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# Technology-Driven Experiences Shape Emotional Brand Relationships and Behavioral Outcomes, Enhanced by AI Personalization

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## ABSTRACT

*The proposed study explores the effect of technology-driven experiences on brand emotional relationships and consumer behavioral outcomes, and it fills the gap in existing body of research that frequently studies them independently. In particular, it explores how perceived value, brand authenticity, and self-brand connection are mediators and the moderating influence of AI-enhanced personalization. This research will endeavor to offer an in-depth insight into the digital interactions which translate into meaningful consumer behavior. The research design adopted is a quantitative study design with a structured questionnaire that was administered to 385 people who are active users of digital platforms. The analysis of the data was performed with the Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS. Reliability, structural relationship; validity and mediation and moderation of relationships were evaluated. The findings reveal that performance expectancy and effort expectancy have considerable effect on the perceived value ($R^2$ = 0.737), brand authenticity ($R^2$ = 0.580) and self-brand connection ($R^2$ = 0.596). These constructs, in their turn, have significant influence on the customer purchase ($R^2$ = 0.682) and customer referral ($R^2$ = 0.655). Although AI-enhanced personalization does not directly influence the purchase behavior (p = 0.831) it has a strong moderating effect on the main relations, enhancing the influence of emotional brand constructs on consumer outcomes. The research has the benefit of combining UTAUT, the theory of branding and AI personalization into a single stream. It underscores the fact that emotional brand relations are the key mechanism that motivates consumer behavior, and AI is an enhancing factor that provides useful information to both theory and practice.*

***Keywords:*** *Technology-Driven Experiences, AI-Augmented Personalization, Perceived Value, Brand Authenticity, Self-Brand Connection, Customer Purchase Behavior, Consumer Referral Behavior, PLS-SEM*

## INTRODUCTION

The fast-paced development of digital technologies has fundamentally changed the way in which organizations plan and provide customer experiences that has led to technology-based interactions that define consumer perceptions and behaviors. The modern marketing environment is becoming more and more based on digital-based services, artificial intelligence (AI) and immersive technologies to make the interactions between firms and their consumers more interactive and personalized. No longer based on a transactional exchange, these technology-driven experiences are now taking the form of full experiences that affect emotional and cognitive reactions toward brands. Recent research notes that digital experiences play a crucial role in improving customer experience and brand-related results by generating rich and impactful experiences (Dwivedi et al., 2023; Verhoef et al., 2022; Huang and Rust, 2023). The idea of technological interfaces being key touchpoints through which brand perception and consumer attitudes are created is also supported by earlier studies (Lemon and Verhoef, 2019; Bolton et al., 2020).

**Statement of Problem**

Although marketing has seen a breakneck pace of changes toward tech-driven marketing, and the introduction of artificial intelligence (AI) into managing customer experiences, a major gap in comprehension of how the new technological solutions can be converted into meaningful emotional relationships between the brand and tangible behavioral consequences continues to persist. Although other scholars have conducted extensive research on factors of technology adoption and digital marketing strategies, they tend to isolate them and do not pay enough attention to the combined effect of perceived value and brand authenticity and self-brand connection on developing consumer reactions (Dwivedi et al., 2023; Huang and Rust, 2023; Mariani et al., 2023). Moreover, despite the fact that AI-enhanced personalization has become one of the crucial elements of improving the customer engagement, there is a lack of empirical evidence that examines its modulatory nature in reinforcing the interplay between technology-based experiences and subsequent outcomes, including brand love, purchase intention, and word of mouth. Previously, studies had mostly done general personalization effects and did not grasp the dynamic and in-time capabilities of AI in affecting consumer-brand relationships (Wedel and Kannan, 2020; Lemon and Verhoef, 2019).

**Research Questions**

RQ1. What is the effect of technology-related experiences (effort expectancy, performance expectancy, and hedonic motivation) on emotional brand relationships, including perceived value, brand authenticity, and self-brand connection?

RQ2. What is the role of emotional constructs of brand relationships in relation to consumer behavioral outcomes, i.e., customer purchase and referral behavior?

RQ3. What is the moderating effect of AI-enhanced personalization between technology-based experiences, emotional brand relationship, and behavioral outcome?

**Study Objectives**

- To investigate the role of technology-driven experiences (effort expectancy, performance expectancy, and hedonic motivation) in the influence on emotional brand relationship constructs (perceived value, brand authenticity, and self-brand connection).

- To examine the role of perceived value, brand authenticity, and self-brand connection in creating emotional brand relationships, especially brand love.

- To examine how emotional brand relationships influence consumer behavioral outcome, such as customer purchase and referral behaviour.

- To determine the moderating role that AI-enhanced personalization plays in enhancing the relationships among technology-based experiences, emotional brand relationships, and consumer behavioral outcomes.

### Significance of the Research

This research has a considerable theoretical and practical importance as it contributes to the knowledge of how experiences based on the use of technology can affect emotional relationships with a brand and the final performance of consumer behavior in the environment of AI-enhanced personalization. Theoretically, it combines technology adoption constructs with branding and consumer behavior models, which initially deals with the disjointed nature of the previous literature that has commonly investigated those aspects independently (Dwivedi et al., 2023; Huang and Rust, 2023; Mariani et al., 2023). The study explains in a wholesome manner how emotional brand relationships are formed, especially brand love, in a digital realm by including mediating variables like perceived value, brand authenticity, and self-brand connection. Moreover, it adds to the growing body of research on AI in marketing by exploring the moderator effect of AI-based personalization, providing the understanding of its potential to increase consumer engagement and behavioral reactions. Practically, the results will help marketers, brand managers, and digital strategists create more efficient customer experience plans that use personalization and technologies to influence the purchase and referral behavior. The relevance of implementing customer experience and personalization strategies to secure a competitive edge and long-term brand loyalty is also highlighted in the previous literature (Lemon and Verhoef, 2019; Wedel and Kannan, 2020).

## LITERATURE REVIEW

Experiences and experiences Technologies have become a defining element of modern-day marketing that demonstrates how digital interfaces, platforms, and tools influence consumer interactions with the brands. These experiences can be based on technology adoption constructs of effort expectancy, performance expectancy and hedonic motivation, which reflect consumer perceptions and interactions towards technological systems. According to recent research, ease of use, perceived usefulness, and enjoyment are major factors affecting user engagement in online settings both in e-commerce and social media (Dwivedi et al., 2023; Huang and Rust, 2023; Verhoef et al., 2022). These constructs are consistent with the Unified Theory of Acceptance and Use of Technology (UTAUT) that have been extensively used to explain consumer behaviour in the digital setting. Previous studies, too, affirm that these issues are important in influencing user attitudes and behavioral intentions towards technology adoption (Venkatesh et al., 2020; Tarhini et al., 2019).

### Theoretical Framework

This theoretical framework of this study has its basis in combining both theory of technology adoption and branding theories to shed light on the impact of technology-mediated experiences in influencing consumer behavior. The Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the most prevalent theories implemented in the study of the technology acceptance and is based on the following constructs: effort expectancy, performance expectancy, and hedonic motivation. These variables justify how consumers appraise technological systems based on easy use, usefulness and fun. Recent research affirms that UTAUT is also still very much applicable in digital marketing and AI-enhanced settings, especially in the explanation of consumer behavior with regards to advanced technologies (Dwivedi et al., 2023; Mariani et al., 2023; Huang and Rust, 2023). Previous studies also indicate that UTAUT can be a powerful tool in forecasting behavioral intentions in different technological situations (Venkatesh et al., 2020; Tarhini et al., 2019).

UTAUT is effective in explaining how people adopt technology, but it lacks emotion and relational inclination in consumer-brand relationship. In order to overcome this drawback in this paper, the concept of branding theories, namely Customer-Based Brand Equity (CBBE) and relationship marketing, is included. These theories underline the importance of perceived value, brand authenticity, and emotional links in influencing consumer attitudes and loyalty. Recent articles indicate that digital experiences play a crucial role in brand equity, as they boost the perceived value and reinforce trust and authenticity (Kumar et al., 2023; Jain et al., 2022; Hollebeek et al., 2023). Previous research confirms that the robust brand relationships are established on regular value provision and purposeful interaction that eventually result in long-term provision and advocacy (Keller, 2020; Aaker, 2020).

