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FORECASTING CONSUMER DEMAND AND ANALYZING THE IMPACT OF SOCIAL MEDIA INFLUENCER MARKETING ON BRAND EQUITY USING ARIMA AND SEM MODELS

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SUMMARY

Organizations are increasingly using analysis to understand consumer buying habits in order to understand what type of promotional strategies work best for their products. This is due to the fact that digital platforms have a greater influence on a consumer's purchasing decisions. A complete quantitative approach is designed to understand the impact of social media influencer marketing on brand equity and to forecast the demand for a product. Using historical sales data to forecast future consumer behaviour, the two statistical models, namely, ARIMA and SEM, were used to study the effect of promotion through influencers on consumer perceptions, purchase intent, consumer engagement, and brand equity. For the empirical analysis, the study relied on data from 1,248 responses to an online survey and total monthly retail and e-commerce sales data, combined with the ARIMA model, which used historical purchasing patterns, seasonality, and social media influencer engagement metrics to build forecasts of future consumer demand patterns. The ARIMA model produced a MAPE of 4.82%, RMSE of 3.41, forecast accuracy of 95.18%, and a correlation coefficient of 0.93, which shows that the forecasting model is very reliable in predicting future demand. The results show that the credibility of the influencer has a significant effect on the engagement of consumers ($\beta = 0.81$) and their trust ($\beta = 0.72$), which in turn has a significant effect on consumers' intention to purchase ($\beta = 0.76$) and brand equity. The theoretical model is found to be an acceptable model with fitness indexes such as CFI = 0.95, RMSEA = 0.041, GFI = 0.93, and Chi-square/df = 2.11. The results have shown that marketers' use of influencer marketing is crucial for the creation of brand equity and the predictability of demand. The integrated forecasting model can serve as a practical application for organizations seeking to create effective marketing strategies, leverage a customer-centric decision-making process, and ultimately, have a precise forecast of future demand in the current competitive digital landscape.

Key words: *social media influencer marketing, brand equity analysis, consumer demand forecasting, ARIMA model, structural equation modeling, consumer purchase intention, digital marketing analytics*

INTRODUCTION

Research from [1] indicates that companies employ digital influencers to influence their brand image in two ways: the direct impact on shoppers' perception of their brands and their perception of how they purchase products, and the ability to enhance customer satisfaction as they feel like they are a part of a positive community around the brand and products. The increasing reliance on social network sites has altered how marketers create ads, with new approaches using predictive analytics and consumer behaviour modelling to inform marketing decisions [2].

Brand equity is now an important strategic asset as it is linked to customer loyalty, market positioning, and long-term organizational profitability for the firm. Studies have shown that consumers tend to associate the credibility, authenticity, expertise, and trustworthiness of an influencer with the quality of the brand, and this positively influences both the likelihood of them purchasing from that brand and developing an attachment to the brand [3]. In earlier research, it has been shown that congruence between the influencer and product, and relevance of content, positively impact consumer trust in the brand and increase their level of engagement with the brand [4]. Furthermore, digital influencers have also been positively contributing to creating stronger emotional bonds between consumers and brands, leading to higher retention rates and purchasing decisions by consumers [5]. Due to this, there has been increased recognition of the need to integrate analytics from social media with quantitative forecasting approaches to better understand shifting demand patterns in the marketplace.

Forecasting future consumer demand is essential for optimizing the supply chain, planning for inventory, estimating sales, and handling market segmentation. Many businesses find value in using an accurate forecasting model to predict future customers' demand given different kinds of market conditions and shifting consumer preferences. One of the most widely adopted time-series methods used in business analytics is the ARIMA. The ARIMA model can be useful because they provide ability to analyze data for seasonal patterns, examine how demand changed over time, and evaluate how consumers purchase goods at a certain point in time [6]. By leveraging ARIMA-based forecasting models, a company can better allocate its resources, reduce operational uncertainty, and support strategic planning based on data-driven decision making [7]. However, if a company only relies on historical sales data to forecast consumer demand, it may miss important information regarding how social media and influencers impact consumer behaviour.

SEM is a strong statistical methodology used in the analysis of more complex or latent variable relationships such as influencer credibility, consumer trust, intention to purchase, customer engagement, and brand equity, as proposed by [8]. In addition, SEM allows for an overall analysis of both direct (one-step) and indirect (multiple steps) causes/effects between many constructs at once; thus, this method enhances the interpretability of behavioral marketing models as proposed by [9]. In combination, the use of ARIMA and SEM provides an integrated analytical framework linking demand forecasting with behavioral consumer analytics; however, the combination of these two methods is still a relatively undeveloped research area in both management science and technical research.

There is growing interest in studying both influencer marketing and how customers react to products; however, the current literature does not provide a comprehensive view of the relationship between these two areas from a quantitative perspective. Most existing approaches look either at predicting what customers do or measuring their feelings about brands separately, which does not give a framework for understanding them together as part of integrated analytic systems [10].

