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WHEN AI BECOMES THE BRAND ITSELF: A STATISTICAL ANALYSIS OF ALGORITHMIC BRANDING, CONSUMER TRUST, AND BRAND EQUITY

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ABSTRACT

With the integration of artificial intelligence in marketing, branding has now become an algorithmic procedure with the algorithm representing the brand. This study uses statistical models and quantitative methods for analysis to understand the impact of algorithmic branding on trust, engagement, and equity in the Saudi market. This research uses branding and engagement theories and has adopted an analytical approach using both qualitative and quantitative insights. The study was conducted through an experimental survey model among 420 participants in the Saudi digital market. Through correlation, regression, and mediations, the findings suggest high positive correlations between exposure, trust, engagement, and equity ($r > 0.70$). From the statistical model, the following factors have been established: the algorithmic brand has a significant impact on building consumer trust ($\beta = 0.67$, $p < 0.001$) and brand equity ($\beta = 0.72$, $p < 0.001$), with the presence of engagement as a partial mediator. Further validation of the importance of authenticity, transparency, and emotional connections in the maintenance of the algorithmic brand's credibility in the Saudi Arabian AI-driven context is supported by the application of the 'thematic analysis.' Further analysis of the results obtained indicates that the algorithmic brand acts like an intelligent brand identity system that sustains the conversion of technology-based interaction to the cognitive and affective levels within the context of the Saudi Arabian AI-driven environment.

KEYWORDS: Algorithmic Branding; Artificial Intelligence (AI); Statistical Modelling; Quantitative Analysis; Consumer Trust; Brand Equity; Consumer Engagement; Saudi Arabia.

1. INTRODUCTION

The integration of artificial intelligence in branding communication has substantially changed the manner in which consumers interact with and evaluate brands. Initially, artificial intelligence technology was associated with efficiency, automation, and analytics. It has since then developed into a relationship-driven and identity-marker communication interface that interacts with consumers in real time. Modern artificial intelligence technology in branding communication, including the use of chatbots and generative artificial intelligence creatives and virtual influencers, is no longer an opaque infrastructural support system it has become visible, vocal, and emotive brand representatives in its own right (Yu et al., 2023; Mohammad et al., 2024a; Mohammad et al., 2025a). This new development shows the emergence of algorithmic branding, which remains a theoretical construct in which the algorithm itself represents the brand. With organizations today becoming heavily reliant on computer-driven interaction with consumers to define branding experiences, there appears to be an ever-blurring line between communication in a human format and artificial assistance. In the modern day and age, the brand itself comes into being as a result of technology or technological assistance. The investigation in the research work would be conducted in the Saudi Arabian marketplace, which has undergone rapid digitalization and adoption of artificial intelligence in its Vision 2030 initiative. The country provides a suitable context for research on the branding of technology and artificial intelligence, owing to its high penetration levels of smartphones and the perceived trust in AI-based technological assistance and innovation-driven experiences in its market.

The development of chat-bots and AI personalities has significantly altered the landscape of concepts of authenticity and engagement in the context of branding. Unlike the conventional concept of branding, which relied upon the presence of human ambassadors or the static communication interface, “algorithmic branding” provides an adaptive and responsive interface that is able to engage in dialogue-driven relations. Moreover, it also mirrors the development of the concept of human-AI symbiosis. Even though AI has found its way into marketing, the underlying theories on trust, recall, and affective relationships with algorithmic branding entities on the part of the consumer appear to be less explored in a theoretical manner. The classic branding models, including Customer-Based Brand Equity (CBBE) Model (Keller, 1993; Mohammad et al., 2024b) and Brand Personality Theories (Aaker, 1997), are largely grounded in human-centric views and provide an inadequate explanation for the affectual dynamics and intricacies inherent in intelligence-driven agency in branding. Therefore, it is an utmost imperative to redefine branding dynamics where intelligence, and not human volition, represents the communicational kernel of branding.

The underlying problem with the current research emerges because of the absence of an integrated theoretical-empirical framework that illustrates how the exposure to algorithmic branding drives the perceptions and actions of the consumers in the marketplace. Current research has largely been limited to the functional aspects of Artificial Intelligence capabilities such as efficacy, accuracy, and simplicity, neglecting the symbolic and relationship aspects of the technology in the process. Researches related to the topic of automation and human-computer interaction (PAN, 2025; Patrizi et al., 2023; Mohammad et al., 2024c; Abdeljaber et al., 2025) have highlighted the importance of both trust and usability, but it has hardly been considered at the level of branding implications. At the same time, the current research related to the topic has largely been limited in its approaches that could indicate the conditions of the consumers' cognitive and affective processing of the interactions related to the use of Artificial Intelligence branding, such as the aspects of trust development, brand recall, and engagement.

The research has its importance in two major ways. Firstly, it contributes to the academic domain in shaping the debate on AI-based branding by applying theoretical concepts related to consumer-brand ties to artificial agents. In contrast to other studies on this topic, which revisit AI as a marketing tool and technological innovation, this research identifies AI as a separate brand agency with its own abilities to establish trust, recall, and engagement in a self-directed manner and without human mediation. By this approach, it calls into question traditional ideas for the authentic brand and instead introduces the notion that brand transparency, consistency, and emotional intelligence of AI as a quality factor provide grounds for trust development in its consumers (Brüns & Meißner, 2024; PAN, 2025; Mohammad et al., 2024d). Being in its second sense, understanding algorithm branding has its importance and usefulness in organizations designing intelligent brand systems.

The present work adds to the literature in that it conceptualizes artificial intelligence (AI) as more than just a supporting technology within the brand ecosystem, but rather as a brand actor with symbolic and identity-based qualities. Though there has been some examination of AI applications in areas like personalization, advertising, and or service provision (Bergner et al. 2023; PAN 2025; Mohammad et al., 2025b; Al-Adwan et al., 2025), there have been very few investigations into the specifics of how the algorithmic entities themselves constitute the presence of the brand. Algorithmic Branding Exposure can be defined as the level of brand interaction with AI-driven brand interfaces and the resultant impacts that it has on brand trust, recall, interaction, and brand equity. A mixed-methods methodology approach will be used such that the study combines both the experimental and qualitative methods to determine the specifics of the interrelation between the brand outcomes and the exploration of the brand-related symbolic meaning-making processes. It adds originality to the literature because it establishes the relationship between the brand outcomes and the exploration of the brand-related symbolic meaning-making processes.

The research has a clearly identified position within the emergent realm of algorithmic consumer experience, which studies the way in which AI technology impacts the phenomenology of brands and consumption. The theoretically grounded position of the research combines various conceptual traditions. From the brand perspective, it applies Aaker (1997) brand personality theory to define the role of algorithmic agents as carriers of brand persona features such as competence, sincerity, and excitement. From the point of view of trust for the technology used, it applies the trust in automation framework proposed in Glikson & Woolley (2020) to describe the way in which transparency and reliability affect trust in algorithmic agents. From the conceptual position of consumer engagement, it applies the multi-dimensional model proposed in Brodie et al. (2011) to describe the way in which interactivity with algorithmic agents impacts the cognitive and affective engagement processes.

