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Effects of AI Virtual Anchors on Brand Image and Loyalty: Insights from Perceived Value Theory and SEM-ANN Analysis

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Abstract: AI virtual anchors are an emerging innovation that are gaining significant attention, as they hold promising applications across various fields. This study examines how users perceive live product selling by AI virtual anchors and its impact on brand image and brand loyalty. A two-stage PLS-SEM and ANN approach was employed to analyze data from a sample of 336 individuals in China who had experienced and utilized AI virtual anchors for purchases during branded live streaming sessions. The findings indicate that perceived usefulness, perceived enjoyment, and novelty positively impact brand image, with artificial neural network (ANN) analysis identifying brand image as the primary predictor. Furthermore, brand image acts as a mediator between these user perceptions and brand loyalty. These insights offer brand managers a strategic approach to utilize AI virtual anchors for fostering a positive brand image and building loyal customer bases. The study also contributes to the academic understanding of consumer behavior and brand management in the context of AI.

Keywords: perceived value; brand image; brand loyalty; artificial intelligence virtual anchors; structural equation modeling; neural network analysis

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1. Introduction

With the rise of the popularization of the application of artificial intelligence (AI) and other technologies, the forms and special effects of online live streaming are becoming more diverse. User numbers continue to rise steadily; as of December 2023, 816 million people in China were using online live broadcasting, making up 74.7% of all netizens. The rapid popularity of live-streaming has facilitated the emergence of a new business model, namely live-streaming commerce. The size of e-commerce live-streaming users was 597 million as of December 2023. The rapid rise of live-streaming commerce gives brands more options, such as online sellers who often employ live-streaming to boost their sales [1].

Such live streaming takes place in real-time on social media platforms, with the collaboration of the anchors' labor [2,3], and they make use of potent network externalities to highlight materials and/or product attributes to draw in additional followers [4]. As the main body of social live streaming, online anchors can be divided into two categories: real-life webcasters and artificial intelligence virtual anchors [5]. Currently, there is no unified definition of AI virtual anchors in academic circles, but most scholars agree that they are AI-driven digital creations capable of autonomously performing live streaming tasks similar to those of human anchors, representing an application of virtual humans in the live streaming field [6,7]. Notably, AI has been widely employed as a tool in the development of live streaming. For instance, to strengthen consumer rights and improve their brand image, several global firms, including Shiseido, Philips, Hélène, Lancôme, Procter & Gamble, and L'Oreal, have already implemented AI anchoring in their online stores [8].

Despite the exponential potential of AI's smart tool attributes and their potential to have a huge impact on consumers and brands, less academic attention has been paid to how AI can enhance brand image and brand loyalty. Most current research in this area primarily focuses on the impact of AI on consumer attitudes and behavioral intentions [9–11]. Indeed, leveraging AI virtual anchors in live streaming has significant potential to bolster brand image and loyalty. With the capability of 24/7 live streaming, it can attract a vast consumer base through features like personalized recommendations. This can effectively assist brands in addressing various challenges they encounter [12].

A few studies have focused on the role of AI in forming brand loyalty [13], the matching effects of hotel brand image (cool vs. uncool), and AI service agents on brand attitudes [14], as well as the effects of AI services on brand image and customer equity [8]. While these studies provide initial insights, future research could further test the impact of AI virtual anchors on brand image and brand loyalty from more diverse perspectives. Therefore, this study aims to investigate how the use of AI virtual anchors as a live-streaming tool in live-streaming trends can enhance brand image and brand loyalty. This study contributes to addressing the gaps in the existing literature regarding how AI virtual anchors enhance brand image and brand loyalty, while also extending the traditional research focus on consumer attitudes and behavioral intentions. Furthermore, this study offers strategic guidance for marketing practitioners, enabling them to leverage AI technology more effectively to enhance brand equity and foster brand loyalty.

2. Theoretical Framework

In the digital age, the impact of AI on branding has gained increasing popularity [15]. AI is extensively utilized in branded businesses to help companies streamline complex operations, reduce costs, enhance the quality of goods and services, and maximize profits through innovative collaborative strategies [16]. This ever-evolving technology facilitates the delivery of brand services and even fosters new forms of corporate interactions with customers [17]. Scholars have noted that AI is highly effective in addressing practical problems and making real-time or near real-time decisions as a substitute for human intervention [18]. Furthermore, AI seamlessly integrates with businesses and marketers to create, organize, and utilize knowledge in marketing, enabling global brand sales [19]. Consequently, AI is profoundly transforming brand preferences, marketing strategies, and customer attitudes [20].

The current research builds upon Zeithaml's [21] theory of perceived value, emphasizing that the value perceived by customers is a top priority for organizations aiming to enhance their sustainable competitive advantage. With advancements in technology, AI virtual anchors have become widely utilized to explore the relationship between user loyalty and brand perception, focusing on perceived value [22]. Yuan et al. [8] empirically demonstrated that the accuracy and problem-solving abilities of AI services significantly enhance brand image. Additionally, using SEM, Huang et al. [23] identified perceived enjoyment as a crucial factor, while Cheng et al. [24] highlighted perceived usefulness and perceived risk as key variables. Building on these findings, we extended the existing research framework by incorporating interactivity and novelty to better understand how users' experiences with AI virtual anchors in live streaming affect brand image and loyalty.

Detailed information on all variables and their interrelationships in this study is presented below. The theoretical model of this study is shown in Figure 1.

