EXPERIENCING AI-DRIVEN VIRTUAL INFLUENCERS: EFFECTS ON CONSUMER WELL-BEING AND PURCHASE INTENTION

Anjali Raghuvanshi
Amity University Noida
ORCID: 0009-0005-2159-2513
Deepa Kapoor
Amity school of business, Amity University Noida
ORCID: 0000-0002-7755-1631
Ruchika Gupta
Mangalmay institute of management and technology, Greater Noida
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ABSTRACT
This study examines how AI-driven virtual influencer attributes influence consumers experiential values on social media platforms and how these experiences subsequently affect consumer well-being and purchase intention. Drawing on the Stimulus–Organism–Response (S–O–R) framework and Experiential Consumption Theory, the study adopts a quantitative research design using survey data collected from 302 social media users who interact with virtual influencer content. Partial Least Squares Structural Equation Modelling (PLS-SEM) is employed to test the proposed relationships among virtual influencer attributes, experiential values, consumer well-being, and purchase intention. The findings reveal that anthropomorphism is the most influential virtual influencer attribute, significantly enhancing cognitive value, emotional satisfaction, and hedonic enjoyment, while other attributes exhibit differentiated effects across experiential dimensions. Furthermore, experiential values positively influence consumer well-being, which in turn strongly predicts purchase intention. This study contributes to the emerging literature on AI-driven influencer marketing by highlighting the role of experiential value in enhancing consumer well-being and driving behavioural outcomes.

Keywords*: Virtual influencers, Informativeness, Interactivity, Personalization, Anthropomorphism, Hedonic enjoyment, Cognitive value, Emotional satisfaction, Consumer well-being, Purchase Intention.*

INTRODUCTION

Brands are increasingly using virtual influencers to communicate with consumers on social media platforms. These digital personas help promote products, sharing lifestyle content, and interact with users like human influencers (Stein et al., 2024). For marketers, virtual influencers offer control, consistency, and scalability

(Audrezet et al., 2025). For consumers, interactions with AI-driven influencers represent a fundamentally different consumption experience, that blends technology, persuasion, and emotional engagement (Liu et al., 2026). Existing studies treat virtual influencer exposure as a functional marketing stimulus, focusing on outcomes such as attitudes, trust, or buying intention (Gerlich, 2023; Kim and Park, 2023). This outcome-focused approach overlooks a key issue: the types of experiences virtual influencers create for consumers during social media interactions. Without understanding these experiential processes, it remains unclear why some virtual influencers are persuasive while others fail to build effective audience relationships. Understanding these experiences is significant because social media interactions gradually shape not only consumption decisions but also consumers emotional states and sense of well-being (Ostic et al., 2021). While prior research has examined the effectiveness of virtual influencers in driving engagement(Allal-Chérif et al., 2024) and purchase intention, much less is known about how these virtual influencers interactions are actually experienced by consumers. Virtual influencers primarily operate within highly visual and aspirational domains such as fashion and beauty, where consumers actively process information, form emotional connections, and seek enjoyment (Liu, 2022). Yet research has paid limited attention to how specific virtual influencer attributes influence experiential values, and how these experiences extend beyond the platform to affect consumers perceived well-being. These issues are especially relevant in the Indian social media context, where rapid digital adoption, high social media engagement, and aspirational consumption patterns amplify the influence of online content creators (Statista, n.d.). As Indian brands increasingly experiment with AI-generated influencers, understanding how consumers experience and respond to these digital personas becomes both a managerial and consumer welfare concern. However, empirical evidence on virtual influencer–driven experiences in emerging markets remains limited (Laszkiewicz and Kalinska-Kula, 2023).To address these gaps, this study examines how key virtual influencer attributes shape consumers experiential values on social media. Drawing on the Stimulus–Organism–Response framework and experiential consumption theory, the study conceptualizes virtual influencer attributes as stimuli that evoke experiential values which in turn influence consumer well-being and purchase intention. By unpacking these experiential pathways, this research provides a clearer understanding of how AI-driven virtual influencers affect consumers not only as buyers, but also as individuals navigating digitally mediated consumption experiences. This paper is organised as follows: Section 2 reviews the literature on virtual influencers on social media platforms, SOR framework and experiential consumption theory followed by the hypothesis's formulation. Section 3 details the study's methodology, while Section 4 demonstrates the results and findings. Section 5 discusses the findings, implications. Finally, section 6 discusses the limitations and direction for future research.