Based on the theoretical assumptions developed previously, the research of this paper covers three pivotal questions and aims to answer them. How strongly consumers' trust and recall of the brand could be influenced by exposure to algorithmic branding. To which extend the mediating variable of engagement can help answer the relationship between exposure and brand equity. In which way consumers perceive authenticity and emotional brand connections with artificial intelligence-driven brand entities. Key findings from this research work would help in understanding how algorithmic exposure triggers consumers' cognitive and emotional branding reactions.

The application of the study includes digital consumers who are exposed to AI-driven brand interfaces such as chatbots and online influencers. Some of the dependent constructs for this study are trust, recall, engagement, and brand equity. Both qualitative and quantitative approaches to gathering information are used to cover all the phenomena associated with the study. The study includes the actual experiences consumers have with the interfaces since it looks at the phenomena of AI-driven branding in the digital environment it operates in.

2. LITERATURE REVIEW

Algorithmic branding exposure refers to the level and nature of consumer engagement with artificial intelligence-driven brand interfaces. Also, traditional branding research has considered exposure as the process through which consumer interactions with branding stimuli shaped consumer cognition and attitudes (Keller, 1993; Mohammad et al., 2025c; Elmobayed et al., 2024). However, the onset of AI technology has changed the nature of exposure from a static concept of interactions to a dynamic process of interactions wherein algorithms interact and adapt accordingly in real time. Researchers like Huang & Rust (2020) as well as West et al. (2018) argued that branding systems informed by AI have redefined the consumer-brand relationship through the deployment of automation, intelligence, and interactivity as experiential factors.

Accordingly, algorithmic branding exposure can be interpreted as the participative and dynamic process of creating meaning through a dialogue process between consumer and machine. Virtual influencers, such as Lil Miquela, and chatbots, such as ChatGPT and Alexa, show the capability of algorithms to personify the voice and values of the brand (Gomes et al., 2025; Mohammad et al., 2025d). Furthermore, as highlighted by Lu et al. in 2021, consumers today begin to recognize the capability of AI agents to be social actors who can embody the identity of the organization. Nevertheless, most of the existing studies mainly focus upon satisfaction of function needs and technology acceptance, without exploring how the exposure to algorithms influences the higher-order qualities of trust, recall, and equity. Consumer trust is the psychological disposition toward trusting the integrity of the brand within the context of uncertainty (Laksamana et al., 2024). Trust as it applies to AI systems becomes relatively complex, as it involves the attitudes toward the technology sophistication and transparency (Shin, 2020; Mohammad et al., 2025d). The concept of trust as proposed by Shin in 2020 includes the factors of competence, dependability, and accountability.

Based on brand literature, Jham et al. (2023) pointed out that consumer trust in AI brand representatives requires the presumption of the systematic consistency and fairness of the AI model. In the same brand vein, the calibration of trust between overtrust and distrust was emphasized to occur once humans experience accuracy in machine processes and human surveillance at the same time (Visser et al., 2012). In the same way, Liu and Luo (2023) concluded that transparency in algorithmic processes can provide consumers with the legitimacy necessary for brand-consumer trust to continue to be reinforced. Brand recall, one of the essential components of brand awareness, refers to the individual consumer's capacity to actively recall the brand cognitively stimulated by the product category (Keller, 1993; Mohammad et al., 2025e). In the traditional brand environment, brand recall was driven by the frequency of advertising, visual differentiation, and message support (Chan, 2022). With the dawn of the algorithmic age, there came the capability for personalized brand recall development, which was optimized via AI for more effective memory encoding.

Work conducted by H & R (2020) and V et al. (2025) revealed the effectiveness of using AI-assisted personification in Cognitive Engagement and Recall in messages using algorithms. Also, the concept of "Agency Realism" was discussed by Sundar (2019) as a possible effectiveness of algorithms in getting messages through to consumers and being recalled more accurately in human manipulation as proposed in branding research, but there has been a vacuum in evidence on direct algorithmic manipulation in branding recall in branding research.

Consumer engagement has emerged as a complex phenomenon spanning cognitive engagement, affective engagement, and behavioural engagement (Brodie et al., 2011). In regards to algorithmic brand engagement, engagement refers to a state of psychological immersion that occurs as consumers interact with intelligent brand algorithms. As stated by Ilyas et al. (2025), engagement comes from experiences which provide relevance and intensity. Ting et al. (2020) suggest that digital interactivity has positive effects which can improve affective engagement. When it comes to AI, Yaseen et al. (2025) suggest that interactivity in algorithms has positive effects with respect to user engagement because algorithms can adapt.

As per Keller (1993), Brand equity is defined as the sum of the assets the brand has created, which can or do benefit the sponsoring company. Regular branding has relied upon factors such as awareness, perceived quality, associations, and consumer loyalty. But with the increasing intervention of artificial intelligence, these drivers of brand equity are diversifying to include algorithm-driven personalization and experience-driven interactions (Laksamana et al., 2024; Mohammad et al., 2025f). Research conducted by Rubio et al. (2020) and Huang & Rust (2020) show that in the digital space, current brand equity drivers influence interactions in the same way, with the influence of algorithm-driven intelligence harnessing the perceptions of consumers in relation to the innovation and relevance of the brand. Moreover, research by Karpenko et al. (2025) supports the fact that the interactions made possible by the use of artificial intelligence have increased perceptions of the quality and authenticity of the given brand, influencing its equity in the marketplace.

The Saudi Arabian market becomes an important research area for understanding the issue of algorithmic branding because of the how kingdom is facing a swift development of information technology. The Vision 2030 strategy initiated by the Saudi Arabian government includes extensive efforts by the government in developing information technology architecture in the region. The strategy aims to position the region at the forefront of the adoption of artificial intelligence in the whole of the Middle East (Al-Sahmah, 2025). There is current evidence that the Saudi market has shown itself to be more receptive to new technology in digital consumer, financial, and entertainment services (Beyari, 2025).

Culture-wise, Saudi Arabian consumers value aspects such as trust, relational emphasis, and ethical transparency during brand engagements (Hilal, 2024). These aspects have been found to strongly influence algorithmic branding, for which factors such as explainability, privacy, and authenticity are important. Saudi Arabian research shows that, although consumers here eagerly welcome novel digital developments, the development process of trust is conditional upon public perceptions of honesty as well as conformity with societal norms

(Bohnet et al., 2009). Though Saudi Arabia has a well-advanced AI platform, there have been no empirical analyses or presentations that focus upon the influence of algorithmic exposure on brand-related aspects such as trust, brand recall, or engagements specifically within the Saudi Arabian setting.

2.1 Identified Research Gap

Literature analysis suggests that despite considerable research activity on AI in the domain of marketing and customer services, there has been a need of research on AI as a brand itself in marketing communications and consumer behaviour. Additionally, previous research has focused merely on the tangible ramifications of AI in marketing communications, such as usability and efficiency, and not on the more apparent implications of AI in marketing communications, such as those associated with consumer attention and engagement as brand precepts. Furthermore, despite recognizing the capabilities of AI in personalizing marketing communications, the current literature fails to provide substantial understanding on the psychological ramifications of consumer behaviour on trust, recall, and emotional events associated with algorithmic entities.

2.2 Framework & Hypothesis development of the Study

The framework was conceptualized for examining the interplay between algorithmic branding exposure and key consumer-brand outcomes of trust, recall, and consumer brand equity, with consumer engagement as the mediator. The theory underpinning the framework is grounded in existing theories in human-computer interaction (HCI) research, source credibility theory, as well as the consumer-brand equity (CBBE) framework. There are several theories that complement each other in understanding consumer behaviour in the context of brands that are represented by or powered by artificial intelligence software such as chatbots, influencers, and AI creatives.