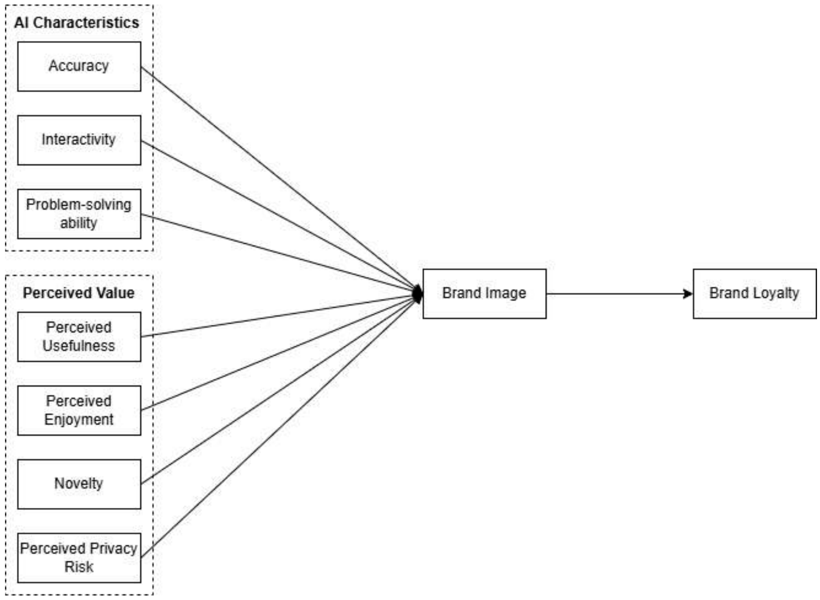

Figure 1. Research framework.

2.1. AI Characterization

In the live streaming domain, AI virtual anchors facilitate dynamic communication and information exchange, fostering an interactive process between the AI and users. This study evaluates AI characteristics through three key dimensions: accuracy, interactivity, and problem-solving ability. Accuracy refers to the fact that AI tools can provide error-free services [25]. Interactivity is a multifaceted concept focusing on interactive actions and processes, such as information exchange and response [26]. This study specifically examines the interactive behaviors of AI virtual anchors with users. Problem-solving capability refers to the ability of AI to accomplish complex tasks through the overall fast processing of data, mainly in terms of improved time and efficiency in problem-solving [4].

The accuracy of AI virtual anchors is directly related to user satisfaction and brand reputation. Users are usually more likely to trust brands that provide highly accurate services, and webcasts that enable real-time social interaction reduce psychological distance as well as customer uncertainty [27], thereby increasing trust in the brand. Based on this, the following hypothesis is proposed:

H1. *AI virtual anchor service accuracy positively affects brand image.*

In the brand's live stream with a large number of followers, the anchor's interactions and the purchasing behaviors of other customers provide a rich emotional experience, emotional connection, and shopping value [28]. When users feel that the interaction with the anchor fulfills their needs and expectations, the result may be an increase in customer satisfaction, loyalty, positive word-of-mouth for the brand, as well as considerable purchase intentions and company profits, which builds a favorable brand image. Therefore, the following hypothesis is proposed:

H2. *AI virtual anchor service interactivity positively affects brand image.*

As AI virtual anchors' problem-solving abilities improve, user satisfaction increases accordingly. Customer satisfaction is one of the ultimate goals sought by organizations, as there will be satisfactory long-term benefits (continued user loyalty and positive word-of-mouth communication) [29]. High problem-solving ability implies that AI virtual anchors can solve users' problems quickly and efficiently, thereby enhancing the user experience, which in turn improves brand image. Based on this, the following hypothesis is proposed:

H3. *AI virtual anchor service problem-solving ability positively affects brand image.*

2.2. Perceived Value Theory

Perceived value theory is widely used in academia. According to Zeithaml [21], perceived value is the consumer's total evaluation of a product's usefulness based on their impressions of what they receive and are offered. It encompasses six dimensions: prestige value, self-satisfaction value, utilitarian value, quality value, hedonic value, and aesthetic value [21,30]. This study focuses on three dimensions of perceived value: perceived usefulness, perceived enjoyment, and novelty. Perceived usefulness refers to the extent to which users believe that an AI virtual anchor can enhance the efficiency of their purchasing process [24]. Perceived enjoyment measures the emotional or hedonic perception, evaluating how pleasurable the experience with the AI virtual anchor is [31]. Novelty reflects the perceived freshness and uniqueness of the experience provided by the AI virtual anchor.

According to perceived value theory, users experiencing high uncertainty with new technological services may perceive a certain level of risk, which can adversely affect their experience. Bonnin [32] suggests that users' assessment of the potential adverse outcomes and uncertainties associated with purchasing or utilizing a service or product is commonly referred to as perceived risk. Moreover, the evolution of AI has heightened concerns about technological control and digital privacy [33]. Perceived privacy risk is defined as the subjective belief that one may incur a loss while pursuing a desired outcome [34]. In this study, privacy risk is utilized to assess the perceived risk among potential consumers when engaging with AI virtual anchors during brand live streaming.

As artificial intelligence is one of the new technologies driving the third industrial revolution, it is necessary to understand the relationships among brand management, perceived usefulness, and AI [24]. In the brand's live stream, users can improve their purchasing efficiency by asking AI virtual anchors for product details and by communicating anytime, anywhere, which will create a positive brand image. Based on this, the following hypothesis is proposed:

H4. *Perceived usefulness positively affects brand image.*

Research indicates that AI-based products and services often possess both utilitarian and hedonic attributes [35,36]. AI virtual anchors, depicted as animated cartoon or anime characters, engage with users in live streaming studios in an entertaining manner, fostering positive emotional connections and thereby enhancing brand image. Based on this, the following hypothesis is proposed:

H5. *Perceived enjoyment positively affects brand image.*

AI virtual anchors offer users novel experiences, including anthropomorphic representations and personalized customization services. These features have the potential to capture users' attention and interest, thereby establishing the groundwork for brand loyalty and achieving strategic business objectives [37]. In addition, users tend to share interesting and unique experiences, and novel AI virtual anchors help to trigger users' sharing on social media, which helps to establish and spread the brand image. Based on this, the following hypothesis is proposed:

H6. *Novelty positively affects brand image.*

AI virtual anchors, as an emerging and complex technology, present many uncertainties for users. For instance, users may be concerned that AI virtual anchors engage in excessive collection of personal information or lack transparency regarding the use of user data, thereby undermining trust in the brand. Based on this, the following hypothesis is proposed:

H7. *Perceived privacy risk negatively affects brand image.*

2.3. Brand Image and Brand Loyalty

Brand equity is regarded as the "added value" endowed to a product through the thoughts, words, and actions of consumers [38], with brand image and brand loyalty considered a significant component of brand equity [39,40]. Keller [41] defines brand image as "the perception of a brand as reflected in the brand associations held in the memory of the consumer", which serves as both the goal and the psychological feedback consumers experience when purchasing a product [42]. In Aaker's [39] view, consumers create their brand image. When determining whether to buy or reject a product, the consumer is greatly impacted by the brand image [43]. West et al. [15] found that AI affects the components of each brand (services, products, etc.).