THEORETICAL BACKGROUND AND HYPOTHESES FORMULATION

VIs offers greater control, consistency, and scalability compared to human influencers, making them well suited for digital-first marketing strategies (Sands et al., 2022). They create value by offering visually appealing content, consistent brand messaging, and interactive experiences that make brand communication more engaging and enjoyable for consumers (Dong et al., 2025). Recent research highlights that VIs are gaining traction in the Indian social media landscape and brands are increasingly experimenting with AI-generated personas to engage audiences indicating an early but growing academic and practical interest in this phenomenon (Jha and Yadav, 2025). While prior research has primarily focused on engagement and purchase-related outcomes, emerging evidence suggests that repeated interactions with aspirational and human-like virtual influencers can shape consumers emotional states and overall sense of well-being (Barari, 2023a). This study adopts experiential consumption theory as its underlying framework to examine how interactions with virtual influencers shape consumers experiential values which in turn influence their well-being and purchase intention.

Experiential consumption theory (ECT)

Experiential consumption theory (Holbrook and Hirschman, 1982a) suggests that consumer value extends beyond products it encompasses the feelings, thoughts and engagement consumers experience during interaction. Such experiences influence how individuals feel during and after consumption and can shape their broader sense of satisfaction and happiness (Bhattacharjee and Mogilner, 2014). Prior research indicates that positive experiential values, such as emotional enjoyment, pleasure, and cognitive engagement, contribute to individuals' subjective well-being by enhancing emotional balance and life satisfaction (Ni and Ueichi, 2024). In digital and social media contexts, consumption is increasingly experiential, as users engage with visually rich and emotionally evocative content rather than physical products (Hollebeek et al., 2019). Repeated exposure to enjoyable and meaningful digital experiences can therefore influence consumers psychological states beyond the immediate interaction (Jaidka et al., 2020a). Accordingly, experiential consumption provides a useful theoretical lens for understanding how experiences generated on social media platforms, including interactions with virtual influencers, can shape consumer well-being over time (Barari, 2023a; Holbrook and Hirschman, 1982b).

S-O-R (Stimulus-Organism-Response):

Mehrabian & Russell's first introduced this model in 1974 (Russell and Mehrabian, 1974).The Stimulus–Organism–Response theory explains how outside environmental factors influence people behaviour by first affecting their internal thoughts and feelings (Wu et al., 2022). This framework is well suited for studying emerging digital technologies as it explains how technologically mediated features function as stimuli that influence consumers internal experiences and responses (Wang and Jiang, 2024). In social media contexts, virtual influencers operate as designed environmental cues rather than purely human actors, making S–O–R particularly relevant for understanding their effects (Lou and Yuan, 2019a).The present study applies the Stimulus–Organism–Response (S–O–R) framework to understand how virtual influencers create experiential values on social media platforms. Virtual influencer attributes such as informativeness, interactivity, personalization, and anthropomorphism serve as the stimuli. These stimuli shape consumers internal experiential states (O), reflected through cognitive value, emotional satisfaction, and hedonic enjoyment. These experiential responses, in turn, lead to outcomes (R) in the form of consumer well-being and purchase intention.

THEORETICAL FRAMEWORK:

The conceptual framework of this study is grounded in the Stimulus–Organism–Response (S–O–R) framework and Experiential Consumption Theory to explain how interactions with virtual influencers shape consumer outcomes. Virtual influencers often function as role models, particularly in domains such as beauty and fashion, encouraging users to observe, follow, and interact more actively with their content (Yan et al., 2024).Such role-model perceptions can enhance involvement, enjoyment, and emotional connection during social media interactions (Prentice et al., 2019).Drawing on S–O–R, virtual influencer attributes namely informativeness, interactivity, personalization, and anthropomorphism are conceptualized as stimuli that consumers encounter during social media interactions. These attributes shape internal experiential states, consistent with Experiential Consumption Theory, which emphasizes that consumers derive value from how they think, feel, and enjoy consumption experiences. Accordingly, the organism component of the framework is represented by experiential value, captured through cognitive value, emotional satisfaction, and hedonic enjoyment. This study examines perceived psychological well-being during social media interactions with virtual influencers. Therefore, this study argues that the experiences created by virtual influencers vary depending on how consumers perceive different influencer attributes, which collectively shape experiential outcomes. Figure 1. depicts the conceptual framework of the study integrating the S–O–R framework and Experiential Consumption Theory. The next section outlines the hypothesized relationships.