Research Objectives

- **RO1:** To analyze the impact of social media influencer marketing on consumer purchase intention and brand equity.
- **RO2:** To evaluate the relationship between influencer credibility, consumer engagement, and brand trust using SEM analysis.
- **RO3:** To forecast consumer demand trends using the ARIMA time-series forecasting model.
- **RO4:** To examine the effectiveness of integrating ARIMA and SEM models for marketing and demand prediction analysis.
- **RO5:** To identify the influence of consumer engagement metrics on future purchasing behaviour and organizational decision-making.

Research Questions:

- **RQ1:** How does social media influencer marketing affect consumer purchase intention and brand equity?
- **RQ2:** What is the relationship between influencer credibility and consumer engagement in digital marketing environments?
- **RQ3:** How effectively can the ARIMA model forecast consumer demand patterns based on historical sales and engagement data?
- **RQ4:** Does the integration of ARIMA and SEM improve analytical accuracy in marketing and consumer behaviour studies?
- **RQ5:** How do engagement-driven marketing activities influence future consumer demand and brand perception?

Hypotheses:

- **H1:** Influencer credibility has a significant positive effect on consumer engagement.
- **H2:** Influencer credibility has a significant positive effect on consumer trust.
- **H3:** Consumer trust positively mediates the relationship between influencer credibility and brand equity.
- **H4:** Consumer engagement significantly influences purchase intention.
- **H5:** Purchase intention has a significant positive effect on brand equity.

Key Contributions:

- The study creates an integrated analytical framework of ARIMA-SEM to predict consumer demand and assess the effects of social media influencer marketing on brand equity at the same time.
- The proposed framework combines time-series forecasting and behavioral modeling to improve predictive accuracy and consumer perception analysis within digital marketing environments.
- The research results confirm the important relationships between the variables of influencer credibility, consumer engagement, purchase intention, consumer trust, and brand equity, with the results of model fit indices in SEM that are satisfactory.
- The study offers valuable managerial insights for retail/e-commerce companies by showcasing how indicators of SME can be applied to demand forecasting, strategic marketing optimization, and customer-centric decision-making.

In this document, Section II reviews the previous research done on influencer marketing. Section III describes the methodology that is used to complete the research project and includes information about the area of study, the sample being studied, how data is collected, the theoretical framework, creating a statistical model, and creating a statistical analysis. Section IV contains the results of the study; the evaluation of the study's predictions; the statistical analysis (i.e., SEM and testing of hypotheses); the implications of the results from this study for businesses; and recommendations for future studies related to integrated commercial forecasting and behavioral marketing analytics. Finally, section V summarizes the key findings and the analytical contribution of the research and recommends directions for future studies that relate to both integrated commercial forecasting and marketing analytics.

LITERATURE REVIEW

Through social media influencer marketing, researchers have worked to identify how digital overreach is impacting overall consumer behaviour and has proven to significantly influence consumer engagement, purchase intention, and brand communication. Different research studies have focused on identifying how effective different influencer-based promotional strategies are in influencing consumer perception and increasing the visibility of businesses through the use of digital platforms. Research relating to the credibility of influencers identified that the level of trustworthiness, expert status, and level of authenticity provided by an influencer greatly enhances the overall level of consumer trust and enhances the overall level of online purchase behaviour [11]. Furthermore, this research concluded that the overall level of emotional connection consumers has to influencers positively influences their level of brand awareness, improves overall customer loyalty, and enhances competitiveness within the digital market.

Various behavioral and statistical models have been used to study how engaging consumers via social media affects their purchasing choices. An analytical investigation into the effectiveness of social media advertising has shown that personalized content and interacting with influencers create higher levels of engagement towards a product and a greater likelihood that consumers make an online purchase [12]. This research shows how organizations are increasingly relying upon data-driven marketing strategies in order to improve both customer acquisition and predict future brand placement in the market.

In order to improve predictive analytics and machine learning for both demand forecasting and marketing optimization, various studies have examined the use of these techniques for retail demand prediction. Time series forecasting techniques such as those using ARIMA-type models have also been effective at forecasting demand trends, stock volatility, and seasonal patterns in buying behaviour [14]. Additionally, when incorporating external data (i.e., customer engagement metrics or online promotional activity) into predictive models, the accuracy of forecasts is enhanced [13]. Overall, the literature demonstrates that ARIMA models have a superior level of predictive ability compared to traditional forecasting approaches regarding forecast accuracy, inventory level optimization, and decision support systems [15]. The studies above illustrate how quantitative forecasting techniques can help businesses with their sustainability, as well as their operational planning.

Consumer behaviour research using SEM has received a lot of attention from researchers in the management field because SEM can assess both direct and indirect relationships between unobserved variables. Studies investigating the effectiveness of social media marketing found that consumer trust acts as a mediator between influence marketing and buying propensity [16] [17].