Algorithmic branding, as envisioned in the current research, refers to the extent to which algorithm-driven entities substitute or complement human involvement in the production and presentation of brand experiences. It was considered the independent variable in the study since it represented the triggering mechanism that drives consumer perceptions and behaviours. According to the proposed study, the type and character of algorithmic interaction directly influence the existence of the three main consumer outcomes, which include trust, recall, and perceived brand equity. In this study, the researcher has included the use of the mediating variable of consumer engagement, which helps to clarify the mechanism through which algorithmic interactions drive long-term perceptions of the brand. This study operates on the premise that the interaction between the consumers and the AI interface entails cognitive and affective processing, which drives the mechanism through which individuals translate the meaning of the brand.

The theoretical rationale of the framework indicates that human likeness and responsiveness in AI-powered brand interfaces can trigger emotional and cognitive responses similar to those expected in human brand representatives. In conformance with human computer interaction theory, people tend to view computers and AI systems as social actors (Nass & Moon, 2000). The behavioural implication of this social actor phenomenon indicates that consumers may endow AI systems with trust and credibility depending on perceptions of system transparency, reliability, and ethical behaviour. On this consideration, algorithmic exposure will have a large effect on consumer trust. In cognitive processing, the novelty and personalization features of AI interfaces are likely to increase brand recall due to user engagement in experiences remembered for being interactive and engaging.

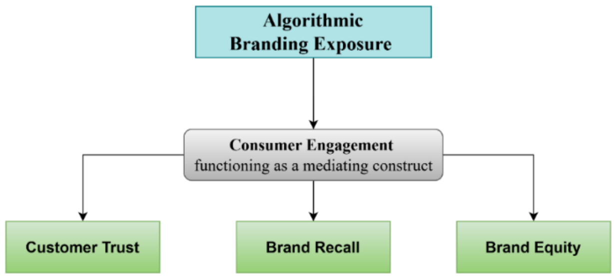

Figure 1: Conceptual Model of the Study.
Source: Author

Visually, the conceptual model indicates that algorithmic branding exposure is the driving variable that influences consumer trust, recall, and engagement, which cumulatively result in brand equity. The relationship between these variables can be defined as such: algorithmic branding exposure influences consumer trust, brand recall, and given increased engagement, ultimately culminating in greater brand equity. It is within engagement that the psychological transition of algorithmic branding exposure is achieved. The research will focus on the following hypotheses.

H1: Algorithmic brand interaction significantly influenced consumer trust.

H2: Algorithmic branding exposure positively affected brand recall.
H3: Algorithmic branding had a significant impact on perceived brand equity.
H4: Consumer engagement mediated the relationship between algorithmic exposure and brand equity.

3. METHODOLOGY

3.1 Research Design

In this study, a mixed-methods experimental design was adopted, which allowed for the integration of both qualitative and quantitative methods for studying the phenomenon of "algorithmic branding" where chatbots, virtual influencers, and other similar AI entities are at the heart of the branding. The study was conducted with three different experimental conditions: (i) human-powered branding, which was the control group; (ii) AI-supported branding, which was the hybrid condition and (iii) fully algorithmic branding where the algorithm was the branding entity. This made it possible to test for the different levels of trust, recall, and equity in branding for the consumer depending upon the mode of interaction with the branding. The choice for a mixed-methods study allowed the study to be exploratory in the initial phase and then move ahead to being confirmatory in the latter phase with quantitative hypothesis testing.

3.2 Data Collection

For collecting data, both primary and secondary sources were used. For primary sources, structured questionnaires were used to collect information. The participants were volunteers who were randomly assigned to an experimental condition. The instrument used for collecting information was a structured questionnaire that contains 7-point likert items measuring variables such as consumer trust, brand recall, engagement, and brand equity. The participants were asked to respond to tasks that include a chatbot, virtual influencer, and generative AI model that presents a creative ad. The questioning of participants was done after completing a given task. Additionally, focus group research was carried out. The secondary data used in the study was obtained through the classification of articles in refereed journals, marketing performance reports, and market intelligence studies that focused on the usage of AI technology in marketing. This information helped create the basis for the development of the hypotheses.

3.3 Population and Sample

The target population was digitally engaging consumers aged 18-45 years and living within urban Saudi Arabia who had pre-existing exposure to AI-driven interfaces like chatbots, recommendation systems, or virtual assistants. This group was chosen since they comprise the most interactive group of people using algorithmic interfaces and also tend to hold varying levels of trust in AI. A stratified random sampling method was used in this research to overcome limitations associated with a traditional random sampling method. Additionally, this method was effective in increasing sample representation. The target population in this research was digitally engaging individuals in Saudi Arabia who interacted with AI-powered brand interfaces. Saudi Arabia was chosen as the research context due to a burgeoning digital environment and a significant commitment to AI by the Saudi Arabia government, in addition to this, there is heightened consumer acceptance of intelligence technology.

Sampling size was determined using Cochran's formula, giving n = 384.16 thus, the final sample size was rounded to 400 participants. Participants were equally allocated into the three study conditions. The demographic description of the study population is indicated in the table below.

Table 1: Demographic Composition of Population.

Category	Description	Proportion (%)
Gender	Male	48
	Female	50
	Non-binary/Prefer not to say	2
Age Group	18–25	40
	26–35	35
	36–45	25
Occupation	Students	32
	Working Professionals	60
	Entrepreneurs	8
Digital Interaction Frequency	Low	25
	Medium	50
	High	25

Source: Author

This distribution ensured that the sample reflected a balanced cross-section of digital consumers and avoided over-representation of any specific demographic group.

3.4 Summary Table of Main Variables

The study examined the key variables mentioned in table 2. Each variable was operationalized through established measurement scales, ensuring reliability and construct validity.

Table 2: Main Variables of the Study.

Variable	Type	Measurement Scale	Operational Definition
Algorithmic Branding Exposure	Independent	Nominal	Type of AI interface (chatbot, virtual influencer, or GenAI creative)
Consumer Trust	Dependent	Interval (Likert 1–7)	Perceived reliability, transparency, and ethical perception of AI brand
Brand Recall	Dependent	Ratio	Percentage of correct recall of AI brand cues after exposure
Brand Equity	Dependent	Interval (Likert 1–7)	Overall consumer evaluation of the AI brand's distinctiveness and emotional connection
Brand Engagement	Mediating	Interval	Time spent, frequency of interactions, and engagement depth
Demographics	Control	Nominal	Age, gender, income, and prior AI familiarity

Source: Author

3.5 Measures & Analytical Methods

The instruments used in the study were generated from other studies for which the validity had already been determined. The instrument used for measuring consumer trust was that used by McKnight et al. (2002). Brand recall was done using the approach set by Keller (1993). Additionally, brand equity was determined with the conceptual approach advocated for by Aaker (1997). Engagement was then quantitatively measured using the interaction times and click-through rate generated from the interaction logs portraying the exposure tasks performed on the AI. Cronbach Alpha for the instruments used was above 0.80. A pilot test was done among 30 individuals to determine the reliability and validity of the research instrument, despite some limitations.