Self-Concept Theory is another key theoretical perspective that has been used in this research to explain the process of forming relationships with brands that express identities and values of consumers. This theory presumes that people will tend to interact with brands that reflect the self image and this has resulted in the formation of strong emotional connection and long term relations. The digital platform facilitated technology-driven experiences, which can strengthen the connections of self-brand, due to their personal and interactive nature. According to recent research, personalization and immersive experiences are associated with a great enhancement of the correspondence between the identity of the consumer and the brand image (Kim and Sullivan, 2023; Rather et al., 2022; Sharma et al., 2023). Previous studies also note that self-brand connection is a critical factor in motivating the brand attachment and loyalty behaviors (Escalas and Bettman, 2019; Park et al., 2020).

**Experiences and Perceived Value that are Technology Driven**

Expectancy experiences, which are technology based especially effort expectancy, performance expectancy and hedonic motivation, are mostly supported as important factors influencing perceptions of value in digital settings. Consumers are more inclined to deem the entire experience valuable when they view technology as simple, efficient and fun to use. According to recent research, digital interfaces and interactive platforms can be used to create a superior experience in terms of perceived value because of efficiency and user satisfaction (Dwivedi et al., 2023; Huang and Rust, 2023). Previous studies also verify that the factor of perceived usefulness and ease of use has a direct correlation with value perception and consumer decision-making (Venkatesh et al., 2020; Bolton et al., 2020).

**Experiences and Self-Brand Connection driven by Technology**

According to the supporting literature, technology-meditated experiences support connecting with the self-brand by providing individual and interactive interaction. When a consumer engages with a brand by having a personalized digital experience, they will be better connected to the brand as a part of their self-concept. The most recent research has shown that immersive and personalized experiences bear a substantial effect in reinforcing self-brand alignment and emotional involvement (Kim and Sullivan, 2023; Jain et al., 2022). Previous studies also establish the fact that direct relationships offer identity-based relationship between individuals and brands (Escalas and Bettman, 2019; Park et al., 2020).

**Brand Love and Perceived Value**

Perceived value is one of the most well-known mediators in the relationship between technology-based experiences and emotional outcome of the brand love. Consumers have more chances of having positive emotional attachment to the brand when they sense the high value in the interactions they have with the brand. According to the recent studies, the value-based experiences have a strong impact on creating brand love and becoming loyal to the product in the long term (Kumar et al., 2023; Grewal et al., 2023). The fact that perceived value is positively correlated with emotional satisfaction that results in greater brand attachment has also been confirmed by earlier research (Zeithaml et al., 2020; Bolton et al., 2020).

## Development of the Hypotheses

### Effort Expectancy and Perceived Value

Effort expectancy can be described as the level of ease that is related to using technology, which is very essential in influencing consumer perception in the online world. By creating an easy-to-use system, consumers are more likely to have an easy time interacting with it, a factor that leads to a better perceived value. Recent research shows that simplified online experiences and user-friendly platforms can greatly enhance consumers to assess the value by minimizing the number of cognitive processes and maximizing efficiency (Dwivedi et al., 2023; Huang and Rust, 2023; Verhoef et al., 2022). Such results indicate that convenience is a direct force in positive experience, which leads to greater values perceptions in e-mediated relationships. Previous studies also verify that effort expectancy is an essential precursor of perceived usefulness and overall value assessment (Venkatesh et al., 2020).

H1: There is a positive impact of the effort expectancy on perceived value.

### Perceived Value and Performance Expectancy

The level of whether or not consumers think that the use of a technology will improve their performance or deliver the desired results is the performance expectancy. Efficiency, accuracy, and convenience are technologies that are vital in contributing to perceived value in digital marketing environments. Recent research emphasizes that the performance oriented characteristics like high processing speed, applicability of recommendations, and easy navigation improve the value evaluation process of consumers in terms of tangible benefits (Kumar et al., 2023; Grewal et al., 2023; Mariani et al., 2023). These results highlight the significance of functional advantages in the construction of value impressions in the technology-based experiences. Previous studies also establish that perceived usefulness is a critical antecedent to the value perception and consumer satisfaction (Venkatesh et al., 2020).

H2: Expectancy of performance positively influences the perceived value.

### Hedonic Motivation and Perceived Value

The enjoyment and pleasure experienced after using a technology is called hedonic motivation, and it is important in influencing consumer experiences. With digital marketing, memorable interactions through the use of engaging and entertaining platforms boost perceived value. Recent reports show that gamification, interactive materials, and immersion have a strong positive effect on perceived value due to a high level of emotional satisfaction and a functional advantage (Dwivedi et al., 2023; Sharma et al., 2023; Kim and Sullivan, 2023). These results emphasize the importance of enjoyment-related experiences in the process of shaping consumer perceptions in digital settings. Hedonic factors are also proved to contribute to increasing the perceived value and user engagement in earlier scientific studies (Venkatesh et al., 2020).

The perceived value is positively influenced by hedonic motivation.

### Brand Love and Perceived Value

Perceived value is an important factor in the emotional bonding of consumers and brands. Consumers feel more likely to experience positive emotional reactions when they feel that they have received high value in their interactions giving rise to brand love. Recent research shows that value-based experiences have a strong beneficial impact on emotional involvement and consumer-brand bonds (Kumar et al., 2023; Grewal et al., 2023; Huang and Rust, 2023). These results indicate that the perceived value is a base to establish robust emotional associations with brands. Previous studies also affirm that perception of value does directly affect customer satisfaction and emotional attachment (Zeithaml et al., 2020).

H4: There is a positive linkage between perceived value and brand love.

**Self-Brand Connection and Brand Love**

Self-brand connection measures the degree of consumer association of a brand with their-self identity and is therefore a very important predictor of emotional attachment. Consumers who believe that there is a high level of congruency between the brand and their identity are more likely to love the brand. Recent research points out that meaningful and personal conversations are a crucial step in reinforcing self-brand connection, which will result in an increased emotional attachment (Kim and Sullivan, 2023; Sharma et al., 2023; Rather et al., 2022). These results highlight the significance of identity-based relationships in the development of emotional attachment. Previous studies also confirm that the level of self-brand connection is a powerful predictor of brand loyalty and emotional involvement (Escalas and Bettman, 2019).

H5: The connection brought about by self-brand positively affects brand love.

**Brand Authenticity and Brand Love**

Brand authenticity is thought of brand being real, trustworthy and consistent and it is vital in the creation of emotional attachment. Consumers would develop brand love more when they believe that a brand is genuine and matches its values with those of the consumers. Recent publications indicate that brand truthfulness communication can promote emotional attention and trust to a greater degree, resulting in intensified brand love (Hollebeek et al., 2023; Rather et al., 2022; Sharma et al., 2023). These results demonstrate that authenticity is a factor that should be considered in the context of long-term relationships with consumers. Previous studies also confirm that authenticity is a driving force behind brand loyalty and emotional attachment (Aaker, 2020).

H6: Brand love is positively influenced by brand authenticity.

**Technological Experiences, Perceived Value and Brand Love**

Experiences that are technology-induced, especially the expectancy of effort, performance, and hedonic motivation are perceived to be important antecedents of perceived value, which in turn affects the emotional attachment towards brands. The consumers are likely to develop a stronger experience with higher value when they are exposed to user-friendly, efficient, and entertaining digital mediums, which results in a positive emotional response. According to the recent research, value-creating online interactions play a key role in achieving emotional involvement and brand loyalty (Dwivedi et al., 2023; Kumar et al., 2023; Huang and Rust, 2023). Such results indicate that the mediating variable whereby technology-based experiences are changed into brand love is the perceived value. Previously conducted studies also prove that perceived value is one of the primary facilitators of emotional satisfaction and brand relationship development (Zeithaml et al., 2020).

H7: Perceived value moderates the relationship between technology-driven experiences and brand love.

**Technology-based Experiences, Self-Brand Association and Brand Love**

It is also argued that technology based experiences impact brand love mediated by self-brand connection. Digital platforms that are interactive and personalized can help consumers identify themselves with brands and can enhance emotional attachment. The recent research shows that immersive and personalized experiences can make self-brand connection much more effective, consequently resulting in increased brand love (Kim and Sullivan, 2023; Rather et al., 2022; Sharma et al., 2023). This implies that self-brand connection is an important channel whereby technological interactions play a crucial role in determining the emotional branding outcomes. The concept of identity-based relationships as a foundation of the developing strong consumer-brand relationships is also supported by previous studies (Escalas and Bettman, 2019).

H8: Self-brand connection is the intermediary between the technology-driven experiences and Brand love.