Recent studies in both management and technical fields have considered how social media (SM) analytical data is integrated into forecasting models. Intelligent marketing system research indicates that utilizing behavioral analytics in conjunction with predictive forecasting is effective for improving both adaptability and responsiveness in organizations' business-to-business (B2B) marketing efforts [18]. Likewise, studies of hybrid analysis models have shown that combining statistical forecasting with consumer perception data (CPD) assists with effective strategic marketing decision-making, improving the accuracy of demand estimation [19]. Additionally, the integration of advanced digital marketing frameworks (ADMF) that incorporate search engine marketing and predictive analytics has been shown to enhance an organization's business intelligence (BI) systems and maximize the effectiveness of customer-focused promotional (CFP) strategies [20].

The analyzed literature reveals that influencer marketing plays an important role in driving consumer engagement, purchase intention, and brand equity via trust-based communication and interactive digital content. Previous studies have established that ARIMA models give a reliable degree of accuracy when predicting consumer demand, and SEM can be used effectively to evaluate the mechanism between various marketing/behavioral constructs. But there is a lack of integration of predictive demand modeling with the assessment of brand equity through the use of social media influencers. The present study addresses this area through the development of a combined ARIMA-semi framework for predicting consumer demand through the use of influencers. The creation of this combined framework provides support to data-based management decision-making processes, optimizes customer engagement, and improves the accuracy of forecasting.

PROPOSED METHODOLOGY

Study Area

This research study examined the digital retail and eCommerce industry regarding how consumers are already utilizing social media to discover new products and make purchasing decisions. The focus of the research was principally on urban and semi-urban area consumers engaging with creative Influencer promotional content on social networks like Instagram, YouTube, Facebook, and X. Based on each of their high levels of influencer marketing, the research targeted consumers of online fashion, electronics, cosmetics, lifestyle, and general retail goods. Additionally, the research included looking at organizational sales datasets collected from all online retail channels to understand past sales demand behaviour and demand forecasting accuracy. The study involved an analysis of social media-influencer activity, consumer engagement scores, and the accuracy of demand forecasts in digital connection businesses.

Sampling Framework

Stratified random sampling was used as the basis for the sampling. The sampling design guaranteed that representation was balanced between categories of consumers. The survey was conducted among active users of social media, online consumers, marketing professionals, and e-commerce customers who regularly engage with influence-based marketing campaigns, making up the sampling frame. The respondents were chosen based on the criteria, including at least once a week using social media platforms, being exposed to influencer ads, and having some experience with online shopping.

After removing incomplete and inconsistent survey responses, a total of 1,248 valid survey responses were obtained. The original sample was made up of respondents between 18 and 45 years of age, who tend to have higher digital platform usage and online purchasing. The organization's dataset consists of total data that allows for SEM and time-series forecasting from 48 brands, which covers retailer and e-commerce monthly sales as well as engagement metrics over time. The final sample size is sufficient to model latent variables and provides enough sample size for predictive analytics.

Data Collection

The use of both primary and secondary data sources provided a complete and overall analytical perspective. Structured online questionnaires, using digital survey platforms, were the main data collection method. The questionnaire was developed with closed-ended questions; a five-point Likert scale was used to construct the questions, “Strongly Disagree” to “Strongly Agree”. The aim of this tool was to assess consumer perceptions of the following factors: Influencer credibility, trust, engagement level, purchase intention, and brand equity. The questionnaire was divided into five major sections: asking demographic questions, credibility measurement of the influencers, consumer engagement behaviour, analysis of purchase intent, and measuring brand equity. Survey responses were screened for reliability and consistency prior to conducting statistical analyses. Reliability of the constructs was assessed using Cronbach’s Alpha reliability testing, and the results indicated that all of the constructs had a Cronbach’s Alpha value above 0.70, which indicates strong internal consistency.

Data collected from electronic sales transactions, social networking sites, and product demand from previous months is analyzed to develop demand forecasts based on ARIMA over the course of the past

48 months. The information provided when collecting the data consists of both monthly sales volume and how often customers engage through liking/sharing/commenting, conversion rates, and metrics on influencer campaign effectiveness. Prior to implementing models for forecasting future sales, data is pre-processed to ensure suitability (normalized), missing values are treated, outliers are removed, and each time series is made stationary.

Conceptual Methodology Framework

In figure 1 shows the integrated framework used to define the research design utilized for the analysis of both consumer Demand Forecasting and the effect of Influence Marketing on Brand Equity. The framework begins with identifying the research problem, formulating research objectives, and developing a conceptual model. In phase two of the method, data is gathered through two different types of sources. These sources are called primary sources, like results from a survey about customers, and secondary sources, such as historical sales records. The analysis of the data consists of two parallel streams of analysis. The first side uses ARIMA-based models to forecast demand, while the second side uses SEM to evaluate the relationships between Influencer Credibility, Consumer Engagement, Purchase Intention, Trust, and Brand Equity.