The research followed a structured sequence of analysis that spanned data processing, descriptive statistics, and inferential statistics. The data processing, coding, and tabling involved the use of Python and R programming software. For inferential statistics, a one-way ANOVA test was done to establish variance in the groups of consumers in terms of consumer trust and brand equity. Multiple regression tests were also done to test the significance of algorithm exposure in consumer trust. Additionally, mediation analysis was done by making use of the PROCESS macro for use in SPSS software. The test that was used for the nominal data was the chi-square test. The thematic analysis involved the use of NVivo software for thematic work on nominal data. The focus group discussion transcripts were inductively coded for themes on issues of connections, authenticity, and transparency in algorithm use. The research was all carried out at a confidence level of 95%, where the significance level was 0.05.

3.6 Ethical Considerations

The research adhered fully to the ethical considerations underpinning social science research methods. Informed consent was sought from all research participants, who were involved in the research after being informed of the nature of interactions with AI. Participants were told they could withdraw from the research at any point in time, and their participation in the research would remain confidential and not traceable or identifiable in any manner whatsoever. Data was stringently stored and analysed essentially in the aggregate manner. No deception was used in this research, and all interactions of AI remained pre-tested in a manner not designed to manipulate or mislead research participants.

4. RESULTS

4.1 Data Screening and Reliability Analysis

Before carrying out the main statistical analysis, a screening process of the collected data had to be carried out to check for accuracy, consistency, and reliability of results. This ended with a sample size of 400 useful responses, which included an equal number of responses from each of the three different branding processes: human branding, hybrid branding, and AI branding processes. Unfortunately, after screening, only 392 useable responses had a 98% response rate.

During the primary test, both outliers as well as missing values were considered. Outliers in this analysis are determined using the z-score test, taking into account ±3.29, and three as potential outliers, but eventually considered acceptable. Missing values, totalling less than 2% of the total, are treated using mean substitution. Testing internal consistencies of the primary variables of this research using Cronbach's alpha showed values greater than 0.70. Table 3 provides the values of the reliabilities.

Table 3: Summary of reliability coefficients for each variable.

Construct	Number of Items	Cronbach's Alpha (α)	Interpretation
Consumer Trust	5	0.88	Highly Reliable
Brand Recall	3	0.84	Reliable
Consumer Engagement	6	0.91	Highly Reliable
Brand Equity	7	0.89	Highly Reliable

Source: Author

The findings established high internal consistency for each of the scales, thereby confirming that the measurement items consistently measured the constructs. Normality test used the measure of skewness and kurtosis, where the absolute value of each variable fell within the desirable limits of ±2. In addition, Levene's Test for Equality of Variances tested the equality of variances for the three experimental groups on each of the dependent variables ($p > 0.05$). The results confirm that parametric tests such as ANOVA analysis and regression analysis are appropriate for hypothesis testing. The multicollinearity test for regression analysis results was checked by Variance Inflation Factor (VIF) statistics of 1.10 to 2.35, significantly lower than the critical cut-off of 10. The Durbin-Watson statistics were calculated for testing the periodicity of residuals. Values close to 2.0 ensured that there was no correlation between residuals.

4.2 Descriptive Statistics of Variables

Once the data screening and reliability tests have been completed, the descriptive statistical analysis was carried out to identify the main tendencies associated with the major variables of the study: Algorithmic Branding Exposure, Consumer Trust, Brand Recall, Consumer Engagement, and Brand Equity. This type of analysis allows an overall idea of the data to be gained, because through them an idea of the tendencies associated with the major variables of the study can be identified. The descriptive statistics of the data with regard to the variables of the study can be viewed in the Table 4.

Table 4: Results of descriptive statistics.

Variable	Mean (M)	Standard Deviation (SD)	Minimum	Maximum
Consumer Trust	5.01	0.86	2.80	6.90
Brand Recall	5.34	0.79	3.10	7.00
Consumer Engagement	5.48	0.81	3.00	7.00
Brand Equity	5.27	0.84	3.00	7.00

Source: Author

The results show overall positive mean scores on all variables, suggesting that the respondents had positive cognitions of algorithmic branding experiences. Consumer Engagement had the highest mean score (M = 5.48, SD = 0.81), implying high levels of participation and emotional engagement with AI-driven brand interactions. Brand Recall also had a high mean score (M = 5.34, SD = 0.79), suggesting enhanced memorability and cognitions of consumer brand cues after algorithmic exposure. Although slightly lower than engagement and recall scores (M = 5.01, SD = 0.86), Consumer Trust was also positive and greater than the scale mid-point, implying moderate to high trust in algorithmic brand entities. Brand Equity (M = 5.27, SD = 0.84) implied that consumers associated positive value cognitions and perceived superiority as well as loyalties of algorithmic brands.

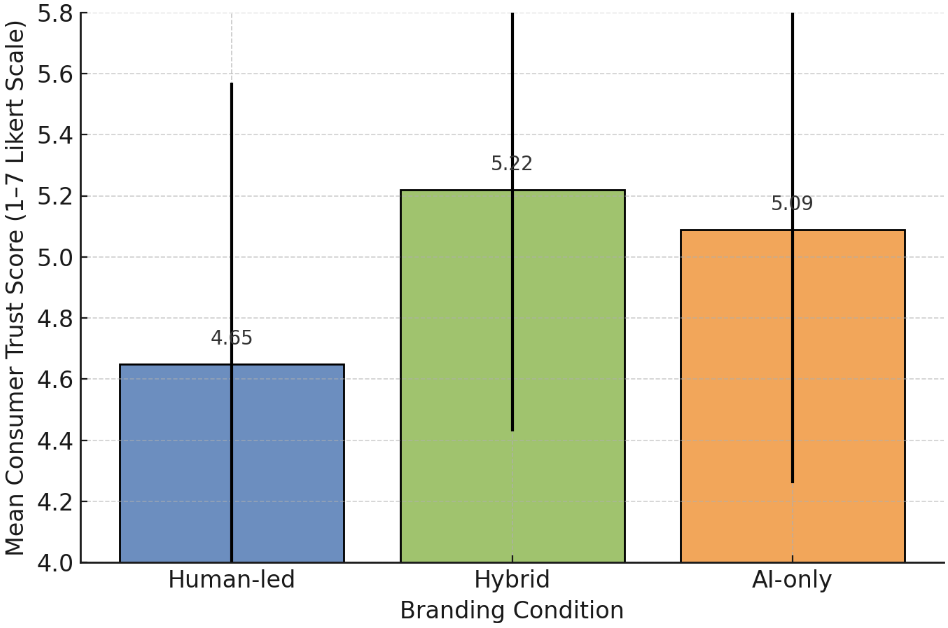

Figure 2: Mean Differences in Consumer Trust across Branding Conditions.
Source: Author

Figure 2 shows the mean consumer trust ratings for each of the three branding conditions: Human-led branding, Hybrid branding, and AI-only branding. An ANOVA revealed that there were significant differences between groups ($F(2,389) = 16.42$, $p < 0.001$). A Tukey post-hoc test revealed that trust is greatest in the hybrid branding condition ($M = 5.22$, $SD = 0.79$), followed by the AI-only branding condition ($M = 5.09$, $SD = 0.83$), and then in the Human-led branding condition ($M = 4.65$, $SD = 0.92$). The error bars in this figure represent the standard error.