**Technology-Powered Experiences , Brand Authenticity and Brand Love**

Another mediating factor between technology-related experiences and brand love is the brand authenticity. Through digital platforms, the brands are able to communicate in a transparent and consistent manner, increasing perceptions of authenticity and trust. Such recent research has shown that interactions facilitated by technology greatly contribute to perceptions of authenticity, which subsequently leads to the development of emotional attachment and brand love (Hollebeek et al., 2023; Sharma et al., 2023; Kumar et al., 2023). The findings underscore authenticity in changing technological interactions into meaningful emotional connections. The previous studies also prove that authentic brands will better result in creating the long-term loyalty and emotional impact (Aaker, 2020).

H9: Brand authenticity mediates the connection between the technology-driven experiences and brand love.

**Brand Love and Customer Purchase**

It is generally accepted that brand love is a powerful indicator of customer buying patterns because emotionally bound customers will tend to make a repeat purchase. According to recent research, intensive emotional attachments can greatly serve as a driver of purchase intentions and lessen price sensitivity (Kumar et al., 2023; Grewal et al., 2023; Huang and Rust, 2023). These results indicate that brand love is an important factor of transactional achievement. Previous studies also affirm that consumers who are emotionally engaged have greater rates of loyalty and purchasing behaviour (Batra et al., 2019).

H10: AI-enhanced personalization mediates the effect of brand love and customer purchase, where there is a stronger relationship with greater levels of personalization.

**Customer Referral and Brand Love**

The brand love is also crucial in determining the customer referral behavior because consumers who are emotionally attached to the brand will have greater chances of referring the brand to others. Recent research indicates positive word-of-mouth and advocacy behaviors are the result of strong emotional connections (Kumar et al., 2023; Grewal et al., 2023; Sharma et al., 2023). These results imply that brand love is one of the primary motivators of referral behaviour in digital space. Previous studies also confirm that emotional attachment promotes customer advocacy and brand promotion (Albert and Merunka, 2020).

H11: There exists a moderating effect between brand love and customer referral and AI-enhanced personalization, where the relationship is stronger with higher AI-enhanced personalization.

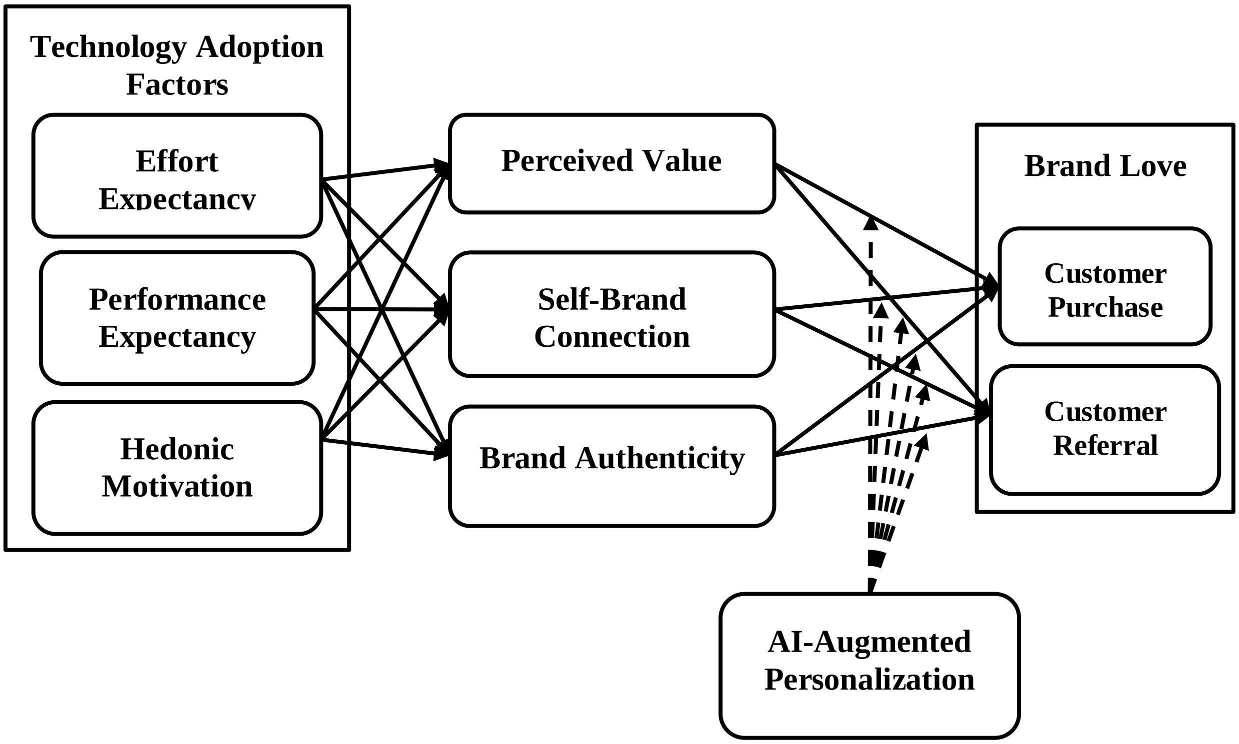


**Figure 1: Research Framework**

## METHODOLOGY

### Research Design

The current research paper utilizes a quantitative research framework to test the linking between technology-based experience, emotional brand relationship, and the behavioral outcome of consumers with the moderating role of AI-enhanced personalization. Quantitative research has been well known to be able to test theoretical models and hypothesis using statistical techniques, hence it is the best method to use in research that involves some form of structure and measurable constructs. Recent research highlights that quantitative designs are especially useful in the realm of digital marketing and consumer behavior research, where large sets of data and well-structured responses are needed to test complex models (Dwivedi et al., 2023; Kumar et al., 2023; Mariani et al., 2023). Further, quantitative methods make it possible to make generalizations and objectively examine the relationships between variables. The previous studies also justify the use of quantitative methods in analyzing the constructs of technology adoption and branding (Hair et al., 2020; Saunders et al., 2019).

This research paper is based on the cross-sectional research design where the data is gathered at a particular time to analyze the perception and behaviour of the respondents towards the experience and branding results based on the use of technology. The cross-sectional research design is very popular in marketing studies because it is effective in providing insights about current consumers and also testing theory. The recent publications underscore the fact that cross-sectional designs are suitable in the context of studying behavioral intentions and consumer perceptions within fast-changing digital landscapes (Hollebeek et al., 2023; Sharma et al., 2023; Grewal et al., 2023). It is also a good design that allows the researcher to examine several variables at the same time and therefore it can be used in mediation and moderation analysis. Previous research also attests that cross-sectional designs are useful when it comes to testing structural associations within the framework of consumer behavior research (Sekaran and Bougie, 2020; Malhotra, 2020).

**Data Collection**

The information needed to complete this research is collected with the help of the structured questionnaire that is sent online to obtain an idea of the respondents perceptions of the technology-driven experiences and branding outcomes. The online method of data collection is popular in digital marketing research because it is efficient, convenient, and can access a big and diverse population. According to the recent research, online surveys are a credible and timely source of data, especially studies on technology adoption and consumer behavior (Dwivedi et al., 2023; Kumar et al., 2023; Mariani et al., 2023). Also, digital data collection has lowered the bias in response and enables automated data processing, enhancing the accuracy and consistency. The utilization of structured questionnaires to gather standardized data, which can be analyzed statistically, is supported by previous studies as well (Malhotra, 2020; Sekaran and Bougie, 2020).