Scholars have commonly defined brand loyalty as the tendency for repeat purchases or continued patronage [44,45]. Hasan et al. [46] argued that a widely adopted technology is more likely to make users loyal to a brand. As AI advances, how users are loyal to a brand has expanded from purchases to their relationship with the brand [47,48]. Therefore, AI is critical to increasing brand equity.

Brand image is an essential factor in building brand loyalty [49,50]. A positive brand image exceeds customer expectations, which leads to choosing a specific brand [51], generating sustained purchasing behaviors and forming brand loyalty, thus establishing a deeper brand relationship [2]. Based on this, the following hypothesis is proposed:

H8. *Brand image positively affects brand loyalty.*

3. Methods

3.1. Participants and Procedures

The research model was tested through a questionnaire. The survey consisted of three parts. In the first part, respondents were screened to determine whether they had ever been exposed to a live AI virtual anchor selling goods. Respondents were asked whether they were familiar with live streaming of AI virtual anchors selling and whether they had ever watched such live streams. Those who answered "no knowledge" or "have not watched" were excluded from further participation. In Section 2, respondents were asked to carefully recall their most recent shopping experience at a branded e-commerce live stream to assess their level of agreement. They were then asked to rate their level of agreement with statements related to the AI virtual anchor's characteristics, perceived usefulness, perceived enjoyment, novelty, perceived privacy risks, brand image, and brand loyalty. The third part collected the respondents' basic information, including gender, age, monthly income, education level, the platforms they regularly use to watch AI virtual anchors' live streaming sessions, and the frequency of their shopping activity within these live streaming sessions. Before beginning this study, all respondents were given a thorough explanation of the goals, methods, possible hazards, and advantages of the research, and their informed consent was obtained. All respondents' personal information was treated with the utmost confidentiality, and their privacy was protected through anonymity.

Formal online questionnaires were distributed to users in China who are aware of and have been exposed to AI virtual anchor live streams through widely used social media tools such as WeChat and Weibo. In this study, the initial sample consisted of 421 participants. After reviewing all completed questionnaires, we excluded responses from users who had not been exposed to live streaming by AI virtual anchors, as well as those from participants who provided identical answers to all questions. Ultimately, we obtained 336 valid questionnaires for our data analysis. The sample size is sufficient as it has exceeded the threshold of 100 samples recommended by Hair [52]. Table 1 shows the demographics of the respondents. It was calculated using the Pandas library in Python.

Table 1. Demographic profile of respondents.

Division		Frequency	Percent (%)
Gender	Male	139	41.4
	Female	197	58.6
	Total	336	100
Age	Under 18	4	1.2
	18–25	170	50.6
	26–30	67	19.9
	31–40	56	16.7
	41–50	26	7.7
	51–60	9	2.7
	Older than 60	4	1.2
Average monthly income	Under 2000	125	37.2
	2001–5000	95	28.3
	5001–8000	63	18.8
	8001–10,000	46	13.7
	More than 10,000	7	2.1
Education level	High school/technical secondary school and below	26	7.7
	Junior college	59	17.6
	undergraduate	181	53.9
	Master	67	19.9
	Doctor	3	0.9
Your daily platform for watching AI virtual anchors sell goods live streaming	Taobao	131	39.0
	TikTok	230	68.5
	Kuai Shou	90	26.8
	Xiongs	71	21.1
	Pendulous	58	17.3
	Jindong	99	29.5
	Bilabial	126	37.5
	Other	6	1.8
How often you shop at AI virtual anchor livestreams	Once a week or less	141	42.0
	2–3 times a week	70	20.8
	More than 4 times a week	35	10.4
	Not sure	90	26.8

3.2. Measures

The scale for this study was a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The 7-point Likert scale performs better in terms of reliability, accuracy, and ease of use compared to the 5-point Likert scale [53]. The scale items were adapted from well-established scales. Items for accuracy, problem-solving ability, and brand image were taken from Yuan et al. [8], items for interactivity were taken from Siddike et al. [54], items for perceived usefulness were taken from Davis [55], items for perceived enjoyment were taken from Sweeney and Soutar [56] and Venkatesh [57] items for novelty from Prebensen and Xie [58], items for perceived privacy risk from Zhou [59], and finally items for brand loyalty from Jacoby et al. [60]. The items for each construct and their associated sources are given in Table 2.

Table 2. Measurement items.

Construct	Item	Measurement Items	References
Accuracy (AC)	AC1	The virtual anchor was able to answer my questions accurately.	[8]
	AC2	The virtual anchor can provide adequate service.	
	AC3	The virtual anchor can provide a complete service.	
	AC4	The virtual anchor can provide a credible service.	
Interactivity (IC)	IC1	I can easily interact with the virtual anchor.	[54]
	IC2	I can easily talk to the virtual anchor.	
	IC3	I can easily chat with the virtual anchor.	
Problem-solving ability (PSA)	PSA1	The virtual anchor was able to answer the questions I asked.	[8]
	PSA2	The virtual anchor was able to provide me with useful answers.	
	PSA3	Overall, the virtual anchor is qualified and competent.	
Novelty (NV)	NV1	Seeing a virtual anchor on a live stream is a unique experience.	[58]
	NV2	Seeing a virtual anchor on the air satisfied my curiosity.	
	NV3	Using a virtual anchor in a live room provides a realistic experience.	
Perceived usefulness (PU)	PU1	The virtual anchor has been very useful in my life.	[55]
	PU2	The virtual anchor has provided me with very useful services and information.	
	PU3	The virtual anchor has increased the efficiency of my purchases.	
Perceived enjoyment (PE)	PE1	Virtual anchors are really fun.	[56,57]
	PE2	Virtual anchors bring me joy.	
	PE3	Virtual anchors make me feel good.	
Perceived privacy risks (PPR)	PPR1	Providing personal information to a virtual anchor is risky.	[59]
	PPR2	Providing personal information to a virtual anchor comes with a lot of uncertainty.	
	PPR3	There are many potential losses associated with providing personal information to a virtual anchor.	