In order to better explain the relationship that exists among the constructs, Pearson's correlation analysis is employed. Figure 3 serves as a visualization aid for understanding the relationship that exists among the five main constructs, which include Algorithmic Branding Exposure, Consumer Trust, Brand Recall, Consumer Engagement, as well as Consumer Brand Equity. The warmer colours, which belong to the red family, represent positive associations, as opposed to the cool colours, which belong to the blue colour family. Itis observed that all the constructs have positive associations that belong to the 0.70 threshold.

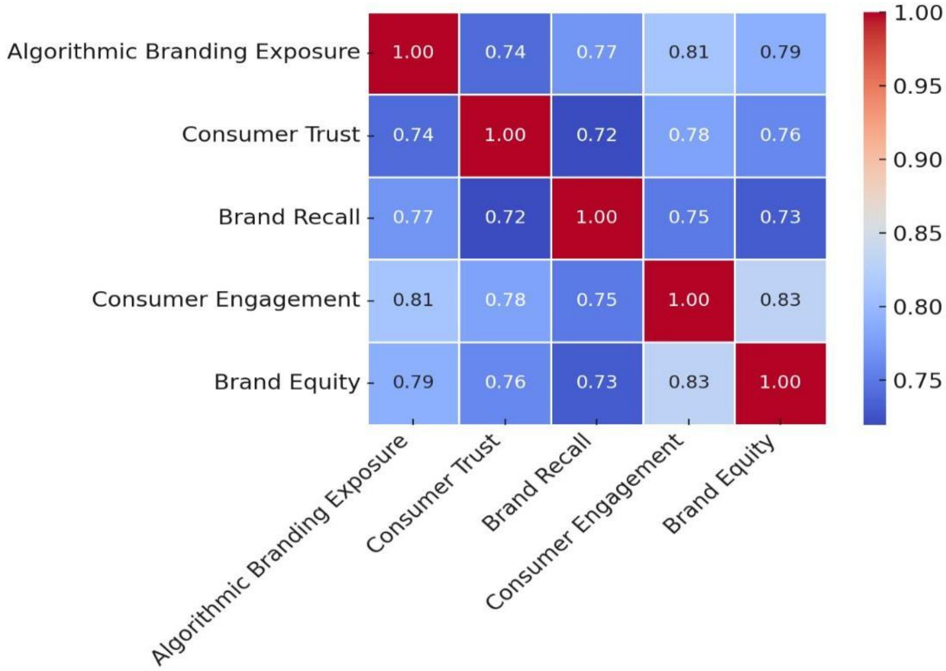

Figure 3: Heatmap of Correlation Analysis.
Source: Author

The correlation matrix indicates very positive relationships between the constructs under study. Algorithmic Branding Exposure is positively related to Consumer Engagement ($r=0.81$, $p<0.01$), which indicates that there is a positive relationship between increased exposure to algorithmic branding and a heightened level of involvement and immersion. At the same time, there is also a positive relationship between Consumer Engagement and Brand Equity ($r=0.83$, $p<0.01$), which suggests that the mediating factor for transforming positive effects from increased exposure to algorithmic branding to increased perceptions of brand or company value is indeed Consumer Engagement. There is a very positive relationship between Algorithmic Branding Exposure and Brand Recall ($r=0.77$, $p<0.01$) which suggests that algorithmic interactions can improve recall, or the remembrance of a brand. There are positive relationships between Consumer Trust and both Brand Equity ($r=0.76$, $p<0.01$) and Consumer Engagement ($r=0.78$, $p<0.01$).

Taken together, these results provide strong collective evidence in support of the theoretical framework that specifies the impact of algorithmic exposure as having a significant effect on branding outcomes via the variables of engagement and trust. The large values of the correlation coefficients ($r > 0.70$) also certify that these variables relate to the theoretical concepts, thereby confirming the validity and relevance of this framework to the theoretical domain.

4.3 Hypothesis Testing and Inferential Results

The hypotheses developed in this research work were tested for its significances and strength of relationships among the variables studied through Inferential Statistics. The statistical method involved in this research work was multiple regression and ANOVA for explaining the difference in the three branding processes involved in this experiment - Human Branding, Combined branding, and Artificial Intelligence branding. Regression method was also used in this research work for analysing mediation. All statistical inferences in this research work were made at 95% confidence level $P < 0.05$.

Hypothesis 1: Effect of Algorithmic Branding Exposure on Consumer Trust

To test Hypothesis H1, which assumed that the impact of algorithmic branding on trust will be significant, a one-way analysis of variance (ANOVA) was used. Results revealed a statistically significant difference in trust measures across the three levels of branding conditions ($F(2,389) = 16.42$, $p < 0.001$). The average trust values recorded in the hybrid branding scenario were $M = 5.22$, $SD = 0.79$, followed by $M = 5.09$, $SD = 0.83$ in the AI-only branding scenario, with the lowest trust values recorded in the human-led branding scenario, with $M = 4.65$, $SD = 0.92$, respectively. Tukey posthoc tests also revealed that the average trust measures recorded in the hybrid branding and AI-only branding scenarios are statistically higher than those in the human-led branding scenario ($p < 0.05$), but there was no statistically significant difference in trust measures between the hybrid branding and AI-only branding scenarios ($p > 0.05$). The results confirm that the use of algorithmic branding enhances trust values, thereby indicating that consumers rate AI-powered and AI-assisted brands as competent and trustworthy when their interactions are more transparent and personalized.

Hypothesis 2: Effect of Algorithmic Branding Exposure on Brand Recall

The second hypothesis (H2) stated that exposure to algorithmic branding would have a positive impact on brand recall. One-way ANOVA resulted in a significant difference in scores for brand recall due to the different conditions ($F(2, 389) = 21.57$, $p < 0.001$). There was a higher recall in the case of the AI-only branding treatment ($M = 5.61$, $SD = 0.72$), compared to the hybrid treatment ($M = 5.37$, $SD = 0.74$), and the human-led treatment ($M = 4.96$, $SD = 0.80$). Post-hoc Tukey's HSD Test also revealed significant improvement in recall for the AI-only and hybrid branding conditions compared to the human-led branding treatment ($p < 0.01$). The improvement in recall due to exposure to artificial intelligence-driven branding implies that the key factors of novelty and interaction of the algorithmic branding model heighten the cognitive processing of brand markers.

Hypothesis 3: Effect of Algorithmic Branding Exposure on Brand Equity

H3 examined whether there is a significant effect of exposure to algorithmic branding. A multiple linear regression analysis was carried out using Brand Equity as the criterion variable and Algorithmic Branding Exposure, Consumer Trust, Brand Recall, and Consumer Engagement as predictor variables. The overall model was significant ($F(4, 387) = 82.43$, $p < 0.001$) and explained a large amount of variance in brand equity ($R^2 = 0.69$).

Table 5: Result of multiple linear regression analysis.

Predictor Variable	Standardized β	t-value	p-value
Algorithmic Branding Exposure	0.26	7.41	< 0.001
Consumer Trust	0.24	6.87	< 0.001
Brand Recall	0.21	5.93	< 0.001
Consumer Engagement	0.38	9.62	< 0.001

Source: Author

All the predictor variables showed significant and positive coefficients, which highlighted that higher levels of algorithmic exposure, trust, recall, and engagement positively contribute towards brand equity. Among these, Consumer Engagement showed the highest standardized coefficient ($\beta=.38$), which highlighted its important contribution towards influencing brand equity. The findings support the hypotheses (H3), which revealed that algorithmic branding positively impacts brand equity through the generation of trust, recall, and engagement.