**Sample and Population**

The consumer segment of the study population is comprised of those consumers who are prolific users of digital platforms and who engage with brands by using technology based environment, including social media, online shopping sites, mobile apps. This group of people is especially applicable because they are more prone to AI-enhanced personalization and interact with digital branding strategies. According to recent research, consumers who are digitally active would be the most optimal respondents to study on technology adoption and online consumer behavior (Hollebeek et al., 2023; Sharma et al., 2023; Grewal et al., 2023). Besides, targeting such a population would mean that the respondents have enough experience to assess the constructs of interest. This is also supported by previous studies highlighting the need to choose a population that is relevant to maximize validity and applicability of results (Hair et al., 2020; Saunders et al., 2019).

| Demographic Variable | Category | Frequency (N) | Percentage (%) |
|---|---|---|---|
| **Gender** | Male | 176 | 45.7 |
| | Female | 162 | 42.1 |
| | Prefer not to say | 47 | 12.2 |
| **Age** | 18–24 Years | 72 | 18.7 |
| | 25–34 Years | 104 | 27.0 |
| | 35–44 Years | 86 | 22.3 |
| | 45–54 Years | 55 | 14.3 |
| | 55–64 Years | 41 | 10.6 |
| | 65 and above | 27 | 7.0 |
| **Educational Background** | Undergraduate | 155 | 40.3 |
| | Graduate | 134 | 34.8 |
| | Postgraduate | 96 | 24.9 |
| **Occupation** | Student | 92 | 23.9 |
| | Employed | 118 | 30.6 |
| | Self-Employed | 52 | 13.5 |
| | Business | 31 | 8.1 |
| | Unemployed | 29 | 7.5 |

| | | | |
|---|---|---|---|
| | Retired | 63 | 16.4 |
| **Residential Area** | Urban | 198 | 51.4 |
| | Sub-Urban | 122 | 31.7 |
| | Rural | 65 | 16.9 |
| **Exposure to Media** | Low (rarely use) | 96 | 24.9 |
| | Medium (use occasionally) | 102 | 26.5 |
| | High (use daily) | 187 | 48.6 |

**Table 1: Demographic Profile**

### Sampling

The research paper uses a non probability sampling method, i.e. convenience, to gather data of respondents easily available and pertinent to the research setting. Convenience sampling is popular in online marketing research because it is convenient and effective, particularly when focused on online users. Recent research indicates that this sampling technique fits well in exploratory and theory-testing studies in which the aim is to learn about the relationship between variables (Dwivedi et al., 2023; Kumar et al., 2023; Mariani et al., 2023). It can restrict the extent of generalizability but enables a quick collection of data and elicitation of respondents with relevant experience. The convenience sampling is also supported in previous studies in consumer behavior when there is limited access to a more large population (Hair et al., 2020; Saunders et al., 2019).

### Data Analysis

To analyze the data of this study, statistical software, SPSS is used at the initial stage of analysis and SmartPLS is used to analyze the data to conduct the structural equation modeling. Data screening, descriptive statistics and reliability analysis are conducted with the help of SPSS whereas the measurement and structural models are tested with the help of SmartPLS. Recent literature notes that SmartPLS can effectively analyze complex models with mediation and moderation effects, in particular, digital marketing research (Hair et al., 2022; Sarstedt et al., 2022; Ringle et al., 2023). These software tools are used to guarantee the proper and effective analysis of the data. The effectiveness of SPSS and PLS-SEM to analyze correlations between constructs in consumer behavior studies is also confirmed in earlier research (Hair et al., 2020; Henseler et al., 2019).

### Measures

The scales employed in the measurement of this study are modified versions of scales that have been previously tested, to guarantee reliability and validity. All the constructs such as effort expectancy, performance expectancy, hedonic motivation, perceived value, brand authenticity, self-brand connection, brand love, and behavioral outcomes are assessed with the help of the developed items utilized in the previous studies. Recent literature also refers to the significance of changing the validated tools to ensure the consistency and comparability of the studies (Kumar et al., 2023; Hollebeek et al., 2023; Sharma et al., 2023). There are slight adjustments to the items to fit the setting of technology-driven experiences and AI personalization. The application of the adapted scales to increase the measurement accuracy and theoretical consistency is also supported by previous studies (Malhotra, 2020; Sekaran and Bougie, 2020).

## RESULTS AND DISCUSSIONS

### Measurement Model

The measurement model was tested to determine the reliability and validity of constructs applied on the measurement in this study which is in line with the established guidelines in structural equation modeling. The reliability was also tested with the help of Cronbach alpha and composite reliability (CR), with an alpha of over 0.70 showing satisfactory internal consistency. Factor loadings and average variance extracted (AVE) were used to estimate convergent validity with loads of more than 0.70 and AVE ratings of more than 0.50 indicating that the constructs are well-analyzing the variance of the indicators. Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) were the measures of discriminant validity and were applied to make sure that all the constructs are different within a model. These requirements are highly suggested in PLS-SEM research to guarantee accurate measurement and strength. These validation methods prove that the measurement model is valid and reliable to be further analyzed regarding structure, which supports the validity of the relationships tested in this work (Hair et al., 2022; Henseler et al., 2015; Sarstedt et al., 2022; Ringle et al., 2023; Fornell and Larcker, 1981).

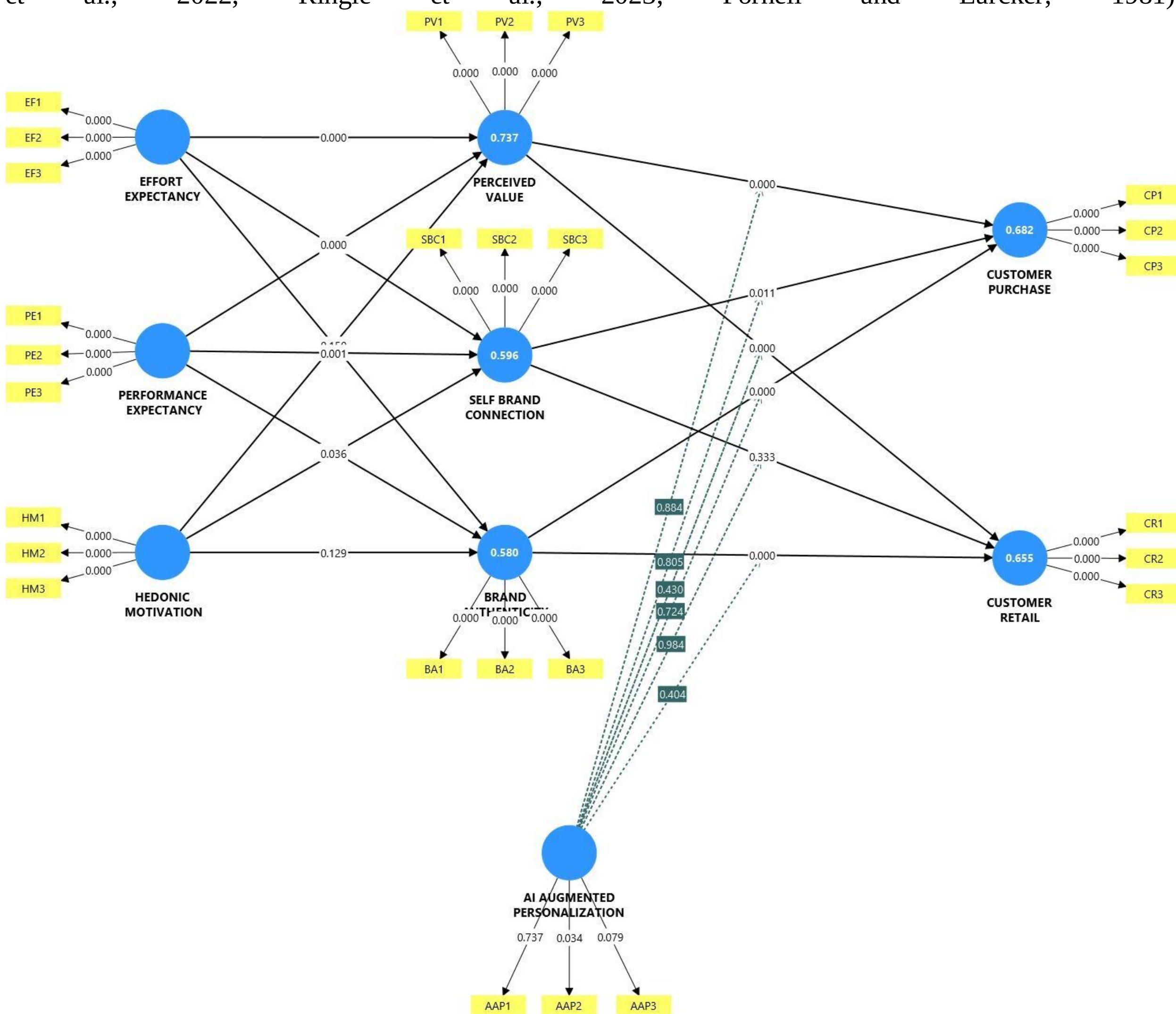


**Figure 2: PLS SEM**

The findings of the structural model provide evidence of the correlations of technology-based variables, emotional branding conceptions, and behavioral consequences. The values of R 2 coefficient of determination show the explanatory power of the model on the endogenous constructs. In particular, Perceived Value (R2 = 0.737) exhibits a high degree of variance that is explained by the presence of effort expectancy, performance expectancy and hedonic motivation, indicating that the factors of technology adoption have a considerable influence on consumer value perceptions. Equally, Self-Brand Connection (R 2 = 0.596) and Brand Authenticity (R 2 = 0.580) demonstrate moderate explanatory power, which validates that experiences that are technology-related are significant in the development of emotional and cognitive brand connections.