HYPOTHESES DEVELOPMENT:

Impact of VI Informativeness on experiential values

Customer experience during social media interactions depends heavily on how much useful information virtual influencers provide about the products (Xu et al., 2020a). Prior research shows that informative content enhances consumers product understanding and decision confidence. However, its influence on different dimensions of experiential value may vary across interaction contexts. Higher levels of informativeness from virtual influencers can strengthen consumers' sense of cognitive clarity and assurance by reducing uncertainty and improving comprehension of product features (Liu et al., 2025). Conversely, when virtual influencers fail to provide sufficient product information, consumers struggle to feel confident or interested, leading to weaker experiences (Barari, 2023b).Accordingly, informativeness is expected to play an important role in shaping consumers' experiential evaluations during social media interactions.

H1a. Informativeness of VIs has an impact on cognitive value.
H1b. Informativeness of VIs has an impact on emotional satisfaction.
H1c. Informativeness of VIs has an impact on hedonic enjoyment.

Impact of VI Interactivity on experiential values

Interactivity in virtual influencers refers to their capacity to engage in two-way communication and responsive exchanges with audiences through digital platforms, encompassing real-time interactions, personalized responses, and dynamic conversational capabilities that create a sense of dialogue and connection (Davlembayeva et al., 2025a). When users are able to interact with influencer content, they feel more involved rather than remaining passive viewers (Pradhan et al., 2023).Such two-way communication helps users stay mentally attentive and interested in what the influencer is sharing (Naveen Kumar et al., 2025). At the same time, interactivity can enhance the enjoyment of social media use by making interactions feel more lively, engaging, and entertaining(Xu et al., 2020b)(Pradhan et al., 2023). In contrast, the absence of interactive features may lead users to feel disconnected and less motivated to remain engaged with virtual influencer content (Sew et al., 2025). Accordingly, interactivity is expected to play a key role in shaping consumers' experiential responses during interactions with virtual influencers. Based on this reasoning, we propose:

H2a. Interactivity of VIs has an impact on cognitive value.
H2b. Interactivity of VIs has an impact on emotional satisfaction.
H2c. Interactivity of VIs has an impact on hedonic enjoyment.

Impact of VI Personalization on experiential values

Personalization by virtual influencers refers to their ability to tailor content, interactions, and messaging to individual users preferences, behaviours and characteristics through AI-driven customization and dynamic adaptation (Shen, 2024).By tailoring content and recommendations to individual preferences, personalization makes information search feel more relevant and efficient(Ameen et al., 2024).This relevance reduces the mental effort required, helping consumers feel more confident in their decisions (Shen, 2024). In the context of virtual influencers, when personalized posts feel relevant to users, they help consumers better make sense of product information and relate to the message, leading to deeper engagement (Cao et al., 2025).This sense of relevance often leads to more positive feelings during interaction. In addition, content that feels personally meaningful is more likely to keep users engaged and make the interaction feel enjoyable rather than routine (Lou and Yuan, 2019b).Based on this reasoning, the study proposes that personalization plays an important role in shaping users overall experience with virtual influencers on social media. Therefore, we hypothesize that:

H3a.personalization of VIs has an impact on cognitive value.
H3b.personalization of VIs has an impact on satisfaction.
H3c. personalization of VIs has an impact on hedonic enjoyment.

Impact of VI Anthropomorphism on experiential values

Anthropomorphism is the tendency to attribute human-like mental states, intentions, or personalities to non-human agents or objects, making them appear capable of thoughts and feelings(Waytz et al., 2010). In the realm of AI-driven virtual influencers, higher anthropomorphism may foster stronger consumer responses (Davlembayeva et al., 2025b)by activating social and emotional processing typically reserved for human interactions. For instance, human-like VIs such as Lil Miquela, with expressive faces and emotionally nuanced content, may be perceived as more competent and emotionally engaging, leading consumers to pay closer attention, feel more connected, and derive more pleasure from their content (Kim and Park, 2024). However, greater human-likeness may also encourage social comparison, particularly in aspirational settings, which can weaken emotional responses for some consumers (Barari et al., 2025a).In contrast, VIs with lower anthropomorphism those that appear more cartoonish or robotic may evoke weaker engagement and elicit fewer cognitive or emotional evaluations due to their lack of realism (Blut et al., 2021). Given that human-like cues can strengthen consumers' perceptions, attentional responses, and emotional involvement (Li et al., 2023), we propose that anthropomorphic virtual influencers are more likely to shape deeper consumer experiences than their less human-like counterparts.