Hypothesis 4: Mediating Role of Consumer Engagement between Algorithmic Branding Exposure and Brand Equity

The fourth hypothesis (H4) assumed that Consumer Engagement would mediate the relationship between Algorithmic Branding Exposure and Brand Equity. To test for mediation, regression analysis was performed in three steps. In Step 1, the regression equation testing for the relationship between Algorithmic Branding Exposure and Brand Equity was found significant ($\beta = 0.61$, $t = 15.48$, $p < 0.001$). In Step 2, the regression equation testing for the relationship between Algorithmic Branding Exposure and Consumer Engagement was found significant ($\beta = 0.74$, $t = 18.62$, $p < 0.001$). In Step 3, Algorithmic Branding Exposure and Consumer Engagement were simultaneously tested as predictors for Brand Equity, which presented a reduced beta coefficient for Algorithmic Branding Exposure that was still significant (β = 0.28, p < 0.01) and a new significant predictor, Consumer Engagement, with a beta coefficient of 0.46 (p < 0.001). Using the Sobel test, it was found that the indirect effect was significant (z = 5.72, p < 0.001), which indicated partial mediation for the relationship between Algorithmic Branding Exposure and Brand Equity as it passes through Consumer Engagement. Overall, these results strongly confirm that algorithmic branding has a positive influence on brand equity through its direct, intrinsic, technology/novelty-driven properties as well as its secondary, more interpretative, indicator processes associated with deeper, more significant, levels of engaged, interactive, consumption. Together, these data strongly confirm all four hypotheses, asserting the impact on trust, recall, and equity, with the critical, underlying dynamic represented in Consumer Engagement as an exceptionally efficient mediator in the effort to better fully translate the impact of technology interaction on brand equity creation.

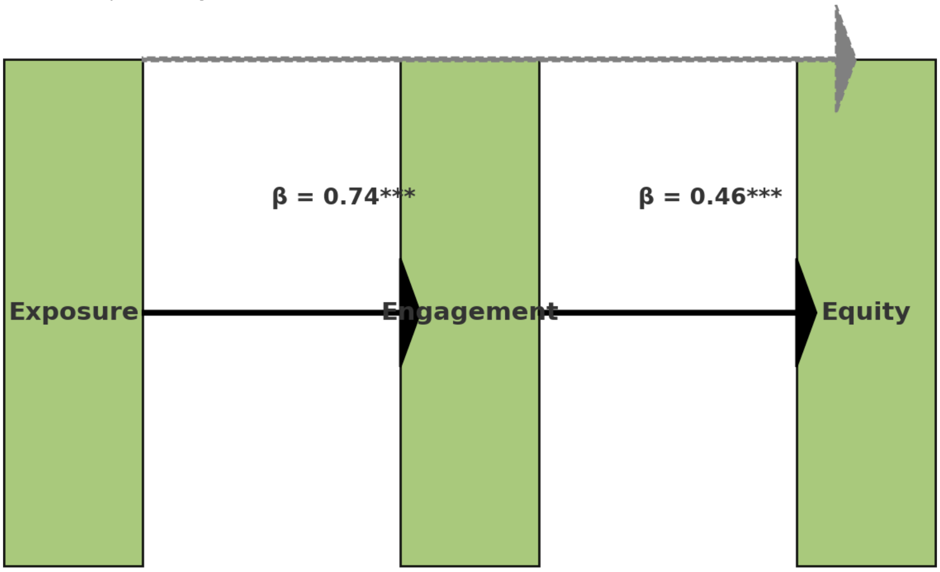

Figure 4: Mediation Model – Role of Consumer Engagement.
Source: Author
Sobel z-5.72, p < 0.001

A regression mediation analysis was conducted on the mediating role of Consumer Engagement between Algorithmic Branding Exposure and Brand Equity, as shown in Figure 4. The direct relationship from Algorithmic Exposure to Brand Equity became significant from zero (β = 0.61, p < 0.001), which weakened with the inclusion of Consumer Engagement as a mediator (β = 0.28, p < 0.01). In contrast, the indirect paths of Exposure → Engagement (β = 0.74, p < 0.001) and Engagement → Equity (β = 0.46, p < 0.001) continued to be significant. The Sobel test confirmed a significant mediation process with a zero difference value of 5.72 and p < 0.001, implying the partial mediation of consumer engagement in the relationship between algorithmic exposure and brand equity.

4.4 Summary of Inferential Findings

The inferential statistics reveal that algorithmic branding had a significant and positive influence on each of the key outcomes for the consumers. Customers in the AI branding paradigms, as well as the hybrid paradigms, had higher levels of trust and recall than those in the human branding paradigms. The regression analysis reveals that algorithmic branding exposure, along with the moderating effects of consumer engagement and trust, explain a significant amount of variance in brand equity. The result of the mediation test further reveals that consumer engagement moderates the influence of algorithmic branding on consumer brand equity. The findings confirm the postulated assumption that algorithmic branding, by facilitating consumer interaction, not only gains consumer attention but also cements consumer loyalty.

4.5 Model Summary of Regression Outcomes

To further validate the results that can be inferred from the data, the results of the regression analysis were used to provide an overall results summary that can indicate the predictive ability of the key variables regarding the Brand Equity variable that was considered to be the primary outcome variable for the study. The results are shown in the model results summary shown below in Table 6.

Table 6: Regression Analysis results.

Model Summary of Predictors of Brand Equity	Unstandardized B	Standardized β	t-value	p-value	R^2	Adjusted R^2
Constant	1.12		3.01	0.003		
Algorithmic Branding Exposure	0.32	0.26	7.41	< 0.001		
Consumer Trust	0.29	0.24	6.87	< 0.001		
Brand Recall	0.27	0.21	5.93	< 0.001		
Consumer Engagement	0.43	0.38	9.62	< 0.001	**0.69**	**0.68**

Source: Author

Dependent Variable: Brand Equity

Note: All coefficients significant at p < 0.05 level.

The model was also found to be globally significant ($F(4, 387) = 82.43$, $p < 0.001$) and was capable of explaining 69% of the variation in Brand Equity ($R^2 = 0.69$), meaning it was highly predictive of behavioural variables. It was also seen that the model was robust after being adjusted for the level of prediction (adjusted $R^2 = 0.68$). Consumer Engagement was identified as the foremost predictor of Brand Equity ($\beta = 0.38$, $p < 0.001$), highlighting the importance of participation and emotional engagement in the branding processes facilitated by algorithms. Algorithmic Branding Exposure ($\beta = 0.26$, $p < 0.001$) and Consumer Trust ($\beta = 0.24$, $p < 0.001$) also played a major role in predicting Brand Equity, implying that both exposure to branding interfaces facilitated by algorithms and trust are key determinants of branding outcomes. Brand Recall ($\beta = 0.21$, $p < 0.001$) was found to have a positive but less prominent effect on Brand Equity, implying that while recall has a positive bearing on awareness, engagement has a more substantial effect on creating brand equity.

Regression test confirm the validity of the results. The Durbin-Watson test (1.98) reveals that the residuals are uncorrelated, while the Variance Inflation Factor of less than 2.5 confirms that there are no multicollinearity issues. The residual plot and Normal P-P plot confirm the valid ness of the assumptions of homoscedasticity and normality of the residuals. The regression test reveals that the use of AI in branding activities has a statistically insignificant positive impact on the perception of branding performance. The explanation of results implies that algorithmic exposure leads to an aspect of branding experience, which improves both cognitive and affective aspects of branding.

