out of the initial contacts, 229 responses met the study's criteria for completeness. The questionnaire designed with Likert-scale, closed-ended questions to ensure consistency and ease of analysis. It included six primary methods identified in the literature for assessing brand value. Before full deployment, a pilot test ensured the instrument's reliability and clarity, with adjustments made as needed. Completed questionnaires screened, and only fully completed responses were included. Data from participants who did not meet eligibility criteria or who provided incomplete answers were excluded. This approach ensured high-quality data, minimizing any potential biases from irrelevant or partial responses.

The demographic composition of the sample indicates. Most respondents are male, comprising 86.03% of the participants, while females comprise only 13.97%, indicating a gender imbalance likely reflective of the professional landscape in brand management and marketing. Age distribution relatively balanced, with a concentration of respondents under 40. The largest age group is 31-40 years (30.57%), followed closely by those under 30 (28.82%) and those above 50 (27.51%). This suggests a blend of early- and mid-career professionals with valuable insights across career stages.

In terms of business type, the sample includes both manufacturing (51.97%) and importing firms (48.03%), representing a diverse industrial background. Regarding management level, the majority hold middle management positions (58.52%), with lower management at 27.07% and heads of management at 14.41%, indicating a strong presence of individuals with operational and strategic roles.

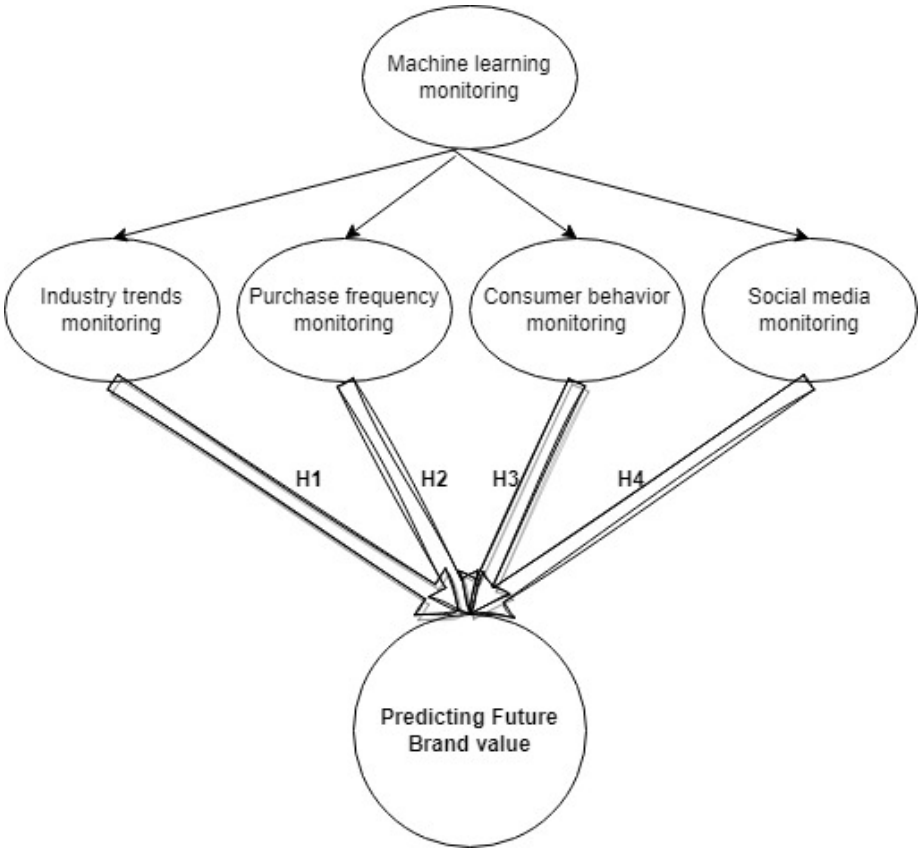

Figure 1. Research model

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Experience levels also vary widely, with a notable bimodal distribution: 27.95% of respondents have over 15 years of experience, while 26.20% have less than two years. This combination of seasoned professionals and newcomers contributes to a varied understanding of market dynamics and brand value development, enriching the study's insights.