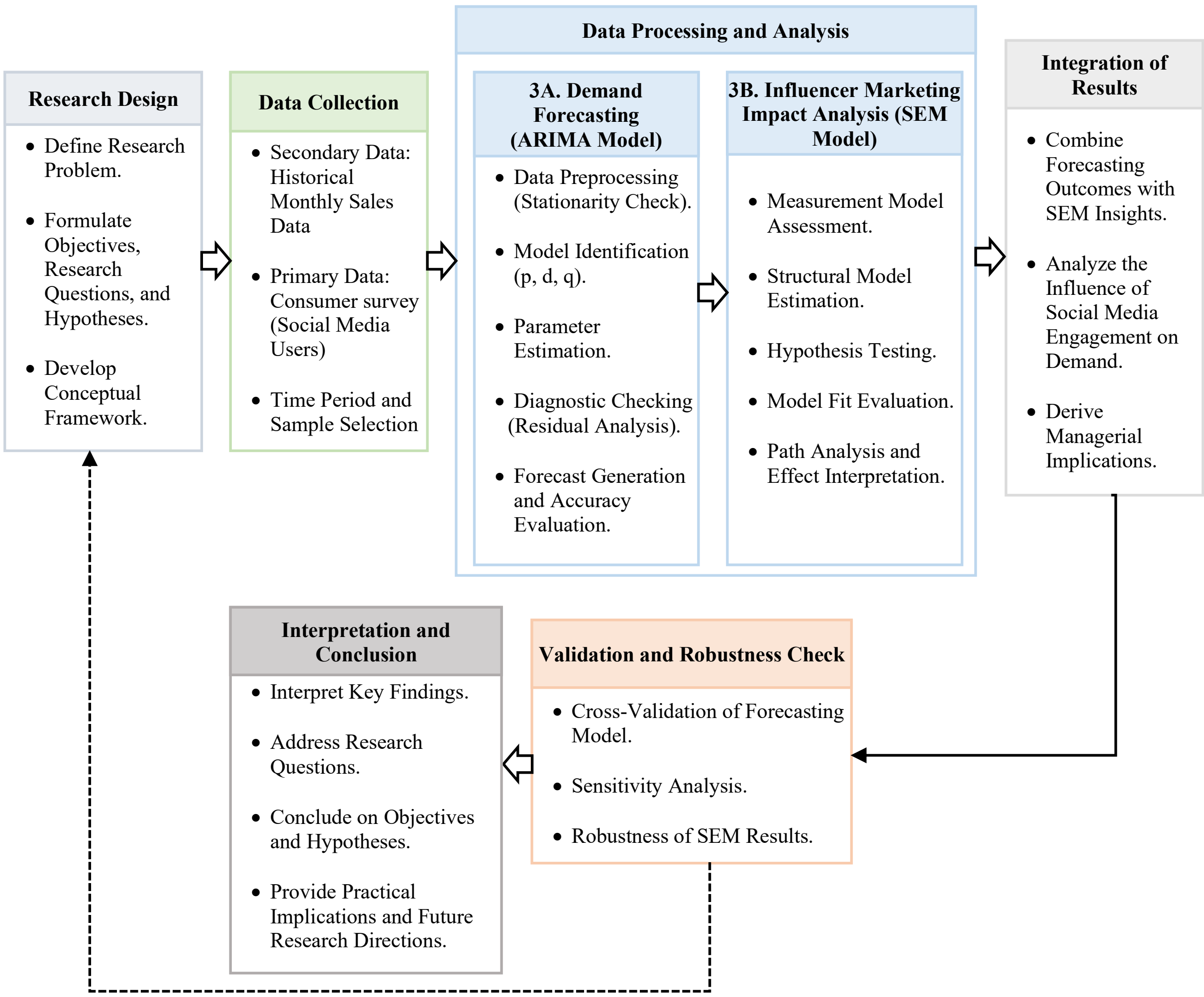

Figure 1. Integrated research framework for consumer demand forecasting

The SEM model from figure 2 is designed to assess how social media influencer marketing affects consumer behaviour and brand equity. The model contains four main latent variables: Influencer Credibility (IC), Consumer Engagement (CE), Consumer Trust (CT), and Brand Equity (BE), as well as the Purchase Intention (PI) dependent variable. All latent variables have multiple observed measures. Influencer Credibility is measured by the characteristics of an influencer (attractiveness, expertise, trustworthiness, and authenticity). Consumer Engagement is quantified through interactions and payments on social media (likes, comments, and shares). Consumer Trust is represented by the different ways in which consumers can trust a marketer (reliability, confidence, and dependability). Purchase Intention is assessed through three methods: interest in purchasing, willingness to purchase, and planning for future purchases. The components of Brand Equity are Brand Awareness, Perceived Quality, and Brand Loyalty. Each of the structural paths represents a hypothesis (H1-H5) that tests different relationships between influencer credibility and consumer engagement/trust/brand equity. H1 looks at direct influencer credibility on consumer engagement; H2 considers influencer credibility's influence on consumer trust; H3 determines whether consumer trust acts as a mediator between influencer credibility and brand equity; H4 looks at the effect of consumer engagement on purchase intention; and H5 tests the direct effect of purchase intention on brand equity. Consumer trust acts as a key mediator in connecting influencer credibility to brand equity by providing an indirect behavioral path through which influencer marketing increases overall brand perception.