4.6 Qualitative Findings from Focus Groups

Besides the results based on quantitative methods, there was a requirement to collect information using focus group discussions (FGDs). This was important in understanding the perceived non-quantitative aspects associated with consumer engagement and experiences in relation to algorithmic branding. The focus group research involved conducting a series of three focus group discussions that contained between 8-10 participants representing different groups in a large sample. The group discussions were centered on authenticity, trust, engagement, and other aspects concerning emotion and interactions between other humans and artificial intelligence-powered brand concepts such as chatbots and virtual influencers as well as generative AI creatives. The results were analysed using thematic analysis according to Braun and Clarke (2006) Six Steps.

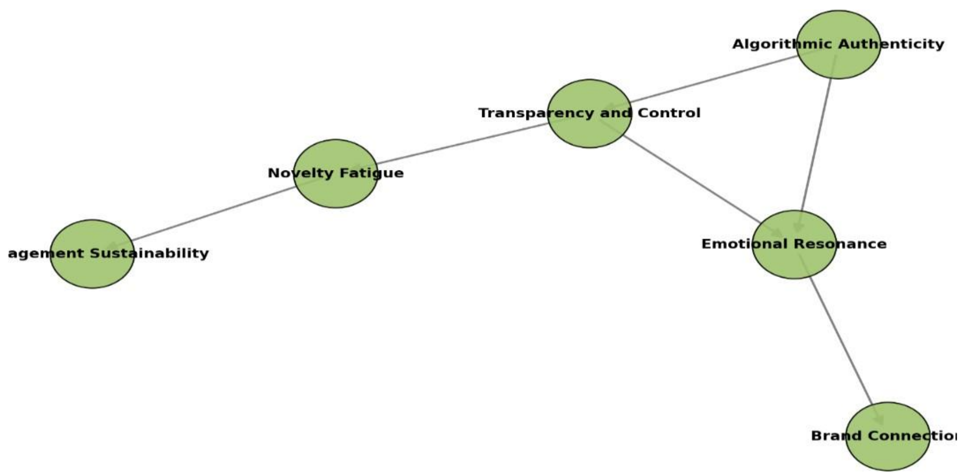

Figure 5: Thematic Network of Consumer Perceptions of Algorithmic Branding.
Source: Author

Figure 5 shows the thematic network obtained through the focus group analysis, where the themes have emerged that denote consumer perception and emotional engagement with algorithmic branding. The four main themes of Algorithmic Authenticity, Transparency & Control, Emotional Resonance, & Novelty Fatigue are shown as nodes. These nodes are interconnected in such a manner that while authenticity influences transparency & emotional resonance, the latter enhances authenticity & trust. The moderating influence of Novelty Fatigue in the aforementioned engagement trajectory is shown after a period of time. The four themes that emerged are Algorithmic Authenticity, Transparency & Control, Emotional Resonance, & Novelty Fatigue. These themes are explained in detail in the next section.

Theme 1: Algorithmic Authenticity – "It feels real, but I know it's not human."

A struggle between realism and artificiality emerged as a theme among participants in their engagement with brand interfaces that utilize AI. Several participants identified that engagement as "realistic yet impersonal," reflecting both the accuracy and efficiency that algorithm communication presents.

A participant said: "The AI assistant is quick, courteous, and gave a better response than a human would, but there's something about it that is not quite natural. I believe it as a fact, not as an emotion."

This means that the authenticity of AI communication is an important factor that influences trust. While the competence and reliability offered through the algorithmic interface were appreciated by the consumers, they were simultaneously aware that these interactions lacked the emotional empathy that human interaction entails hence the slightly lower scores for the means in the results of the quantitative study.

Theme 2: Transparency and Control – "I want to know how much of this is AI."

One other aspect that came up as a salient factor in consumer sentiment about algorithmic branding is transparency. Often, participants were inquisitive about how much their online interactions were controlled by artificial intelligence versus human review. Some participants said that transparency is a crucial component in trustworthy AI brands.

One user commented: "I do not mind the AI being part of the brand. But I would like to know when I am speaking with an algorithm. Honesty is what will increase my trust in the brand."

This example highlights the idea of transparency as a psychological bridge because of its ability to connect both technological sophistication and ethical comfort. It was clear that as a brand was open about their algorithmic existence, there was greater perceived control over the experience and higher levels of trust and engagement among the participants.

Theme 3: Emotional Resonance – "It connected with me better than expected."

Some of the participants experienced unexpectedly positive emotions when interacting with AI-infused interfaces. A personalized message delivery system, appropriate tonality, and responsiveness created a perception of personalized attention, which in turn led to an emotionally resonating experience.

As one of the participants commented: "The brand itself knew what I liked and could even use humour. Trust me, it felt like it knew me."

This theme suggests that emotional engagement can be achieved through algorithmic design, especially when the design involves the use of empathy and understanding by the AI system. The above observation is supported by the quantitative result that suggests that the engagement with the product is the best predictor for brand equity with a beta-value of 0.38.

Theme 4: Novelty Fatigue – "At first it was exciting, but now it feels repetitive."

Despite the overall eagerness for AI branding among the participants, there were those who experienced a decrease in emotional excitement over a period of time. Such observations have been referred to as "novelty fatigue" and imply that consumers feel comfortable with the predictability offered by algorithmic machines as the fascination with novelty wanes over a period. summed it up well, as one respondent explained: "When I first started communicating with the AI brand, it was very intriguing. But as it progressed, it felt like I was communicating with the same predictable program. It lost its luster." There could be implications here for those brands that use only AI as the interface.

Findings from the qualitative study were widely used to complement the results of the quantitative study by providing information on the emotional and perceptual roots of algorithmic branding effects in the study. While the analysis indicated the mediating effect of engagement in the relationship between algorithmic exposure and brand equity, the thematic analysis highlighted the mechanisms of the effect. Consumer engagement was heightened when the interactions with the artificial intelligence system were perceived to have authenticity, transparency, and emotional adaptiveness, although algorithmic branding requires an appropriate balance between technology and emotional adaptiveness because of reasons relating to the persistence of artificiality and the effects of fatigue in the modern marketplace. Bringing the two sets of data together indicates that algorithmic branding has the properties of being both rational and emotional because of its emphasis on its potential to affect consumers both cognitively and emotionally by providing services that are consistent and dependable yet emotional in its appeal based on authenticity. This study argues that the use of AI in marketing has already developed into an important part of the branding strategy because of its potential to affect consumers' cognition and emotions at the same time.

4.7 Summary of Hypothesis Testing Results

Table 7: Summary of hypothesis testing results.