Table 1. Distribution of respondents

Demographic variables	Features	Frequency	Percentage
Gender classification	Male	197	86.03
	Female	32	13.97
Age group	Less than 30 years	66	28.82
	31-40 years	70	30.57
	41-50 years	30	13.10
	Above 50 years	63	27.51
Functioning of business	Manufacturing	119	51.97
	Importers	110	48.03
Staffing levels in management	Lower level management	62	27.07
	Middle level management	134	58.52
	Head	33	14.41
Total experience	Less than 2 years of experience	60	26.20
	3-7 years	54	23.58
	7-11 years	32	13.97
	11-15 years	19	8.30
	Above 15 years	64	27.95

Data were processed using AMOS software to apply Structural Equation Modeling (SEM), a statistical technique for examining relationships between observed and latent variables. SEM chosen for its effectiveness in analyzing complex interrelationships between variables such as industry trends, purchase frequency, and social media impact on brand value. This allowed for comprehensive analysis of the predictive power of these factors on brand value. Figure 1 demonstrates the research model.

3. RESULTS

This part presents a comprehensive examination of the research data, with emphasis on primary analyses such as factor loadings, average variance extracted, correlation, and structural equation modeling (SEM). Table 2. Illustrated the convergent validity for the measurement model. All values were below the threshold of 0.7 factor loading. Besides, the composite reliability for the constructs are above 0.7. Furthermore, the Average Variance Extracted for all constructs are above 0.5 indicating that the model satisfies all the thresholds for the convergent validity.

There are several appropriate statistical methods for assessing the degree of relationship between the variables, but one of the most common is the correlation analysis. Buying patterns, market developments, and consumer patterns, considered independent factors in this study's analysis of the relationship between independent and dependent variables. The results of the correlation study are presented in Table 3, and they indicate a significant and beneficial association between the variables (R-values more than +0.700). Social media monitoring and purchase frequency have the strongest correlation, suggesting that ML can help businesses make better decisions about how to quantify the value of their brands. The monitoring of consumer behavior has the second highest correlation. Money comes into businesses through sales and other channels, and this money needs to used wisely to keep costs down and earnings up; this is why machine-learning technologies are helpful in arriving at judgments quickly.

Table 2. Measurement model convergent validity

Variable	Item	Path loadings	Average Variance Extracted	Reliability
Purchase frequency	PF1	0.98	0.581	0.873
	PF2	0.96		
	PF3	1.00		
Social media monitoring	SMM1	0.98	0.687	0.782
	SMM2	0.96		
	SMM3	1.00		
Consumer behavior monitoring	CBM1	1.10	0.635	0.851
	CBM2	0.86		
	CBM3	1.00		
Industry trend monitoring	ITM1	0.755	0.623	0.831
	ITM2	0.76		

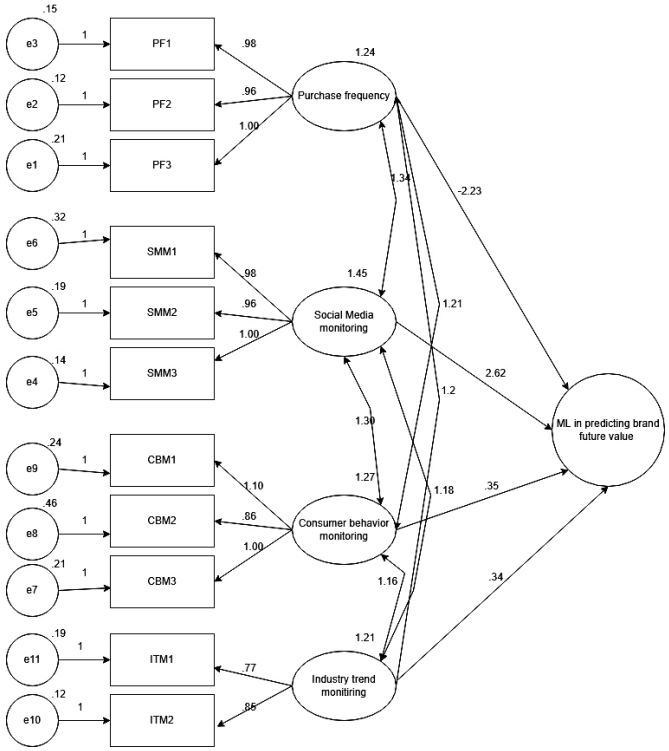

Figure 2. Structural model

Table 3. Correlation analysis

Variable	Purchase frequency	Industry trends monitoring	Consumer behavior monitoring	Social media monitoring
Purchase frequency	1	0.6605	0.82123	0.9271
Industry trends monitoring	0.6605	1	0.7453	0.7248
Consumer behavior monitoring	0.82123	0.7452	1	0.8947
Social media monitoring	0.9271	0.7248	0.8947	1