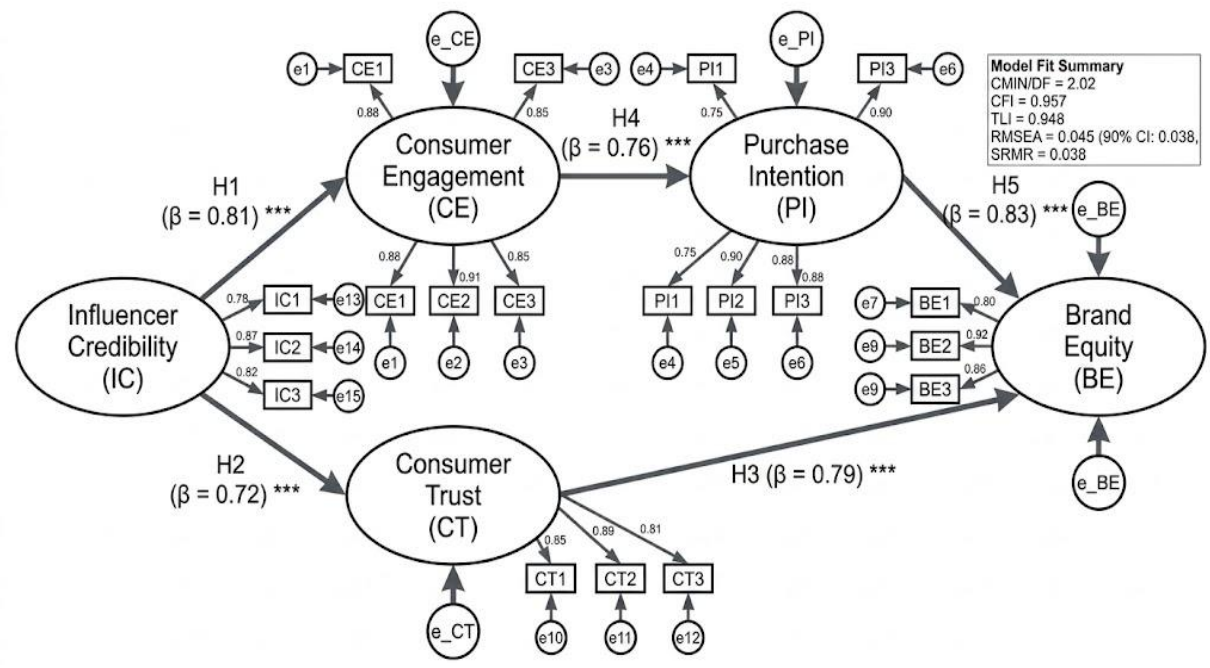

Figure 2. SEM model for influencer marketing and brand equity

Model Details for Analysis

The mixed quantitative analytical method to be used in the proposed research includes the use of forecasting with ARIMA and Structural Equation Modeling. Time series demand forecasting using the ARIMA model is an excellent way to account for the sequential nature of consumers' purchasing patterns over time and for periodic seasonal changes in those same purchasing patterns. The methodology used to identify the appropriate ARIMA parameters for forecasting included testing for stationarity using the Augmented Dickey-Fuller test, checking for the presence of an autocorrelation and a partial autocorrelation, and identifying parameters based upon the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and by minimizing the forecasting errors produced by the ARIMA model.

The ARIMA model structure is represented as Equation 1:

$$ARIMA(p, d, q) \tag{1}$$

where p represents the autoregressive order, d denotes differencing order, and q indicates moving average order. The final optimized forecasting model selected for the study was ARIMA (2,1,2), which provided improved forecasting accuracy and reduced residual error.

The general ARIMA forecasting is expressed as Equation 2:

$$Y_t = c + \sum_{i=1}^{p} \emptyset_i \, Y_{t-i} + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j} + \varepsilon_t \tag{2}$$

where Y_t represents forecasted consumer demand at the time t, c is a constant term, $\emptyset_i$ denotes autoregressive coefficients, θ_j represents moving average coefficients, and ε_t indicates residual error.

To analyze the causal relationships between latent constructs related to influencer marketing and brand equity, SEM was used. The SEM framework has both measurement and structural models. The measurement model analyses the relationship of latent variables to measured variables, while the structural model analyses the interrelationship between latent constructs.

The SEM structural relationship is represented as Equation 3:

$$\eta = B_\eta + \Gamma\xi + \zeta \tag{3}$$

where η represents endogenous latent variables, B denotes the coefficient matrix among endogenous variables, Γ indicates the coefficient matrix relating exogenous and endogenous variables, ξ represents exogenous latent variables, and ζ corresponds to structural disturbance terms.