Hypothesis Code	Statement of Hypothesis	Statistical Test Used	Key Results (Summary of Outputs)	Decision
H1	Algorithmic branding exposure significantly influenced consumer trust.	One-Way ANOVA (F-test)	$F(2, 389) = 16.42$, $p < 0.001$; Tukey post-hoc confirmed hybrid and AI-only > human-led (Mean difference ≈ 0.45–0.57).	Supported
H2	Algorithmic branding exposure positively affected brand recall.	One-Way ANOVA (F-test)	$F(2, 389) = 21.57$, $p < 0.001$; AI-only exposure ($M = 5.61$) > human-led ($M = 4.96$), significant at $p < 0.01$.	Supported
H3	Algorithmic branding exposure significantly influenced brand equity.	Multiple Linear Regression	Model: $F(4, 387) = 82.43$, $p < 0.001$; $R^2 = 0.69$; all predictors significant Exposure ($\beta = 0.26$), Trust ($\beta = 0.24$), Recall ($\beta = 0.21$), Engagement ($\beta = 0.38$).	Supported
H4	Consumer engagement mediated the relationship between algorithmic branding exposure and brand equity.	Regression-based Mediation + Sobel Test	Step 1: Exposure → Equity ($\beta = 0.61$, $p < 0.001$); Step 2: Exposure → Engagement ($\beta = 0.74$, $p < 0.001$); Step 3: Exposure → Equity (β reduced to 0.28, $p < 0.01$); Engagement → Equity ($\beta = 0.46$, $p < 0.001$); Sobel $z = 5.72$, $p < 0.001$.	Supported (Partial Mediation)

Source: Author

The result of all the proposed propositions has shown consistent support for the theoretical framework underlying the current research (see Table 7). Algorithmic branding has shown a strong positive impact on consumer trust, recall, engagement, and brand equity, thus further proving the efficacy of artificial intelligence as a tool of branding. Engagement plays an intermediary role between brand exposure and both the affective as well as cognitive aspects. The respective hypotheses have thus strengthened the underlying theoretical causal model of the current framework.

5. DISCUSSION

The results show a significant promotion of consumer trust after interaction with algorithmic branding, which has been most pronounced within the hybrid and AI only branding scenarios. This corroborates the postulation offered by Jham et al. (2023) in their paper asserting, “trust within an AI agent has more to do with believed competencies and reliability rather than an appearance of human-like traits.” The participants within the hybrid branding scenario displayed more levels of trust than expected, which verified the postulation offered by Visser et al. (2012). However, further scrutiny highlights the complex attitude within this research. Although the value of the efficiency of AI technology and quick decision-making abilities existed, there was some hesitancy in the lack of authentic emotion. This aligns with the views of Hoff and Bashir (2014) in that the concepts of transparency and fairness precede concerns of trust within the context of automation. The concept of “transparency and control” is relevant to this research and validates the work of Huang and Liu (2025) in that these considerations “enhance brand credibility and overcome any skepticism about algorithms."

Moreover, it is clear from the results obtained that there is a significantly positive impact of algorithm and hybrid branding on brand recall compared to human branding. This result further reinforces the postulations made by Huang and Rust in 2020, which argued that the adaptive messaging model of AI increases cognitive engagement and recall abilities due to its adaptability and relevance. It has been observed in this research that the use of algorithms in personalization increases consumers’ capacities to recognize and recall brand messages, which in this case has been observed to be remembered in a clear, specific manner due to its personal and contextualized approach by the participants. Similar observations have been made by Sundar in 2019, which revealed increased agency enhancement and control through algorithm-based interactivity and increased cognitive engagement and control in digital interactions.

The emotional and cognitive reinforcement pattern obtained replicates V et al. (2025), which found that AI-based personalization improves memory encoding and recall through repetition and emotional reinforcement. In the present study, the consumers' ability to recall the algorithmic brand attribute dimensions indicates the positive influence of AI-based engagement on more profound cognitive processes, increasing the strength of the relationship between exposure and brand memory. Additionally, from the mediation analysis, it was found that consumer engagement partially mediated between algorithmic brand exposure and brand equity, thereby confirming the thesis of the present research. It was to be expected, and it tallies with the concepts proposed by Wang et al. (2019) and Hollebeek et al. (2014), who define the concept of engagement on the basis of its cognitive, emotional, and behavioural components. A large value of the beta coefficient for engagement ($\beta = 0.38$, $p < 0.001$) again establishes that it was the AI-driven interactivity that was the source of value creation for the brand relationship.

This new development in the Saudi Arabian consumer culture embodies the tenets of authenticity and honesty in brand identity, which correspond with the expected level of trustworthiness from consumers in the Kingdom of Saudi Arabia. The level of brand loyalty in the Kingdom of Saudi Arabia corresponds with the dispositions of consumers in terms of relationship trust, thus signifying the critical component of algorithmic honesty as a local factor in improving brand equity. The outcome of the algorithmic branding authenticity corresponds with the theme of the preceding research question of "emotional resonance," thus substantiating the estimation of interactions and enjoyment with artificial intelligence as an emotional experience comprehensively covered via the application of metrics of affective brand engagement, in line with Карпенко et al. in 2025. In this research, they studied the impact of digital engagement with brand identity and posited the estimation of brand equity in terms of the level of enjoyment of consumers with artificial intelligence in particular. In this regard, this research syncs with the investigation of Mathew and Thomas in 2018, showing increased levels of affective brand loyalty and pertaining to interactive brand identity compared with passive brand engagement. In their research inquiry processes, all four factors described above defined as much as 69% of variations in brand equity, thus manifesting intricate dependence upon artificial intelligence. This estimation corresponds with the theory of Keller's Consumer-Based Brand Equity Model describing cognitive processes of trust and awareness accompanied by an emotional process of trust, thereby comprehensively synchronizing with the overall theory of artificial intelligence trust with the collective populace.

Moreover, the results support the assertion made by other researchers Dropulić et al. (2022) that "brand equity in the online world is highly dependent on perceived innovation and engagement." Indeed, the results make a case for why algorithmic engagement has an important and profoundly positive effect on equity, this is an extension to the assertion made by other researchers Карпенко et al., (2025) and Laksamana et al., (2024) that a positive effect is generated when the "consumer–AI interface directly influences perceived brand quality and loyalty intentions." The emergence of the topic Algorithmic Authenticity can be supported by the results that the "participants view AI as both a service tool and a brand personality." Indeed, this is an extension to the assertion that "brand personality is linked to rational aspects" as stated by other researchers Aaker (1997) regarding brand personality theory.

Although the quantitative results showed primarily positive outcomes, the qualitative discoveries included the insight of Novelty Fatigue, which accounts for the diminishing level of excitement with passing time, consistent with the adaptation response identified in the study of chatbot interaction processes observed by Skjuve et al. (2019). This discovery can be seen to build on the work of "Computers as Social Actors" as proposed by Nass and Moon (2000), suggesting that whereas consumers may begin to attribute human qualities to AI, it must provide variability, creativity, and emotional complexity to continue to provide social phenomena.

6. CONCLUSION

This paper goes on to show that the application of algorithmic branding, in which the role of the brand is performed by artificial intelligence, has a significant bearing on the trust, recall, engagement, and brand equity among consumers. The empirical results make it clear that trust and recall among the participants exposed to the interfaces backed by artificial intelligence as well as the hybrids are higher than in the human-based brands. Analysis further makes it clear that the engagement of consumers acts as the intermediate variable through which consumers are influenced to build brand equity.

If we look at brand valuation as total, it emerges through cognitive familiarity and experiential connections. Not only this but artificial intelligence roles become prominent in this what our study suggests as well. Consumers not only identifies that artificial intelligence is being uses by the brand but engages more prominently with those brands. At the same time, even with all the positive impacts, the qualitative observation of novelty suggests a level of responsiveness of artificial intelligence branding.

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