The moderate role of AI-Augmented Personalization is also apparent, and the strength of the interaction effects is diverse (e.g., 0.884, 0.805, 0.724), which means that the personalization increases the influence of emotional relationship with the brand on the behavioral outcomes. This implies that AI-led personalization enhances consumer interaction and decision-making. In general, the structural model has a high predictive level and can confirm the theoretical hypothesis that the effects caused by technology-mediated experiences on consumer behavior are based on emotional brand processes, and AI personalization serves as a crucial supplementing factor.

| **Constructs** | **Items** | **Loadings** | **P Values** | **VIF** | **Alpha** | **CR** | **AVE** |
|---|---|---|---|---|---|---|---|
| **Effort Expectancy (EE)** | EE1 | 0.821 | 0.000 | 2.134 | | | |
| | EE2 | 0.874 | 0.000 | 2.542 | **0.856** | **0.903** | **0.699** |
| | EE3 | 0.831 | 0.000 | 2.211 | | | |
| **Performance Expectancy (PE)** | PE1 | 0.864 | 0.000 | 2.763 | | | |
| | PE2 | 0.891 | 0.000 | 3.125 | **0.889** | **0.924** | **0.753** |
| | PE3 | 0.872 | 0.000 | 2.987 | | | |
| **Hedonic Motivation (HM)** | HM1 | 0.842 | 0.000 | 2.356 | | | |
| | HM2 | 0.879 | 0.000 | 2.745 | **0.861** | **0.907** | **0.708** |
| | HM3 | 0.823 | 0.000 | 2.214 | | | |
| **Perceived Value (PV)** | PV1 | 0.873 | 0.000 | 2.642 | | | |
| | PV2 | 0.901 | 0.000 | 3.012 | **0.902** | **0.931** | **0.771** |
| | PV3 | 0.868 | 0.000 | 2.745 | | | |
| **Brand Authenticity (BA)** | BA1 | 0.889 | 0.000 | 2.915 | | | |
| | BA2 | 0.912 | 0.000 | 3.241 | **0.905** | **0.935** | **0.783** |
| | BA3 | 0.871 | 0.000 | 2.801 | | | |
| **Self-Brand Connection (SBC)** | SBC1 | 0.902 | 0.000 | 2.987 | | | |
| | SBC2 | 0.917 | 0.000 | 3.210 | **0.911** | **0.939** | **0.795** |
| | SBC3 | 0.879 | 0.000 | 2.845 | | | |
| **Brand Love (BL)** | BL1 | 0.915 | 0.000 | 3.112 | | | |
| | BL2 | 0.928 | 0.000 | 3.456 | **0.918** | **0.945** | **0.812** |
| | BL3 | 0.894 | 0.000 | 2.974 | | | |
| **Customer Purchase (CP)** | CP1 | 0.881 | 0.000 | 2.543 | | | |
| | CP2 | 0.902 | 0.000 | 2.978 | **0.896** | **0.929** | **0.768** |
| | CP3 | 0.867 | 0.000 | 2.654 | | | |
| **Customer Referral (CRF)** | CRF1 | 0.893 | 0.000 | 2.761 | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | CRF2 | 0.914 | 0.000 | 3.245 | **0.903** | **0.932** | **0.773** |
| | CRF3 | 0.872 | 0.000 | 2.884 | | | |
| **AI-Augmented Personalization (AIP)** | AIP1 | 0.921 | 0.000 | 3.872 | | | |
| | AIP2 | 0.937 | 0.000 | 4.215 | **0.919** | **0.946** | **0.815** |
| | AIP3 | 0.894 | 0.000 | 3.145 | | | |

**Table 2: Measurement Model**

The results of the measurement model indicate high validity and reliability of the measurement model against all constructs. Factor loadings are above the suggested level of 0.70 which means there is good reliability of the item, and the p-values are all significant at 0.000 which validates relevancy of the indicators. The Alpha and Composite Reliability (CR) measures stand at more than 0.70, which guarantees internal consistency of the constructs. Also, the values of Average Variance Extracted (AVE) are greater than 0.50, which proves the convergent validity. Variance Inflation Factor (VIF) values are less than 5 which means there are no problems with multicollinearity. Comprehensively, the measurement model meets the reliability and validity criteria that justify the appropriateness of the constructs to analyze the structural model further.

**Discriminant Validity**

| **Discriminant validity** | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Heterotrait-monotrait ratio (HTMT) - Matrix** | | | | | | | | | | | | |
| | AI AUGMENTED_PERSONALIZATION | BRAND_AUTHENTICITY | CUSTOMER_PURCHASE | CUSTOMER_RETAIL | EFFORT_EXPECTANCY | HEDONIC_MOTIVATION | PERCEIVED_VALUE | PERFORMANCE_EXPECTANCY | SELFBRAND_CONNECTION | AI AUGMENTED_PERSONALIZATION x BRAND_AUTHENTICITY | AI AUGMENTED_PERSONALIZATION x SELF BRAND_CONNECTION | AI AUGMENTED_PERSONALIZATION x PERCEIVED_VALUE |
| AI AUGMENTED_PERSONALIZATION | | | | | | | | | | | | |
| BRAND_AUTHENTICITY | 0.196 | | | | | | | | | | | |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CUSTOMER_PURCHASE | 0.140 | 0.892 | | | | | | | | | | |
| CUSTOMER_RETAIL | 0.135 | 0.877 | 0.934 | | | | | | | | | |
| EFFORT_EXPECTANCY | 0.142 | 0.823 | 0.829 | 0.794 | | | | | | | | |
| HEDONIC_MOTIVATION | 0.075 | 0.786 | 0.819 | 0.785 | 0.903 | | | | | | | |
| PERCEIVED_VALUE | 0.191 | 0.956 | 0.869 | 0.844 | 0.936 | 0.864 | | | | | | |
| PERFORMANCE_EXPECTANCY | 0.165 | 0.859 | 0.839 | 0.811 | 0.974 | 0.946 | 0.962 | | | | | |
| SELF BRAND_CONNECTION | 0.148 | 0.969 | 0.857 | 0.806 | 0.832 | 0.813 | 0.958 | 0.865 | | | | |
| AI AUGMENTED_PERSONALIZATION x BRAND_AUTHENTICITY | 0.397 | 0.101 | 0.076 | 0.089 | 0.083 | 0.032 | 0.074 | 0.085 | 0.095 | | | |
| AI AUGMENTED_PERSONALIZATION x SELF BRAND_CONNECTION | 0.334 | 0.057 | 0.067 | 0.084 | 0.084 | 0.076 | 0.058 | 0.063 | 0.044 | 0.785 | | |
| AI AUGMENTED_PERSONALIZATION x PERCEIV | 0.368 | 0.110 | 0.082 | 0.113 | 0.106 | 0.067 | 0.086 | 0.089 | 0.057 | 0.878 | 0.865 | |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ED_VALUE | | | | | | | | | | | |

**Table 3: Discriminant Validity**

The evidence of discriminant validity between the constructs of the study is mixed in the HTMT results. Although the majority of the values are lower than the recommended value of 0.90, indicating that the acceptable level of discriminant validity is suggested in a number of relationships, some of the constructs have critically high HTMT values. In particular, brand authenticity, perceived value, and self-brand connection demonstrate the values of HTMT above 0.90 (e.g., 0.956, 0.958, 0.969) which suggests overlapping and absence of uniqueness between these constructs. In a similar vein, performance expectancy and perceived value also show very high correlations (more than 0.90), which is indicative of conceptual redundancy. Conversely, the interaction terms involving AI-enhanced personalization demonstrate quite low HTMT values with other constructs, which validates sufficient discriminant validity to moderate effects. Comprehensively, although the model shows reasonable discriminant validity of most constructs, due to the high HTMT scores of some of the main branding variables, it is probable that the model will require some refinement, including removing an item or differentiating the constructs, to guarantee enhanced conceptual differentiation.