Table 4 and Figure 2 illustrated the hypotheses results, as it showed that Monitoring industry trends exerted a significant positive influence on brand future value (*H1*: $\beta = 2.228$, $p \leq 0.001$), suggesting that increased attention to industry trends was associated with enhanced perceived future value for the brand. Consequently, *H1* was accepted. Similarly, purchase frequency monitoring demonstrated a significant positive influence on brand future value (*H2*: $\beta = 2.681$, $p \leq 0.001$), implying that tracking purchase frequency was positively related to perceptions of the brand's future value. *H2* was, therefore, accepted.

Furthermore, customer behavior monitoring was found to have a significant positive influence on brand future value (*H3*: $\beta = 0.353$, $p \leq 0.001$), indicating that monitoring customer actions positively related to the brand's future value assessment. Thus, *H3* was accepted. Finally, social media monitoring also showed a significant positive influence on brand future value (*H4*: $\beta = 0.345$, $p \leq 0.001$), suggesting that attention to social media signals was positively associated with the brand's future value. Thus, *H4* was accepted.

Leaders in the corporate world are in an ideal position to concentrate on the most crucial factors that will increase profitability. Leaders can generate accurate forecasts of the brand's future value with the help of machine learning tools and methodologies. Moreover, other areas, such as operating expenditures and expenses, can assessed to cut them through other methods. Managers know that accurate forecasting of brand, value's potential is crucial to the growth of a company, and that it must managed as such. Administration can have faith in the continued success of the brand thanks to machine learning algorithms.

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Table 4. Hypotheses testing

Hypothesis	Path	Original sample (β)	Sample mean	Standard deviation	p-value	Hypothesis
H1	Monitoring industry trends → Brand future value	2.228	–2.112	0.116	≤0.001	Accepted
H2	Purchase frequency monitoring → Brand future value	2.681	2.565	0.116	≤0.001	Accepted
H3	Customer behavior monitoring → Brand future value	0.353	0.276	0.077	≤0.001	Accepted
H4	Social media monitoring → Brand future value	0.345	0.26	0.085	≤0.001	Accepted

4. DISCUSSION

H1 is supported by the data (β = 2.228, p > 0.001); this hypothesis states that monitoring developments in a particular industry is essential when trying to forecast the worth of a given brand. Findings from this study corroborate those of Swaminathan et al. (2020), who found that predicting a brand's future success and value calls for examining the effect and opportunities given by new technology, changing demography, and other market factors. Gupta et al. (2021) found that companies could gain an edge over competitors during transition periods by anticipating future market trends. This finding is consistent with the correlation between monitoring industry trends and predicting future brand value in this study.

According to the reviewed research, purchase frequency is a significant factor in estimating brand value (Liu et al., 2020). Knowing a customer's buying habits and tailoring your interactions with them accordingly can boost customer loyalty (Bag et al., 2021) and brand awareness (Alzate et al., 2022). The results of this investigation (β = 2.681, p > 0.001) support the knowledge gained from the literature review, providing further evidence in favor of *H2*.

This study's results (β = 0.353, p > 0.001) imply that keeping tabs on consumer behavior can shed light on the audiences, motives, priorities, and decision-making processes that customers take into account before making a purchase (Lynch & Barnes, 2020). Business executives can find out if the public's perception of their company is consistent with their beliefs by polling customers, which supported by the results of this study (Baran & Woznyj, 2020). Brands cannot succeed without an in-depth understanding of the market and the factors influencing and encouraging consumers to make purchases. Building a mechanism for anticipatorily evaluating consumer behavior is essential to foreseeing a brand's worth (Zhao et al., 2022). This means that the third hypothesis is correct.