Table 2. *Cont.*

Construct	Item	Measurement Items	References
Brand image (BI)	BI1	The brand is attractive (branding means applying the brand of the virtual anchor in the live stream, below).	[8]
	BI2	This brand is reliable.	
	BI3	This brand has a great reputation.	
Brand loyalty (BL)	BL1	I will continue to use this brand because I am happy with it (brand means the brand that applies the virtual anchor in the live stream, below).	[60]
	BL2	I'll use the brand, regardless of the competitor's deal.	
	BL3	I will be purchasing more products and services from this brand.	

4. Results

4.1. Common Method Bias (CMB)

During the data collection process, we ensured the anonymity of respondents' answers and emphasized that there were no right or wrong responses. Harman's single-factor test is a common method used to detect CMB in questionnaire data. Given that both predictor and outcome variables were sourced from a single respondent group, the potential for CMB was a concern. For this purpose, the Harman test was used in this study [61]. The findings of the statistical analysis demonstrated that the single component accounted for 25.53% of the variance in total. According to Wong et al. [62], there is no CMB issue because this fraction is less than 50%.

4.2. Multivariate Statistical Assumptions

We looked at the mean square deviation, multicollinearity, linearity, and normality of the data as criteria for multivariate statistical tests. To evaluate the linearity, we employed an ANOVA analysis of variance with the Pandas and SciPy libraries in Python [63,64]. Table 3 confirms both linear and nonlinear correlations between external and internal variables from a linear point of view. When the *p*-value is less than 0.05, there is a linear link between the constructs. All the relationships between the constructs, except those between accuracy, perceived usefulness, perceived enjoyment, novelty, and brand loyalty—all of which have *p*-values greater than 0.05—are nonlinear components according to the *p*-values that deviate from linearity.

To evaluate the multicollinearity problem, we analyzed VIF and tolerance, which revealed that the VIF values varied from 1.556 to 4.495, which is less than the conventional threshold of 10. Tolerances ranged from 0.222 to 0.643, all of which are greater than 0.10, indicating that there is no multicollinearity problem [65]. We analyzed the standardized residual scatterplot to determine the presence of homoscedasticity, and because the residuals are distributed along the straight diagonal, the homoscedasticity assumption is satisfied. To assess the normality of the data distribution, we performed a one-sample Kolmogorov–Smirnov test using Python's Pandas and SciPy libraries [66]. The results of the test are shown in Table 4, and since all *p*-values were less than 0.05, the data distribution was non-normal. PLS-SEM is suitable for exploratory investigations because it does not require large sample sizes or assumptions of normality [61]. Therefore, PLS-SEM was used.

For this purpose, the measurement and structural models were evaluated using Smart PLS 4 software [67].

Table 3. ANOVA test for linearity.

		Sum of Squares	df	Mean Square	F	Sig.
AC * BL	(Combined)	302.478	22	13.749	18.611	0.000
	Linearity	283.781	1	283.781	384.124	0.000
	Deviation from Linearity	18.698	21	0.890	1.205	0.244
IC * BL	(Combined)	259.338	18	14.408	16.646	0.000
	Linearity	209.974	1	209.974	242.594	0.000
	Deviation from Linearity	49.364	17	2.904	3.355	0.000
PSA * BL	(Combined)	320.978	18	17.832	26.572	0.000
	Linearity	285.301	1	285.301	425.131	0.000
	Deviation from Linearity	35.677	17	2.099	3.127	0.000
PU * BL	(Combined)	352.810	18	19.601	34.346	0.000
	Linearity	339.487	1	339.487	594.887	0.000
	Deviation from Linearity	13.324	17	0.784	1.373	0.147
PE * PL	(Combined)	309.105	18	17.172	24.236	0.000
	Linearity	289.690	1	289.690	408.852	0.000
	Deviation from Linearity	19.415	17	1.142	1.612	0.060
NV * PL	(Combined)	309.185	18	17.177	24.251	0.000
	Linearity	297.086	1	297.086	419.439	0.000
	Deviation from Linearity	12.099	17	0.712	1.005	0.452
PPR * PL	(Combined)	174.812	17	10.283	9.111	0.000
	Linearity	94.735	1	94.735	83.938	0.000
	Deviation from Linearity	80.077	16	5.005	4.434	0.000
BI * BL	(Combined)	396.342	18	22.019	50.811	0.000
	Linearity	382.455	1	382.455	882.556	0.000
	Deviation from Linearity	13.887	17	0.817	1.885	0.019

Table 4. One-sample Kolmogorov–Smirnov test for normality of distribution.

	N	Normal Parameters, [a]		Most Extreme Differences			Kolmogorov-Smirnov Z	Asymp. Sig. (2-Tailed)
		Mean	Std. Deviation	Absolute	Positive	Negative		
AC1	336	5.03	1.363	0.230	0.131	−0.230	0.947	0.000
AC2	336	5.02	1.246	0.198	0.133	−0.198	0.968	0.000
AC3	336	5.01	1.383	0.177	0.110	−0.177	0.962	0.000
AC4	336	4.91	1.465	0.172	0.095	−0.172	0.953	0.000
IC1	336	5.06	1.318	0.218	0.157	−0.218	0.956	0.000
IC2	336	5.08	1.400	0.182	0.107	−0.182	0.959	0.000
IC3	336	4.99	1.369	0.191	0.120	−0.191	0.959	0.000
PSA1	336	5.05	1.278	0.218	0.128	−0.218	0.962	0.000
PSA2	336	4.93	1.408	0.217	0.155	−0.217	0.947	0.000