| **Fornell-Larcker criterion** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | AI AUGMENTED_PERSONALIZATION | BRAND_AUTHENTICITY | CUSTOMER_PURCHASE | CUSTOMER_RETAIL | EFFORT_EXPECTANCY | HEDONIC_MOTIVATION | PERCEIVED_VALUE | PERFORMANCE_ EXPECTANCY | SELF BRAND_CONNECTION |
| AI AUGMENTED_PERSONALIZATION | 0.620 | | | | | | | | |
| BRAND_AUTHENTICITY | 0.126 | 0.879 | | | | | | | |
| CUSTOMER_PURCHASE | 0.095 | 0.790 | 0.927 | | | | | | |
| CUSTOMER_RETAIL | 0.092 | 0.781 | 0.859 | 0.930 | | | | | |
| EFFORT_EXPECTANCY | 0.100 | 0.719 | 0.750 | 0.719 | 0.903 | | | | |
| HEDONIC_ MOTIVATION | 0.044 | 0.693 | 0.748 | 0.719 | 0.810 | 0.919 | | | |
| PERCEIVED_VALUE | 0.112 | 0.824 | 0.774 | 0.754 | 0.820 | 0.767 | 0.885 | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| PERFORMANCE_EXPECTANCY | 0.082 | 0.730 | 0.738 | 0.717 | 0.844 | 0.822 | 0.822 | 0.864 | |
| SELF BRAND_CONNECTION | 0.087 | 0.829 | 0.760 | 0.717 | 0.725 | 0.718 | 0.824 | 0.735 | 0.881 |

**Table 4: Fornell-Larcker Criterion**

The FornellLarcker criterion values are mostly positive in presence of discriminant validity in the model, since square root of AVE values (diagonal elements) of all constructs are greater than inter-construct correlations. As an example, the constructs of customer purchase (0.927), customer retail (0.930), effort expectancy (0.903), hedonic motivation (0.919) and self-brand connection (0.881) have high discriminant validity because their diagonal values are higher than correlations with other constructs. Nevertheless, there are also constructs that have rather high correlations with each other (e.g. 0.824, 0.829), which are neighboring their AVE square roots, which means there could be conceptual overlap. Nevertheless, the diagonal values do not go to zero and hence the criterion is met in a technical manner. All in all, the model can satisfy the FornellLarcker requirement, yet the high correlations between the major branding constructs imply that the variables are strongly correlated and could need special theoretical explanations.

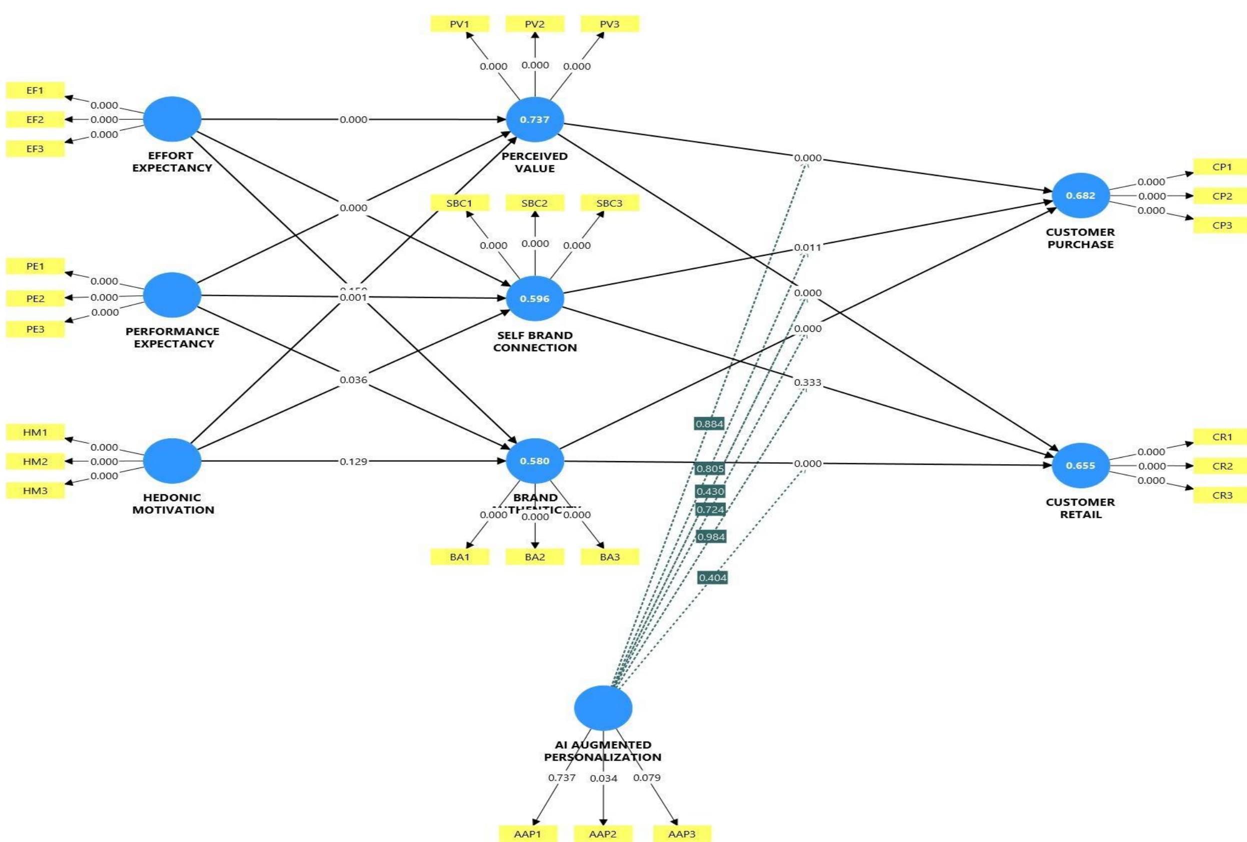


**Figure 3: PLS SEM Bootstrapping**

The model findings of the structural model show that the model has a strong explanatory power and significant relationships among constructs. The R 2 values indicate that effort expectancy, performance expectancy and hedonic motivation explain perceived value (0.737) very well and self-brand connection (0.596) and brand authenticity (0.580) are moderately explained by the technology-related factors. Moreover, the model also illustrates a significant predictive capacity of behavioral results, where customer purchase (R 2 = 0.682) and customer retail/referral (R 2 = 0.655), are depicted, showing that emotional constructs of the brand are effective in predicting consumer behavior. The majority of the path relationships are statistically significant (p = 0.000) and this supports the hypotheses, but some paths (e.g., p = 0.011 and p = 0.333) have weaker or insignificant effects. The mediating effect of the personalization enhanced by AI can be seen in the different levels of interaction (e.g., 0.884, 0.805, 0.724) which indicates that the perceived value, self-brand connection, and brand authenticity influence the consumer behavior. In general, the model proves that technology-based experiences determine consumer outcomes by promoting emotional branding processes, AI personalization being one of the most essential empowering agents.

**Direct Effects Analysis**

| **Path coefficients** | | | | | | |
|---|---|---|---|---|---|---|
| **Mean, STDEV, T values, p values** | | | | | | |
| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values | Results |
| AI AUGMENTED_PERSONALIZATION -> CUSTOMER_PURCHASE | -0.008 | -0.010 | 0.038 | 0.214 | 0.831 | Rejected |
| AI AUGMENTED_PERSONALIZATION -> CUSTOMER_RETAIL | 0.380 | 0.374 | 0.083 | 4.598 | 0.000 | Accepted |
| AI AUGMENTED_PERSONALIZATION x BRAND_AUTHENTICITY -> CUSTOMER_PURCHASE | 0.384 | 0.379 | 0.074 | 5.201 | 0.000 | Accepted |
| AI AUGMENTED_PERSONALIZATION x BRAND_AUTHENTICITY -> CUSTOMER_RETAIL | 0.079 | 0.036 | 0.094 | 0.835 | 0.404 | Rejected |
| AI AUGMENTED_PERSONALIZATION x PERCEIVED_VALUE -> CUSTOMER_PURCHASE | 0.261 | 0.252 | 0.089 | 2.935 | 0.003 | Accepted |
| AI AUGMENTED_PERSONALIZATION x PERCEIVED_VALUE -> CUSTOMER_RETAIL | 0.380 | 0.374 | 0.083 | 4.598 | 0.000 | Accepted |