SEM model fitness was evaluated using multiple statistical indicators, including Comparative Fit Index (CFI), Goodness of Fit Index (GFI), RMSEA, Tucker-Lewis Index (TLI), and Chi-square to degrees of freedom ratio. Acceptable threshold values were used to validate the structural stability and reliability of the proposed behavioral framework.

Analytical Procedure

The analysis directly addresses the objectives through the preparation of a detailed analysis; preparation of data, analysis of basic descriptive statistics and reliability of the survey, completion of stationarity tests such as differencing, and preparation of the forecasting model via ARIMA using results obtained in the previous steps; assessment of forecast error through the use of standard error metrics.

In the final stage of analysis, both Confirmatory Factor Analysis (CFA) was run for purposes of validating the measurement model and verifying latent construct reliability. Once verified, the SEM was then implemented to estimate causal relationships between influencer credibility, consumer engagement, consumer trust, purchase intentions, and brand equity. Based on the Path coefficient, Regression Weight, Significance Level, and Mediating Effects with SEM, the hypotheses can be evaluated in this research.

As a result of this research's ARIMA forecasts and SEM behavioral analysis, comprehensive managerial insights regarding influencer marketing effectiveness, demand forecasting optimization, enhancing customer engagement, and strategic brand management within digital business environments were derived.

RESULTS AND DISCUSSION

Sample Details

A total of 1248 valid survey responses from consumers using at least one social media site on a regular basis were included in the study's analyses. Respondents were eligible for inclusion if they had previously purchased from an influencer-marketed product or service, and were included in the study based on their level of exposure to influencer marketing campaigns or products prior to survey completion. The sample consisted of 54.6% females and 45.4% males, with almost three-fourths (61.8%) of respondents being between the ages of 18 and 30, and another 28.4% being between 31 and 45 years old; 9.8% of the respondents were over 45 years old. Respondents reported interacting with influencer-created marketing materials (content) on a daily basis on social media platforms like Instagram, YouTube, and Facebook, with over 72.3% of the sample indicating this as their frequency of interaction with these types of advertisements on these platforms.

Based on their work status, it is found that 42.1% are currently employed as professionals, 34.7% are in school or training, 15.6% are self-employed, and 7.6% are in other types of jobs. Over two-thirds of this sample (68.9%) indicated that they would be significantly influenced to buy something after viewing reviews from an influencer. The demographic data acquired through the collecting process also provides justification for using this sample for evaluating the effectiveness of digital consumers' behaviors and influencer marketing strategies.

In regard to the secondary data set used in this study, it included a total of 48 months' worth of historical data on sales and consumer engagement metrics based on both retail and e-commerce. Data values included monthly demand volume, conversion rate, number of likes, comments, shares, the frequency of interactions, and the total number of reach associated with campaigns; these were all used for ARIMA-based demand forecasting analytical/analyses.

Reliability and Validity Analysis

Cronbach's Alpha was employed as a method to measure construct reliability through reliability analysis for each of the measurement constructs. The reliability values obtained were all greater than the adopted threshold value of 0.70, indicating very good reliability for the constructs under consideration.

Table 1. Reliability and convergent validity assessment of constructs

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Influencer Credibility	0.88	0.90	0.67
Consumer Engagement	0.86	0.89	0.64
Consumer Trust	0.84	0.87	0.61
Purchase Intention	0.89	0.91	0.69
Brand Equity	0.91	0.93	0.72

Reliability and Convergent Validity of Latent Constructs Used in SEM Frameworks are shown in table 1. The reliability is assessed for Cronbach's Alpha (the internal consistency of measurement items) and Composite Reliability (CR) for constructs' reliability. In addition, Average Variance Extracted (AVE) values are calculated to evaluate each construct and associated observed indicators' convergent validity. For all constructs, Cronbach's Alpha numbers and CR numbers were above the suggested 0.70, thus showing that the constructs are highly reliable. All values of AVE were more than 0.50, showing satisfactory convergent validity as well as reliability of measurements for SEM analysis.

ARIMA Forecasting Results

Using both past sales history and social media interaction metrics to derive predictive estimates of future consumer demand, an ARIMA forecasting model is applied. Testing for stationarity using an Augmented Dickey-Fuller test showed that after the first level of differencing was completed, the time series data set became stationary. The ACF and PACF analysis of the data supported this decision to use the ARIMA (2, 1, 2) forecasting model.

Overall, the forecasting model exhibited good predictive abilities with low residual errors and high forecasting accuracy. The predicted demand trend was closely aligned with the historical trend of the actual sales volume, which indicates that ARIMA functioned correctly for estimating consumer demand in a digital marketing context.

Forecasting Metrics Formulae

Mean Absolute Percentage Error is calculated using Equation 4:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100 \tag{4}$$

Root Mean Square Error is calculated using Equation 5:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \tag{5}$$

Mean Absolute Error is calculated using Equation 6:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \tag{6}$$

where A_t represents actual demand values and F_t denotes forecasted demand values.