Table 4. *Cont.*

	N	Normal Parameters, [a]		Most Extreme Differences			Kolmogorov-Smirnov Z	Asymp. Sig. (2-Tailed)
		Mean	Std. Deviation	Absolute	Positive	Negative		
PSA3	336	5.01	1.371	0.198	0.165	−0.198	0.954	0.000
PU1	336	4.79	1.440	0.169	0.101	−0.169	0.953	0.000
PU2	336	4.90	1.411	0.184	0.125	−0.184	0.959	0.000
PU3	336	4.78	1.501	0.197	0.097	−0.197	0.947	0.000
PE1	336	4.95	1.363	0.199	0.116	−0.199	0.965	0.000
PE2	336	5.01	1.499	0.179	0.093	−0.179	0.965	0.000
PE3	336	4.99	1.359	0.214	0.140	−0.214	0.968	0.000
NV1	336	5.49	1.378	0.222	0.136	−0.222	0.965	0.000
NV2	336	5.36	1.418	0.239	0.124	−0.239	0.965	0.000
NV3	336	4.93	1.490	0.164	0.095	−0.164	0.956	0.000
PPR1	336	5.33	1.284	0.201	0.123	−0.201	0.968	0.000
PPR2	336	5.28	1.311	0.206	0.131	−0.206	0.956	0.000
PPR3	336	5.29	1.423	0.219	0.120	−0.219	0.953	0.000
BI1	336	5.10	1.304	0.214	0.132	−0.214	0.959	0.000
BI2	336	4.91	1.425	0.188	0.107	−0.188	0.950	0.000
BI3	336	5.02	1.441	0.199	0.109	−0.199	0.959	0.000
BL1	336	5.07	1.443	0.182	0.106	−0.182	0.950	0.000
BL2	336	4.80	1.413	0.162	0.108	−0.162	0.965	0.000
BL3	336	4.86	1.364	0.188	0.115	−0.188	0.959	0.000

[a] Calculated from data.

4.3. Measurement Model

Based on the results of Smart PLS 4, we assessed the internal reliability and convergent validity of the model [68]. The results in Table 5 show that the Cronbach's alpha values and composite reliability (CR) of the constructs exceeded the recommended minimum value of 0.7. Therefore, we confirmed that the measurement model has adequate internal reliability [69]. From a convergent validity perspective, the size of the extracted average variance (AVE) was above 0.50, thus validating the convergent validity of the construct [70,71].

Table 5. Reliability and convergent validity.

Construct	CR	Cronbach's Alpha	AVE
Accuracy (AC)	0.874	0.870	0.720
Interactivity (IC)	0.905	0.905	0.840
Problem-solving ability (PSA)	0.857	0.857	0.777
Perceived usefulness (PU)	0.876	0.876	0.801
Perceived enjoyment (PE)	0.892	0.892	0.822
Novelty (NV)	0.831	0.831	0.748
Perceived privacy risks (PPR)	0.850	0.850	0.768
Brand image (BI)	0.886	0.886	0.815
Brand loyalty (BL)	0.879	0.879	0.806

Note: CR = Composite reliability, AVE = Average variance extracted.

To assess the discriminant validity of the model, several methods were used. First, we used the traditional Fornell–Larcker criterion to measure discriminant validity by comparing the correlation between the constructs with the square root of the AVE for each construct. The square root of the AVE for each construct was greater than the correlation coefficient, indicating sufficient discriminant validity, and the results are shown in Table 6. We then examined the cross-loadings, and the item loadings for each factor were higher than the cross-loadings for the other factors. Additionally, we evaluated discriminant validity using the HTMT standard [72]. Table 7 demonstrates that all HTMT ratios are below 0.90, with the exception of the ratios between problem-solving ability and perceived usefulness, and accuracy; perceived usefulness, novelty, brand loyalty, and brand image; perceived usefulness and brand loyalty; and perceived enjoyment and novelty, which all slightly exceed 0.90. As indicated in Table 8, we investigated the upper bound of the HTMT confidence interval for situations where the HTMT ratio exceeds 0.90 in accordance with earlier study methods [73]. All the results were below 1. Therefore, the discriminant validity of all constructs was satisfactory.

Table 6. Fornell–Lacker's criterion for discriminant validity.

	AC	BI	BL	IC	NV	PE	PPR	PSA	PU
AC	0.849								
BI	0.747	0.903							
BL	0.735	0.848	0.898						
IC	0.71	0.641	0.628	0.917					
NV	0.709	0.776	0.748	0.68	0.865				
PE	0.722	0.757	0.743	0.705	0.786	0.907			
PPR	0.486	0.421	0.429	0.423	0.574	0.456	0.876		
PSA	0.813	0.739	0.733	0.725	0.727	0.733	0.436	0.882	
PU	0.82	0.809	0.798	0.649	0.727	0.746	0.406	0.775	0.895

Note: Diagonal element is the square root of AVE.

Table 7. Heterotrait-Monotrait Ratio (HTMT).

	AC	BI	BL	IC	NV	PE	PPR	PSA
AC								
BI	0.848							
BL	0.836	0.958						
IC	0.799	0.716	0.702					
NV	0.827	0.902	0.869	0.784				
PE	0.815	0.849	0.833	0.783	0.91			
PPR	0.555	0.48	0.484	0.483	0.685	0.52		
PSA	0.942	0.848	0.842	0.823	0.858	0.837	0.507	
PU	0.939	0.917	0.908	0.729	0.847	0.842	0.462	0.895

Note: The results marked in bold indicate HTMT N 0.9.

Table 8. HTMT confidence interval.

	Original Sample (O)	Sample Mean (M)	2.50%	97.50%	Sample Mean (M)	Bias	2.50%	97.50%
BI <-> AC	0.848	0.848	0.78	0.91	0.848	0	0.778	0.908
BL <-> AC	0.836	0.835	0.774	0.889	0.835	0	0.771	0.887
BL <-> BI	0.958	0.958	0.922	0.993	0.958	0	0.922	0.993
IC <-> AC	0.799	0.799	0.717	0.868	0.799	0	0.711	0.863
IC <-> BI	0.716	0.716	0.616	0.806	0.716	0	0.614	0.804
IC <-> BL	0.702	0.702	0.593	0.792	0.702	0	0.586	0.789
NV <-> AC	0.827	0.827	0.745	0.898	0.827	0	0.744	0.897
NV <-> BI	0.902	0.902	0.83	0.959	0.902	−0.001	0.827	0.956
NV <-> BL	0.869	0.869	0.809	0.924	0.869	0	0.807	0.923
NV <-> IC	0.784	0.784	0.689	0.865	0.784	0	0.684	0.861
PE <-> AC	0.815	0.815	0.737	0.88	0.815	0	0.732	0.878
PE <-> BI	0.849	0.849	0.78	0.909	0.849	0	0.777	0.907
PE <-> BL	0.833	0.832	0.769	0.889	0.832	0	0.766	0.889