Furthermore, this result supports the fourth hypothesis (β = 0.345, p > 0.001). Beds are a popular topic of conversation and product review on social media platforms (Nazir et al., 2020). Therefore, according to Nazir et al. (2020), keeping an eye on social media can aid businesses in foreseeing their brand's future worth and communicating effectively with customers. This supported further by the research conducted by Lang et al. (2022), who discovered that consumers place a monetary value on intangible brand equity. Thus, the fourth hypothesis is correct. This study found that machine learning-monitored customer behavior and social media could predict brand value. Consumer buying frequency is another variable. If companies want to envision their brands' future value and make consumers buy their products, they need to track purchase frequency and consumer behavior for accurate and valuable data. Consumers will also pay more attention to a brand if they notice primarily good reviews online. Online remarks and sentiments are popular, attractive, and trustworthy, so consumers copy them. Online reviews and their reception affect consumers' brand perceptions. Businesses must also evaluate how consumers' activities, product frequency, and social media responses affect market trends. Positive brand reactions increase sales.

CONCLUSION

The purpose of this study was to investigate the role of machine learning in monitoring key market factors – industry trends, purchase frequency, consumer behavior, and social media metrics – to predict future brand value. The findings demonstrate that machine learning enables precise predictions by

analyzing historical data and identifying relevant patterns. This approach enhances decision-making by automating processes and providing actionable insights at all organizational levels. The model effectively integrates various factors influencing brand value, such as market trends and customer interactions, to generate tailored reports that support informed managerial decisions. From this, concluded that machine learning is a powerful tool for businesses seeking to improve efficiency, predict outcomes, and manage resources effectively. Despite its success, the study's limited sample size restricts generalizability. Future research should address this limitation by expanding the dataset and exploring company-specific prediction tools to refine and diversify the applicability of brand value forecasting models.

AUTHOR CONTRIBUTIONS

Conceptualization: Ahmad Al Adwan, Ghaiath Altrjman.
Data curation: Ahmad Al Adwan.
Formal analysis: Ahmad Al Adwan, Ghaiath Altrjman.
Investigation: Ahmad Al Adwan.
Methodology: Ahmad Al Adwan.
Project administration: Ahmad Al Adwan, Ghaiath Altrjman.
Supervision: Ahmad Al Adwan.
Validation: Ghaiath Altrjman.
Visualization: Ghaiath Altrjman.
Writing – original draft: Ahmad Al Adwan.
Writing – review & editing: Ahmad Al Adwan, Ghaiath Altrjman, Lu'ay Al-Mu'ani

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APPENDIX A

Table A1. Questionnaire

Variable	Category	Selection (✓)
Gender classification	Male	☐
	Female	☐
Age group	Less than 30 years	☐
	31-40 years	☐
	41-50 years	☐
	Above 50 years	☐
Business function	Manufacturing	☐
	Importers	☐
Management level	Lower-level management	☐
	Middle-level management	☐
Total experience	Less than 2 years	☐
	3-7 years	☐
	7-11 years	☐
	11-15 years	☐
	Above 15 years	☐

Please rate your agreement with each statement in Table A2 (1 = strongly disagree, 5 = strongly agree).

Table A2. Statements

Construct	Item No.	Statement	1 (SD)	2 (D)	3 (N)	4 (A)	5 (SA)
Industry trend monitoring (*H1*)	1	My organization actively tracks industry trends to assess brand positioning.	o	o	o	o	o
	2	Industry trend analysis helps predict changes in our brand's market value.	o	o	o	o	o
	3	We adjust branding strategies based on shifts in industry trends.	o	o	o	o	o
Purchase frequency monitoring (*H2*)	4	My company monitors how often customers purchase our products/services.	o	o	o	o	o
	5	Tracking purchase frequency helps forecast brand loyalty and value.	o	o	o	o	o
	6	Changes in purchase frequency influence our brand investment decisions.	o	o	o	o	o
Customer behavior monitoring (*H3*)	7	We analyze customer preferences and buying patterns to evaluate brand perception.	o	o	o	o	o
	8	Understanding customer behavior improves our ability to predict brand equity.	o	o	o	o	o
	9	Customer feedback directly affects our brand development strategies.	o	o	o	o	o
Social media monitoring (*H4*)	10	My organization tracks brand mentions and sentiment on social media.	o	o	o	o	o
	11	Social media engagement metrics (likes, shares) influence brand valuation.	o	o	o	o	o
	12	Viral trends on social media affect our brand's perceived value.	o	o	o	o	o
Brand value prediction (*DV*)	13	Our brand's financial value closely tied to the above monitoring activities.	o	o	o	o	o
	14	We use data from these monitoring efforts to forecast future brand performance.	o	o	o	o	o
	15	Overall, these metrics improve the accuracy of our brand valuation models.	o	o	o	o	o

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