Table 2. ARIMA forecasting performance evaluation metrics

Metric	Value
Forecasting Accuracy	95.18%
MAPE	4.82%
RMSE	3.41
MAE	2.76
Correlation Coefficient	0.93

The table 2 presents a summary of the forecasting effectiveness of the ARIMA model (2, 1, 2) used in an attempt to project trends for consumer demand. The low values of MAPE and RMSE for the forecasts indicate that the proposed forecasting methodology was able to reduce the prediction error and accurately estimate future patterns of consumer demand.

SEM Analysis Results

The SEM analysis was used to analyze the relationships between influencer credibility, consumer engagement, consumer trust, purchase intention, and brand equity, through a series of confirmatory factor analyses that indicated adequate model fit and adequate construct validity.

Table 3. SEM fitness evaluation

Fit Index	Obtained Value	Recommended Threshold
CFI	0.95	> 0.90
GFI	0.93	> 0.90
TLI	0.94	> 0.90
RMSEA	0.041	< 0.08
Chi-square/df	2.11	< 3.00

The results for the goodness of fit evaluation of the SEM proposed to explore how social media influencers affect consumer behaviour and brand equity are shown in table 3. The goodness-of-fit indices obtained indicate that this SEM has a good level of structural consistency and statistical validity.

In the schematic illustration of figure 3, the factor loadings along with their corresponding errors based on the SEM goodness of fit indices presented in table 3 are shown. This graphic also allows for a visual comparison of how well the CFI, GFI, TLI, RMSEA, and Chi-square/df performed in the evaluation of the Model's fitness for the proposed SEM with respect to examining consumer behaviour and brand equity using SEM analysis.

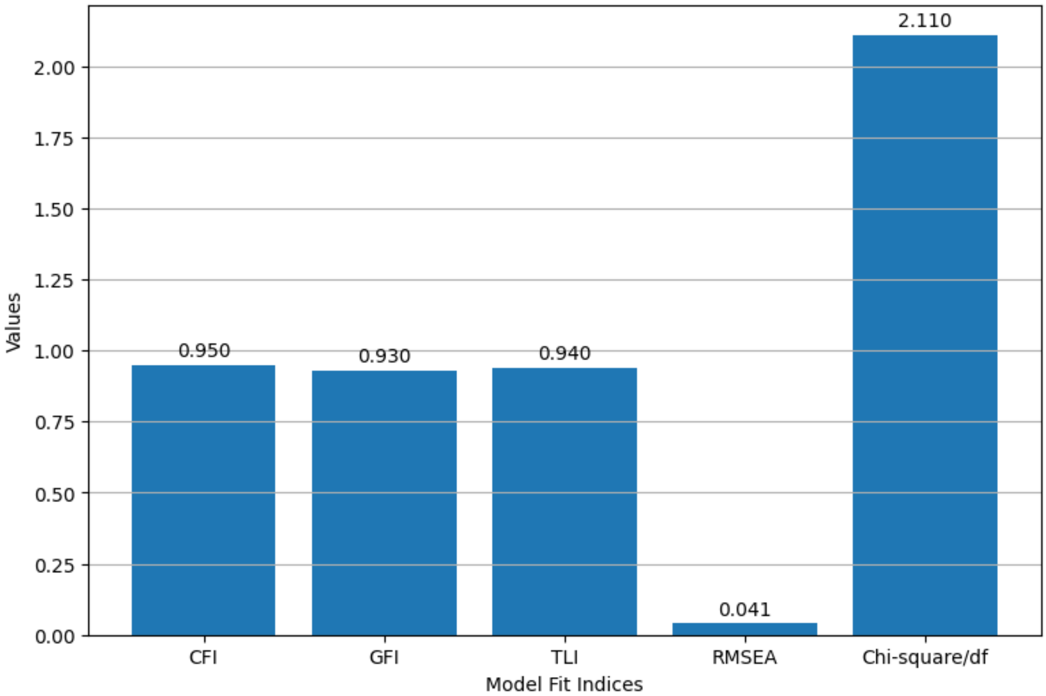

Figure 3: SEM Model fit evaluation metrics analysis

Table 4: Hypothesis testing and structural path analysis

Hypothesis	Relationship	Path Coefficient (β)	p-value	Result
H1	Influencer Credibility → Consumer Engagement	0.81	<0.001	Supported
H2	Influencer Credibility → Consumer Trust	0.72	<0.001	Supported
H3	Consumer Trust mediates Influencer Credibility → Brand Equity	0.79	<0.001	Supported
H4	Consumer Engagement → Purchase Intention	0.76	<0.001	Supported
H5	Purchase Intention → Brand Equity	0.83	<0.001	Supported