Table 8. *Cont.*

	Original Sample (O)	Sample Mean (M)	2.50%	97.50%	Sample Mean (M)	Bias	2.50%	97.50%
PE <-> IC	0.783	0.783	0.687	0.863	0.783	0	0.68	0.858
PE <-> NV	0.91	0.91	0.85	0.962	0.91	0	0.848	0.961
PPR <-> AC	0.555	0.554	0.416	0.678	0.554	−0.001	0.41	0.673
PPR <-> BI	0.48	0.48	0.312	0.636	0.48	0	0.31	0.634
PPR <-> BL	0.484	0.484	0.333	0.628	0.484	0	0.328	0.623
PPR <-> IC	0.483	0.483	0.334	0.615	0.483	0	0.333	0.614
PPR <-> NV	0.685	0.685	0.548	0.806	0.685	0	0.538	0.8
PPR <-> PE	0.52	0.519	0.381	0.65	0.519	−0.001	0.379	0.648
PSA <-> AC	0.942	0.943	0.889	0.99	0.943	0.001	0.885	0.987
PSA <-> BI	0.848	0.848	0.753	0.925	0.848	0	0.745	0.92
PSA <-> BL	0.842	0.843	0.741	0.918	0.843	0.001	0.722	0.911
PSA <-> IC	0.823	0.823	0.742	0.891	0.823	−0.001	0.739	0.89
PSA <-> NV	0.858	0.859	0.764	0.936	0.859	0.001	0.754	0.93
PSA <-> PE	0.837	0.838	0.752	0.907	0.838	0	0.741	0.902
PSA <-> PPR	0.507	0.508	0.341	0.667	0.508	0.001	0.333	0.661
PU <-> AC	0.939	0.94	0.902	0.975	0.94	0.001	0.9	0.973
PU <-> BI	0.917	0.917	0.869	0.96	0.917	0	0.868	0.959
PU <-> BL	0.908	0.908	0.865	0.946	0.908	0	0.864	0.946
PU <-> IC	0.729	0.729	0.618	0.82	0.729	0	0.609	0.814
PU <-> NV	0.847	0.847	0.779	0.907	0.847	0	0.775	0.904
PU <-> PE	0.842	0.842	0.768	0.909	0.842	0	0.764	0.905
PU <-> PPR	0.462	0.462	0.309	0.607	0.462	0	0.306	0.603
PU <-> PSA	0.895	0.896	0.792	0.97	0.896	0.001	0.778	0.963

4.4. Structural Model

Based on previous studies [74], we used a bootstrapping program with 5000 samples in Smart PLS 4 to test the significance of the path coefficients. The structural model shows that four out of eight paths are significant. The structural model (Figure 2) shows that four out of eight paths are significant. Table 9 shows that perceived usefulness ($\beta = 0.369$, $p < 0.001$), perceived enjoyment ($\beta = 0.150$, $p < 0.05$), and novelty ($\beta = 0.304$, $p < 0.001$) have a significant effect on brand image, and that brand image ($\beta = 0.848$, $p < 0.001$) has a significant effect on brand loyalty. Therefore, H4, H5, H6, and H8 were supported. The novelty of AI virtual anchors is consistent with Hasan et al. [46], and the significant effect of perceived usefulness is consistent with Yang et al. [75]. Similarly, the significant effect of perceived enjoyment is consistent with Yang et al. [75] and Wong and Haque [76]. Finally, brand image (beta = 0.848, t = 48.331) has a significant effect on brand loyalty, and therefore hypothesis H8 is supported. This is consistent with Watson et al. [77] and Mehta and Tariq [78].

Table 9. Path analysis.

Hypotheses	Path	β	T Statistics	*p* Values	Remark
H1	AC -> BI	0.083	1.278	0.101 ^{ns}	Not supported
H2	IC -> BI	−0.011	0.187	0.426 ^{ns}	Not supported
H3	PSA -> BI	0.082	1.3	0.097 ^{ns}	Not supported
H4	PU -> BI	0.369	5.806	0.000 **	Supported
H5	PE -> BI	0.15	1.745	0.041 *	Supported
H6	NV -> BI	0.304	3.547	0.000 **	Supported
H7	PPR -> BI	−0.043	1.028	0.152 ^{ns}	Not supported
H8	BI -> BL	0.848	48.331	0.000 **	Supported

Note: * $p < 0.05$, ** $p < 0.001$, ns = not significant.

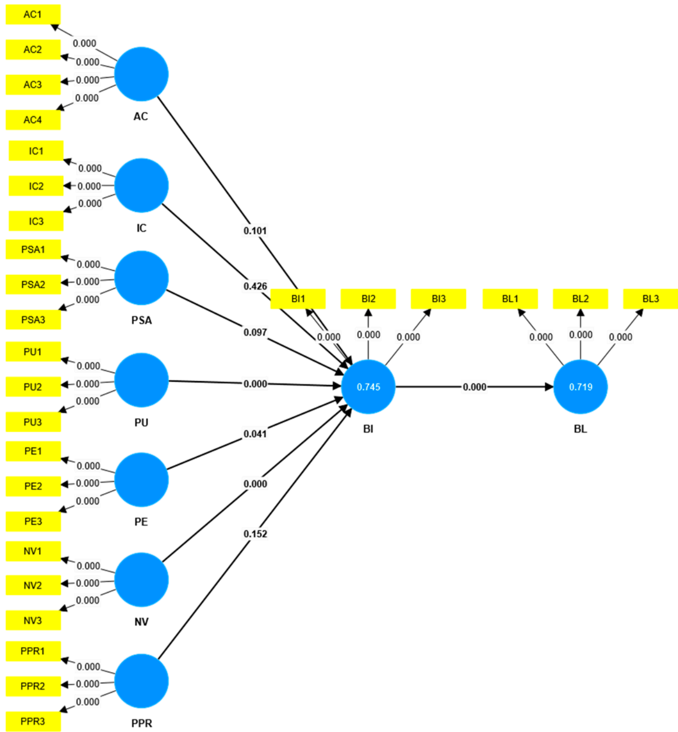

Figure 2. Structural model.