H4a. Anthropomorphism of VIs has an impact on cognitive value.
H4b. Anthropomorphism of VIs has an impact on emotional satisfaction.
H4c. Anthropomorphism of VIs has an impact on hedonic enjoyment.

Impact of experiential values on Consumer well-being

Consumer well-being reflects individuals overall sense of life satisfaction, happiness, and emotional fulfillment, extending beyond product-related outcomes (Barari, 2023a).Positive experiences can enhance how satisfied and fulfilled consumers feel in their daily lives (Holbrook and Hirschman, 1982c) .Cognitive value provides consumers with useful knowledge and confidence, emotional satisfaction fosters feelings of comfort and connection, and hedonic enjoyment delivers pleasure and positive affect (Lou and Yuan, 2019c). Collectively, these experiential values are expected to strengthen consumers' overall well-being by enhancing their sense of fulfillment and contentment. Therefore, we propose that the richness and positivity of experiences consumers have with virtual influencers play a crucial role in shaping their well-being, affecting how satisfied, emotionally fulfilled, and content they feel in their lives.

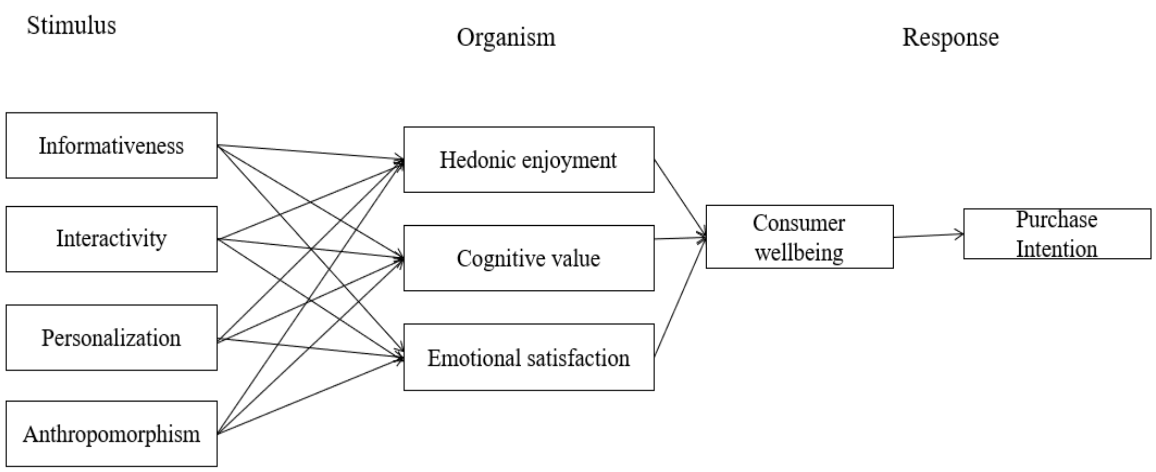
H5: (a)Cognitive value, (b)Emotional satisfaction and (c)Hedonic motivation have an impact on consumer well-being.

Impact of consumer well-being on Purchase Intention

Consumer well-being captures individuals feelings of happiness, satisfaction, and emotional balance that arise from their experiences, going beyond basic satisfaction with products or services (Barari, 2023a).Consumer well-being has gained increasing attention in marketing research, particularly in influencer-driven contexts, as it reflects consumers' subjective feelings of satisfaction, happiness, and psychological comfort derived from consumption experiences (Li and Yu, 2022). Prior studies suggest that higher levels of consumer well-being generate positive affect and perceived value, which foster favorable attitudes, commitment, and loyalty toward brands (Kim et al., 2018; Müller-Pérez et al., 2025). These positive psychological states subsequently strengthen consumers behavioural intentions, including their willingness to purchase (Jamil et al., 2024). Accordingly, consumers who experience enhanced well-being from influencer interactions are more likely to develop stronger purchase intentions. Based on this reasoning, we hypothesise that:

H6: Consumer well-being has an impact on purchase intention.