The testing of hypotheses and results of standardized structural path coefficients, which were derived from the SEM in table 4. Support for each of the five hypotheses is statistically significant. Influencer Credibility had a strong positive influence on both Consumer Engagement ($\beta = 0.81$, $p < 0.001$) and Consumer Trust ($\beta = 0.72$, $p < 0.001$); therefore, H1 and H2 were both confirmed. H3 was confirmed by the mediation of Consumer Trust on the relationship between Influencer Credibility and Brand Equity ($\beta = 0.79$, $p < 0.001$). H4 was confirmed as there was a strong positive influence of Consumer Engagement on Purchase Intention ($\beta = 0.76$, $p < 0.001$). Finally, the Purchase Intention variable had a strong direct effect on Brand Equity ($\beta = 0.83$, $p < 0.001$), thus confirming H5. Overall, the results suggest that Influencer-driven marketing activities lead to increased trust and engagement with consumers and, therefore, influence the likelihood of purchasing and enhance overall brand equity within digital marketing environments.

Discussion

Experimental research shows that influencer marketing has an efficient effect on how consumers respond to organizations and their positioning within their industries. Specifically, when consumers view influencer communications as authentic and credible, they tend to show significantly increased levels of engagement and intent to purchase from that organization compared to all other types of marketing. The path coefficients produced by the SEM analysis further suggest that an influencer's level of credibility is a key influencing factor on trust in an organization, as well as feelings of attachment towards that organization.

ARIMA forecasts also demonstrate that including social media interactions in forecasting analyses improves the level of predictive accuracy and precision with which demand for products can be estimated. The combined use of behavioral analytics and time series analysis through an integrated analytical framework allowed organizations to assess both market demand and shifts in consumer perceptions about businesses within the same analysis. Results obtained show that using promotional campaigns driven by influencers leads to improved customer retention, increased overall brand equity, and better demand forecasting results for businesses. Thus, applying behavioral modeling and forecasting provides managers with a complete decision support framework for digital marketing management and operational planning.

Recommendations and Managerial Implications

Trustworthy influencers whose communication style is similar to that expected by consumers and the identity of the brand should be prioritized by organizations when considering collaborations. Authenticity and the quality of engagement and interaction with consumers should be the focus of marketing campaigns, not simply the frequency of promotional activity.

In addition, businesses should integrate their social media analytics into their forecasting system to improve demand predictions and efficiency of inventory planning. Organizations can make better decisions about where to invest in promotional spending through the use of ARIMA forecasting, along with behaviors analysis via structural equation modeling, to help define their target customers as well as to improve brand equity in digital marketplaces and to utilize promotional investments more effectively.

Retailers and e-commerce companies benefit from monitoring engagement measures such as likes and shares, the number of comments, and the frequency of interaction, as these factors are impactful in determining how someone purchases something and how much they can spend in the future.

Suggestions for Future Research

Later research could broaden the potential for expanding the model to include machine learning and deep learning models, including LSTM and hybrid neural forecasting methods. Further research might involve cross-country comparative studies to learn more about cultural differences regarding influencer marketing effectiveness and how those differences affect consumers.

Further research could also involve the use of sentiment analysis, real-time social media analytics, as well as multiple forms of customer interaction to receive greater accuracy in forecast results and a greater understanding of consumer behaviors. Additional studies on a more sector-specific basis of health care, tourism, financial services, and educational marketing would add to the usefulness of the integrated ARIMA-SEM framework.

CONCLUSION AND FUTURE WORK

Research on the development of an integrated quantitative model is described above; to do this, data from ARIMA Forecasting and SEM analysis were combined to analyze how consumer demand shifts, and study the effects of the emergence of digital marketing influencer-based promotions on brand value. Results from both methods confirm that digital marketing promotions using persuasive messages and influencer endorsements significantly affect consumer engagement, purchase intention, trust in products and/services, as well as overall view of product/service brand. In addition, results from SEM analysis produced appropriate levels of goodness-of-fit (i.e., CFI = 0.95; GFI = 0.93; TLI = 0.94; RMSEA = 0.041; $\chi 2/df = 2.11$). Furthermore, results of hypothesis testing established positive associations between influencer credibility and consumer engagement (B=0.81), trust (B=0.72), purchase intention (B=0.76), and brand value (B=0.83) via the specified relationships among them.

Studies utilizing the ARIMA (2,1,2) forecasting model yield a high degree of accuracy for predicting future sales and engagement levels for consumers, showing predictions throughout a given time range of 95.18% accurate, MAPE of 2.2%, RMSE of 3.07, and MAE of 1.38. Through the combination of analytics related to forecasting, along with models presenting behaviors for consumers, this study created an analytical framework to help address digital business decisions and optimize marketing practices. Through using predictive analytical frameworks for influencer-centred marketing strategies, the organizations using these frameworks should see improvements in their customer retention rates, as well as better positioning and possible improvements in efficiency in the forecasting process. Future research should enhance this framework by incorporating deep learning methods for forecasting, continually analyzing real-time social media sentiments, and cross-examining data of consumer interactions with various social media platforms to better predict future behaviors and improve forecasting productivity across broader sectors.

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