However, accuracy (β = 0.083, *p* = 0.101), interactivity (β = −0.011, *p* = 0.426), problem-solving ability (β = 0.082, *p* = 0.097), and perceived privacy risk (β = −0.043, *p* = 0.152) did not have a significant effect on brand image. Therefore, H1, H2, H3, and H7 were not supported. The insignificant accuracy contradicts the findings of Yuan et al. [8]. This discrepancy may be attributed to differences in the survey sample or potential psychological biases. Another plausible explanation is that users prioritize the entertainment performance of AI virtual anchors and place lower importance on their accuracy. Therefore, hypothesis H1 is not supported. Interactivity (β = −0.011, *p* = 0.426) is not significant and the negative effect contradicts the proposed positive effect, therefore hypothesis H2 is not supported. This is consistent with the findings of Yuan et al. [8], which may be due to several negative interactive experiences, including unnaturalness of the interaction, inaccurate responses, or not meeting user expectations. For these consumers, human recommenders are perceived as more competent than AI counterparts [35]. In addition, the insignificant problem-solving ability contradicts the findings of Yuan et al. [8], potentially due to the challenges AI virtual anchors face in ensuring 100% user satisfaction when addressing problems. While consumers are more likely to rely on AI for solutions and perceive a high-quality service experience when it effectively resolves their issues and answers their questions, which is critical for enhancing brand image [79], expectations regarding problem-solving ability can vary significantly among users. Additionally, users may encounter AI virtual anchors with differing levels of problem-solving competence, leading to inconsistent experiences. As a result, the problem-solving ability of all AI virtual anchors cannot be guaranteed to have a uniformly positive impact on brand image. Therefore, hypothesis H3 is not supported. Furthermore, even though the path coefficient for perceived privacy risk (β = −0.043, *p* = 0.152) is negative, there is no statistical evidence to affirm its negative impact on brand image, as the *p*-value exceeds 0.05. This could be attributed to insufficient data evidence supporting a negative relationship or the need for a larger sample size to enhance statistical sensitivity. Another possibility is that respondents aged 18–25 made up 50.6% of the total sample (as shown in Table 1). As digital natives, this demographic is highly receptive to emerging technologies and may therefore be less concerned about the privacy risks associated with AI virtual anchors. Consequently, H7 is not substantiated.

4.5. Significance Test for Mediating Effects

It has been demonstrated that bootstrapping works better than other mediation tests for determining the relevance of the mediating role of brand image [80]. We run bootstrapping tests on 5000 bootstrapping samples using Smart PLS 4. Three significant mediating effects are indicated by the results displayed in Table 10. In other words, brand image acts as a mediator between perceived usefulness, perceived enjoyment, and novelty as drivers of brand loyalty.

Table 10. Specific indirect effect.

	Original Sample (O)	T Statistics	p Values
AC -> BI -> BL	0.07 ^{ns}	1.283	0.100
IC -> BI -> BL	−0.009 ^{ns}	0.187	0.426
NV -> BI -> BL	0.258 **	3.574	0.000
PE -> BI -> BL	0.127 *	1.75	0.040
PPR -> BI -> BL	−0.036 ^{ns}	1.034	0.151
PSA -> BI -> BL	0.07 ^{ns}	1.287	0.099
PU -> BI -> BL	0.313 **	5.769	0.000

Note: * $p < 0.05$, ** $p < 0.001$, ns = not significant.

4.6. Neural Network Analysis

We use a multi-analytic approach for several reasons. First, conventional statistical methods are more suitable for modeling linear relationships and can only identify linear relationships between variables [81], which may oversimplify the complexity of adoption decisions. Examples of these techniques include standard linear models like multiple regression analysis (MRA) and SEM. Second, neural networks are highly robust and adaptive compared to linear models [81,82]. Finally, ANNs have outperformed traditional statistical techniques (e.g., MRA, SEM, logistics) due to their high predictive accuracy [83]. However, due to their "black-box" nature, ANN methods are not suitable for causal analysis and hypothesis testing [84]. Therefore, in order to complement the strengths of SEM and artificial neural networks, a hybrid two-stage approach was used, where SEM was first used to verify the validity of the causal relationships and then the significant predictors identified in the PLS-SEM analysis were used as input neurons to the artificial neural network model [85] in order to quantify the significance of each variable and predict brand loyalty.

The multilayer perceptron (MLP), the most widely used artificial neural network model [86], was used in this investigation. The artificial neural network model's input neurons were the significant factors from the SEM-PLS path analysis (see Figure 3). Sigmoid activation functions were used for the input and hidden layers [87]. In order to minimize the overfitting problem, we utilize two libraries in Python for ten-fold cross-validation: the KFold in sklearn.model_selection and the NumPy library. In total, 10% of the data were used for testing and the remaining 90% were used for training the neural network [88], and the root mean square of error (RMSE) was generated [89]. Table 11 illustrates that the training and testing processes have comparatively low average RMSE values of 0.574 and 0.629, respectively. Consequently, we verify that the model fits the data better.

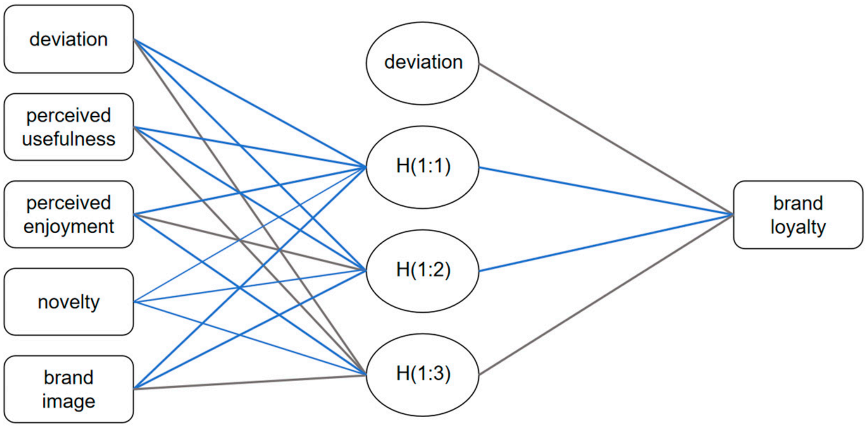

Figure 3. Artificial neural network diagram.

Table 11. RMSE for neural network models.