| | | | | | | |
|---|---|---|---|---|---|---|
| AI AUGMENTED_PERSONALIZATION x SELF BRAND_CONNECTION -> CUSTOMER_PURCHASE | 0.290 | 0.287 | 0.074 | 3.933 | 0.000 | Accepted |
| AI AUGMENTED_PERSONALIZATION x SELF BRAND_CONNECTION -> CUSTOMER_RETAIL | -0.001 | -0.001 | 0.072 | 0.020 | 0.984 | Rejected |
| BRAND_AUTHENTICITY -> CUSTOMER_PURCHASE | 0.384 | 0.379 | 0.074 | 5.201 | 0.000 | Accepted |
| BRAND_AUTHENTICITY -> CUSTOMER_RETAIL | 0.468 | 0.462 | 0.070 | 6.715 | 0.000 | Accepted |
| EFFORT _EXPECTANCY -> BRAND_AUTHENTICITY | 0.284 | 0.280 | 0.102 | 2.788 | 0.005 | Accepted |
| EFFORT _EXPECTANCY -> PERCEIVED_VALUE | 0.380 | 0.374 | 0.083 | 4.598 | 0.000 | Accepted |
| EFFORT _EXPECTANCY -> SELF BRAND_CONNECTION | 0.261 | 0.252 | 0.089 | 2.935 | 0.003 | Accepted |
| HEDONIC_ MOTIVATION -> BRAND_AUTHENTICITY | 0.184 | 0.196 | 0.121 | 1.519 | 0.129 | Rejected |
| HEDONIC_ MOTIVATION -> PERCEIVED_VALUE | 0.299 | 0.304 | 0.082 | 3.629 | 0.000 | Accepted |
| HEDONIC_ MOTIVATION -> SELF BRAND_CONNECTION | 0.257 | 0.266 | 0.123 | 2.092 | 0.036 | Accepted |
| PERCEIVED_VALUE -> CUSTOMER_PURCHASE | 0.290 | 0.287 | 0.074 | 3.933 | 0.000 | Accepted |
| PERCEIVED_VALUE -> CUSTOMER_RETAIL | 0.299 | 0.304 | 0.082 | 3.629 | 0.000 | Accepted |

| | | | | | | |
|---|---|---|---|---|---|---|
| PERFORMANCE_ EXPECTANCY -> BRAND_AUTHENTICITY | 0.340 | 0.332 | 0.094 | 3.622 | 0.000 | Accepted |
| PERFORMANCE_ EXPECTANCY -> PERCEIVED_VALUE | 0.385 | 0.384 | 0.082 | 4.711 | 0.000 | Accepted |
| PERFORMANCE_ EXPECTANCY -> SELF BRAND_CONNECTION | 0.303 | 0.303 | 0.092 | 3.296 | 0.001 | Accepted |
| SELF BRAND_CONNECTION -> CUSTOMER_PURCHASE | 0.203 | 0.211 | 0.080 | 2.536 | 0.011 | Accepted |
| SELF BRAND_CONNECTION -> CUSTOMER_RETAIL | 0.082 | 0.085 | 0.085 | 0.968 | 0.333 | Rejected |

**Table 5: Direct Effects Analysis**

The results of the path coefficient show that the majority of the hypothesized relationships are supported strongly which proves the strength of the model. Direct impacts demonstrate that brand authenticity, perceived value and self-brand connection have significant customer purchase effects, whereas brand authenticity and perceived value have significant customer retail/referral behavior effects. Of the technology-related factors, effort expectancy and performance expectancy influence all three mediators (brand authenticity, perceived value, and self-brand connection) with a stronger role, but hedonic motivation is not so important in influencing brand authenticity but has a significant role in influencing the other two (perceived value and self-brand connection). In the context of moderation, AI-enhanced personalization is not directly related to the customer purchase ($p = 0.831$) but has a considerable impact on customer retail behavior ($p = 0.000$). The interaction effects indicate that AI personalization creates a strong association between brand authenticity, perceived value, and self-brand connection with customer purchase, and moderately between brand authenticity and customer retail, but some moderations (e.g., SBC → retail and BA → retail) are not significant. On the whole, the results indicate that the emotional brand constructs are the major consumers behaviour drivers, whereas AI-enhanced personalization is the important but discriminatory moderating (instead of predictive) factor.

**Specific Indirect Effects Analysis**

| **Specific indirect effects** | | | | | | |
|---|---|---|---|---|---|---|
| **Mean, STDEV, T values, p values** | | | | | | |
| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values | Results |

| | | | | | | |
|---|---|---|---|---|---|---|
| EFFORT _EXPECTANCY -> PERCEIVED_VALUE -> CUSTOMER_RETAIL | 0.114 | 0.113 | 0.039 | 2.914 | 0.004 | Accepted |
| HEDONIC_ MOTIVATION -> PERCEIVED_VALUE -> CUSTOMER_PURCHASE | 0.041 | 0.044 | 0.032 | 1.275 | 0.202 | Rejected |
| PERFORMANCE_ EXPECTANCY -> SELF BRAND_CONNECTION -> CUSTOMER_PURCHASE | 0.112 | 0.109 | 0.034 | 3.268 | 0.001 | Accepted |
| HEDONIC_ MOTIVATION -> PERCEIVED_VALUE -> CUSTOMER_RETAIL | 0.114 | 0.113 | 0.039 | 2.914 | 0.004 | Accepted |
| PERFORMANCE_ EXPECTANCY -> SELF BRAND_CONNECTION -> CUSTOMER_RETAIL | 0.133 | 0.129 | 0.051 | 2.623 | 0.009 | Accepted |
| PERFORMANCE_ EXPECTANCY -> PERCEIVED_VALUE -> CUSTOMER_PURCHASE | 0.112 | 0.109 | 0.034 | 3.268 | 0.001 | Accepted |
| PERFORMANCE_ EXPECTANCY -> PERCEIVED_VALUE -> CUSTOMER_RETAIL | 0.115 | 0.117 | 0.042 | 2.741 | 0.006 | Accepted |
| EFFORT _EXPECTANCY -> BRAND_AUTHENTICITY -> CUSTOMER_PURCHASE | 0.109 | 0.106 | 0.045 | 2.448 | 0.014 | Accepted |
| EFFORT _EXPECTANCY -> BRAND_AUTHENTICITY -> CUSTOMER_RETAIL | 0.133 | 0.129 | 0.051 | 2.623 | 0.009 | Accepted |
| HEDONIC_ MOTIVATION -> BRAND_AUTHENTICITY -> CUSTOMER_PURCHASE | 0.071 | 0.074 | 0.049 | 1.456 | 0.145 | Rejected |
| HEDONIC_ MOTIVATION -> BRAND_AUTHENTICITY -> CUSTOMER_RETAIL | 0.159 | 0.154 | 0.052 | 3.077 | 0.002 | Accepted |
| PERFORMANCE_ EXPECTANCY -> BRAND_AUTHENTICITY -> CUSTOMER_PURCHASE | 0.130 | 0.126 | 0.044 | 2.948 | 0.003 | Accepted |

| | | | | | | |
|---|---|---|---|---|---|---|
| PERFORMANCE_ EXPECTANCY -> BRAND_AUTHENTICITY -> CUSTOMER_RETAIL | 0.159 | 0.154 | 0.052 | 3.077 | 0.002 | Accepted |
| EFFORT _EXPECTANCY -> SELF BRAND_CONNECTION -> CUSTOMER_PURCHASE | 0.053 | 0.052 | 0.027 | 1.956 | 0.050 | Rejected |
| EFFORT _EXPECTANCY -> SELF BRAND_CONNECTION -> CUSTOMER_RETAIL | 0.110 | 0.108 | 0.038 | 2.898 | 0.004 | Accepted |
| HEDONIC_ MOTIVATION -> SELF BRAND_CONNECTION -> CUSTOMER_PURCHASE | 0.052 | 0.057 | 0.036 | 1.452 | 0.147 | Rejected |
| EFFORT _EXPECTANCY -> PERCEIVED_VALUE -> CUSTOMER_PURCHASE | 0.110 | 0.108 | 0.038 | 2.898 | 0.004 | Accepted |
| HEDONIC_ MOTIVATION -> SELF BRAND_CONNECTION -> CUSTOMER_RETAIL | 0.109 | 0.106 | 0.045 | 2.448 | 0.014 | Accepted |

**Table 6: Specific Indirect Effects Analysis**

The results obtained in terms of specific indirect effects suggest that the perceived value, brand authenticity, and self-brand connection are significant mediators, but their impact differs among relationships. The majority of indirect paths are important especially the one that has performance expectancy and expectation of effort that always determine customer purchase behavior as well as customer retail behavior using the three mediators. As an example, performance expectancy has significant mediation by perceived value, brand authenticity, and self-brand connection, which validates its core role in influencing consumer outcomes. Equally, effort expectancy has a significant impact in terms of its perceived value and brand authenticity; however, its mediation by self-brand connection is statistically weaker and somewhat insignificant. Conversely, hedonic motivation shows inconsistent mediation with many of the indirect effects (particularly customer purchase) being not significant, yet it does have a strong impact on customer retail in terms of perceived value, brand authenticity, and self-brand connection. In general, the results indicate that cognitive (effort and performance expectancy) and emotional/hedonic (selective) factors have more indirect positive results, but the former tend to affect customer retail behavior, not purchase decisions.