Network	Training	Testing
1	0.574	0.580
2	0.567	0.682
3	0.572	0.628
4	0.559	0.713
5	0.561	0.747
6	0.584	0.521
7	0.591	0.492
8	0.575	0.630
9	0.570	0.712
10	0.588	0.590
Average	0.574	0.629
Standard deviation	0.010	0.081

To quantify the strength of the predictive power of each input neuron, we computed the average importance of the seven independent variables to predict the dependent variable by performing a sensitivity analysis using the SALib (Sensitivity Analysis Library) library in python. This allowed us to gauge the strength of each input neuron's predictive capacity [85]. With a standardized importance of 65.1%, brand image is the most significant predictor, followed by perceived usefulness (21.0%), novelty (12.9%), and perceived enjoyment (11.6%). The results are displayed in Table 12. From the ANN results, it is evident that brand image is the most critical factor in building brand loyalty, a finding corroborated by Nie and Zeng [90]. As a key predictor, brand image indicates that consumers' overall perception and evaluation of a brand significantly influence their loyalty. This insight highlights the need for brand managers to prioritize optimizing brand image by enhancing the brand's credibility, uniqueness, and appeal to secure long-term consumer support. Perceived usefulness, identified as the second most influential factor, underscores the importance of utility in consumer decision-making. AI virtual anchors must demonstrate their value to consumers by addressing queries, recommending products, or improving shopping efficiency. This result suggests that AI technologies should be designed with a strong emphasis on utility features to foster positive consumer experiences. Novelty and perceived enjoyment further reveal that consumers value not only functional benefits but also innovation and entertainment. Novelty reflects their expectations for cutting-edge technologies, while perceived enjoyment shows that a pleasurable interaction experience can enhance their affinity for the brand. Brands can leverage these insights by creating innovative and engaging content to capture consumer attention and deepen brand loyalty. The ANN findings also provide actionable guidance for practical implementation. The weight distribution of these factors enables brands to allocate resources strategically. For example, prioritizing investments in brand image development while integrating technological advancements and creative content strategies can enhance consumers' holistic perception of the brand and foster loyalty across multiple dimensions.

Table 12. Sensitivity analysis.

Constructs	Importance	Normalized Importance
Perceived usefulness	0.152	21.0%
Perceived enjoyment	0.037	11.6%
Novelty	0.108	12.9%
Brand image	0.606	65.1%

5. Discussion and Conclusions

5.1. Theoretical Contributions

This study combines structural equation modeling and neural network analysis to explore how live product selling by AI virtual anchors influences user perception and brand communication. Existing literature on AI and brand marketing focuses on the study of chatbots [91] and AI voice assistants [13,46,92] and mainly focuses on the characteristics of AI [8] and perceived value [46]. The main theoretical contribution of this study is the construction of a model by integrating the constructs of AI virtual anchor characteristics, perceived value, and perceived risk. The integration of these constructs provides a coherent and comprehensive theoretical framework for understanding the formation of brand image and brand loyalty. It contributes to the research on user behavioral attitudes and brand communication while also aiding the academic community in comprehensively understanding the factors that influence brand image and brand loyalty from various perspectives. We proposed eight hypotheses, of which accuracy, interactivity, problem-solving ability, and perceived privacy risk had no significant effect on brand image. These unproven hypotheses clarify the model's theoretical boundaries and allow for a focus on key variables like brand image, perceived usefulness, perceived enjoyment, and novelty, enhancing the model's explanatory power. The results reflect user preferences in live streaming contexts. Additionally, these untested hypotheses suggest directions for future research, such as examining their role in different audiences or scenarios, to further uncover brand image formation mechanisms. Overall, these findings optimize the model, minimize resource wastage, and provide more focused guidance for brand managers.

In addition, the two-stage SEM-ANN approach offers an innovative analytical framework that not only identifies the key factors influencing consumer brand image and brand loyalty but also leverages neural networks to precisely evaluate the relative importance of these factors. The strength of this method lies in its complementary nature: SEM validates the theoretical framework and establishes causal relationships between variables, while neural networks delve deeper into the complex, nonlinear relationships among them. With its well-defined steps and algorithms, this methodology is highly replicable and adaptable to various research contexts, such as exploring behavioral patterns across different markets or consumer groups. Compared to traditional single-method approaches, this integrated framework serves as a powerful tool for comprehensively analyzing complex user behaviors and the underlying mechanisms of brand communication.

5.2. Practical Contributions

The findings of this study offer valuable insights for brand managers aiming to enhance both brand image and brand loyalty. The results of the study indicate that there is a positive relationship between perceived usefulness, perceived enjoyment, and novelty and brand image, which was identified as the most important predictor of brand loyalty. Brand managers should emphasize the unique features and skills of AI virtual anchors in their branding and webcasting interactions. To demonstrate these qualities more visibly, they can take a more entertaining approach to highlight the professional and entertainment value of AI virtual anchors bringing goods to live brand broadcasts.

AI is an effective tool in creating brand value [15]. The study also points out that brand image plays a mediating role between novelty-brand loyalty, perceived enjoyment-brand loyalty, and perceived usefulness-brand loyalty. By consciously honing their brand image, brand managers can more effectively manipulate and optimize the factors associated with brand loyalty, thereby enhancing the brand's position in the minds of consumers.

5.3. Limitation and Future Direction

While our paper provides theoretical and practical insights for brands, some limitations provide opportunities for future research. First, we used seven dimensions to measure AI services. The path relationship between brand image and brand loyalty can be comprehensively examined from more dimensions in the future. Second, this study focused on AI virtual anchors in live streaming scenarios across all brands, offering a broad scope. However, future research could narrow its focus to a specific brand or compare different brands, delving deeper into the specific impact of AI virtual anchors in brand webcasting rooms on product promotion, thereby providing more targeted practical guidance. For example, a technology-driven brand like Philips may use AI virtual anchors to reinforce its brand image of innovation and technological leadership, while Procter & Gamble might utilize AI virtual anchors to enhance its affinity for home and daily care products. Given their distinct brand positioning, the role of AI virtual anchors in shaping their brand images could vary significantly. Finally, the data in this study came from Chinese consumers only, potentially limiting the generalizability of the findings. Future research could extend our work by conducting a multi-country comparative study of brand image and brand loyalty.

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