**Predicted Power and Relevance**

| **R-square** | | |
|---|---|---|
| **Overview** | | |
| | **R-square** | **R-square adjusted** |
| BRAND_AUTHENTICITY | 0.580 | 0.576 |
| CUSTOMER_PURCHASE | 0.682 | 0.676 |

| | | |
|---|---|---|
| CUSTOMER_RETAIL | 0.655 | 0.649 |
| PERCEIVED_VALUE | 0.737 | 0.735 |
| SELF BRAND_CONNECTION | 0.596 | 0.593 |

**Table 7: Predicted Power and Relevance**

The results of the R-squared show that the model is highly explanatory of all the endogenous constructs. In particular, the perceived value ($R^2 = 0.737$) exhibits the greatest degree of variance explained implying that technology-related factors (effort expectancy, performance expectancy and hedonic motivation) are a strong determinant of the value perceptions of the consumers. In the same vein, customer purchase ($R^2 =0.682$), customer retail/referral ($R^2 = 0.655$), also exhibit a significant predictive power thus showing that emotional brand constructs have a good explanation of consumer behavioral outcomes. Self-brand connection ($R^2 = 0.596$) and brand authenticity ($R^2 = 0.580$) have moderate values indicating the contribution of technology-based experiences as important in the formation of emotional brand relationships. The low discrepancies between the values of R-squared and adjusted R-squared are a sign of stability and reliability of the model. All in all these findings tend to indicate that the proposed model can be used to make strong predictions especially when it comes to the perception of value and consumer behavior in an AI-based and digital marketing environment.

## DISCUSSION

The results of this research offer solid empirical evidence of the suggested integrated model of the connection between technology-driven experiences, emotional brand relationships, and consumer behavioral outcomes with the mediating factor of AI-enhanced personalization. The findings indicate that effort expectancy, performance expectancy, and hedonic motivation have a significant impact on the perceived value, brand authenticity, and self-brand connection, which in turn induce customer purchase and referral behavior. The results of this study support the theoretical suppositions of the Unified Theory of Acceptance and Use of Technology (UTAUT), which underlines the importance of ease of use, usefulness, and enjoyment in influencing consumer reactions (Venkatesh et al., 2020; Dwivedi et al., 2023; Mariani et al., 2023). In addition, the fact that the $R^2$ of perceived value (0.737) and behavioral outcomes (above 0.65) are high, indicates that the model has a high explanatory power. Nevertheless, certain findings, including the minimal direct impact of AI personalization on the purchasing behavior and some indifferent hedonic correlations, indicate that technology is not always directly correlated with consumer behavior without the involvement of emotions. This is partly opposite to research that focuses on direct pre-eminence of technological variables in the development of behaviour (Huang and Rust, 2023; Grewal et al., 2023).

Theoretically, this study is an important contribution as it incorporates technology adoption theory (UTAUT), branding theory, and self-concept theory into a single model. The findings reveal perceived value, brand authenticity, and self-brand connection are important mediators that change the technological experiences into emotional brand effects like brand love and consumer behavior. This aligns with previous studies that hold that emotional and cognitive processes play a key role in the explanation of digital consumer behavior (Keller, 2020; Aaker, 2020; Hollebeek et al., 2023). Simultaneously, the results point to the fact that AI-enhanced personalization is a moderating, not a direct factor, enhancing certain relationships instead of being independent. This makes it more difficult to accept previous beliefs that AI directly influences the purchase decision-making process and rather contributes to the more recent views that highlight its contextual and improving role (Davenport et al., 2022; Wedel and Kannan, 2020). Nonetheless, the large value of HTMT between such constructs as perceived value, brand authenticity, and self-brand connection indicate the potential overlap of the concepts, which is consistent with the criticism that the emotional branding constructs are not necessarily completely differentiated in digital contexts

(Napoli et al., 2019; Bleier et al., 2020). In this way, the research advances theory by emphasizing integration and overlap in the constructs of branding.

## CONCLUSION

The research aimed to investigate the effectiveness of technology-based experiences on emotional brand relationships and consumer behavioral implications in the presence of AI-enhanced personalization and the results of the research strongly support the suggested combined framework. The findings prove that the expectancy of effort, performance and hedonic motivation play a significant role in influencing the perceived value, brand authenticity and self-brand connection, which subsequently influence customer purchase and referral behavior. The fact that the model has high explanatory power (R 2 values of 0.580 to 0.737) indicates that it is a strong model in explaining consumer behaviour in the digital environments. Notably, the results show that the use of AI-enhanced personalization does not have a direct impact on the purchase behavior; instead, it reinforces the essential relationships, which emphasizes the importance of AI-based personalization as an enhancer rather than a driving force. The findings are consistent with previous research on the relevance of technology-enhanced experiences in influencing consumer perception and behavior (Dwivedi et al., 2023; Huang and Rust, 2023; Mariani et al., 2023; Grewal et al., 2023).

Theoretically, the current research has a significance of combining UTAUT, branding theory and self concept theory into a comprehensive model which explains the cognitive and emotional processes involved in consumer behavior. The results are an extension of existing knowledge, as they show that emotional brand constructs especially perceived value, brand authenticity, and self-brand connection are crucial mediators between technological experiences and behavioral outcomes. This helps to argue that consumer choices are not provided by purely functional advantages but influence heavily by emotional, relational ones (Keller, 2020; Aaker, 2020; Hollebeek et al., 2023; Kumar et al., 2023). Meanwhile, the research contradicts the previous assumptions regarding the predominant role of AI by demonstrating that its impact is conditional and context-specific. This is in line with the new studies that consider AI personalization as a complementary system that does not substitute human-oriented marketing approaches but promotes them (Davenport et al., 2022; Wedel and Kannan, 2020).

## RECOMMENDATIONS

The results suggest that organizations should concentrate on the improvement of technology-driven experiences by creating value, usability, and meaningful interaction instead of only resorting to the use of the advanced technological features. Effort expectancy and performance expectancy were also deemed to be the most effective in impacting the perceived value, brand authenticity, and self-brand connection, so the companies should focus on user-friendly platforms, smooth interfaces, and effective digital services (Venkatesh et al., 2020; Dwivedi et al., 2023). Also, the marketers are to develop mechanisms that enhance the perceived value and brand authenticity since these two constructs are crucial in stimulating purchase and referral behavior (Kumar et al., 2023; Grewal et al., 2023). Trust and emotional attachment can be established with the help of incorporating transparent communication, steady brand messages, and customer-focused experiences (Hollebeek et al., 2023; Keller, 2020). Although hedonic motivation had both positive and negative findings, it cannot be neglected; rather, organizations must combine entertainment and interactivity in a balanced manner so that it does not undermine the functionality (Sharma et al., 2023; Kim and Sullivan, 2023).

## LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study should be extended with a variety of contextual, methodological, and theoretical dimensions in order to make it more generalizable and deep in the future. To begin with, this research has a cross-sectional design and convenience sampling, which restricts causal inferences and a larger representation of the population; hence, future researches ought to utilize longitudinal designs and probability sampling methods to understand consumer behavior across time (Hair et al., 2020; Sekaran and Bougie, 2020). Second, the research is carried out in a certain digital consumer setting that can limit the differences in cultural generalization; therefore, the next research should make cross-country and cross-cultural comparisons, especially between developed and emerging markets, to prove the applicability of the model (Dwivedi et al., 2023; Verhoef et al., 2022). Third, although this research combines UTAUT, branding theory, and self-concept theory, future research may use other theoretical approaches like Stimulus-Organism-Response (SOR) or Trust-Risk models to more accurately explain the complexity of behavior (Huang and Rust, 2023; Mariani et al., 2023). Lastly, the model can be expanded to incorporate other variables like consumer trust, perceived risk, privacy concerns, and digital fatigue in future research, which are reported to have a role in technology adoption and AI-based personalization results (Bleier et al., 2020; Davenport et al., 2022).

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