Figure 1 Research Framework Model:



MATERIALS AND METHODS

Research design

This research employed a quantitative approach utilizing a cross-sectional survey design with structured questionnaire to collect data from study participants. The investigation adopted structural equation modelling as the analytical framework, implemented through Smart-PLS version 4.0 software. The PLS-SEM result is based on the outcomes of a bootstrapped sample of 5000. A percentile bootstrap 95% confidence interval is also employed. This methodological choice was made because SEM enables the simultaneous examination of complex relationships among multiple independent and dependent constructs within a single analytical model(Gefen et al., 2000).

Data collection & sample selection

Data were collected through an online survey distributed to 320 eligible respondents, out of which 302 complete and valid responses were received. The questionnaire consisted of three sections: the first section introduced the study's purpose, assured confidentiality and gathered demographic information of the participants (See Table I), while the second and third sections included items related to the various constructs used in the study. Purposive sampling was employed in the study. Specifically, only individuals who use Instagram and you tube and follow at least one virtual influencer were included in the study. This criterion helped ensure that respondents were familiar with AI influencer interactions and could provide informed responses related to the study. All participants were informed about the purpose and procedures of the study, and their verbal consent was obtained prior to participation. Participation in the survey was entirely voluntary. Informativeness was derived from (King et al., 2014) and Interactivity was measured by a three-item scale adapted from (Malarvizhi et al., 2022). The items used to measure personalisation were adapted from (Zhang et al., 2014), and items used to measure Anthropomorphism and Hedonic enjoyment by adapting (Bartneck et al., 2008) and (Bujacz et al., 2014) respectively. Three items were adapted from (Varshneya and Das, 2017) to measure cognitive value. Emotional satisfaction was measured with the scales adapted from (Shin et al., 2021) . scales of consumer well-being and purchase intention were adapted from (Jaidka et al., 2020b) and (Eberle et al., 2022) respectively.

Table 1 Characteristics of respondents

Variable	Cases (%)
Gender	
Male	143 (47.4%)
Female	159 (52.6%)
Age	
Less Than 20	61 (20.2%)
20-30	116 (38.4%)
30-40	95 (31.5%)
Above 40	30 (9.9%)
Education	
High School Diploma or Less	65 (21.52%)
Under Graduate Graduate	70 (23.18%) 78 (25.83%)
Post Graduate	57 (18.87%)
Doctorate	32 (10.60%)
Time Spent on social media in a day	
Less than 1 hour	37 (12.25%)
1-2 hours	129 (42.71%)
2-4 hours	84 (27.81%)
More than 4 hours	52 (17.21%)

DATA ANALYSIS AND RESULTS

Measurement Model

(Joseph F. Hair et al., 2019) recommend that when using reflective measurement models, researchers should indicator weights, ensure collinearity and confirm their statistical significance. In addition to looking at p-values and significance levels, it is also important to examine effect sizes (f^2) (Graciola et al., 2020). According to (Joseph F. Hair et al., 2019) an f^2 value greater than 0.35 indicates a strong effect, while values above 0.02 are considered acceptable. Cognitive Value (R^2 = 0.716), Emotional Satisfaction (R^2 = 0.563), Hedonic Enjoyment (R^2 = 0.621), Consumer Well-Being (R^2 = 0.689), and Purchase Intention (R^2 = 0.712). Overall, the high R^2 values indicate that the proposed model robustly explains key experiential and behavioural outcomes driven by virtual influencer attributes.We first assessed the measurement model. All item loadings were above the acceptable threshold of

0.70(Joe F Hair et al., 2019), showing that each indicator represented its construct well. Cronbach's alpha values for all constructs were above 0.70, the Composite Reliability (CR) values were all above 0.80 (see Table II), the Average Variance Extracted (AVE) values ranged between 0.626 and 0.777 which is above the 0.50 benchmark(J. Hair, M. Hult, M. Ringle, 2014a) These results confirm good internal consistency and convergent validity. We also checked multicollinearity. All VIF values were below 4.0, indicating that collinearity was not a concern(Hair, 2009). Therefore, our measures manifested good psychometric properties. The square root of AVE for every variable must be higher than all the correlations it has with other variables. In my results, the square root of AVE for every construct was clearly greater than the corresponding inter-construct correlations. Because of this, the Fornell–Larcker test confirms that all constructs are distinct from one another, and there is no overlap that would create discriminant validity problems (see Table IV.). We also checked discriminant validity using the HTMT ratio of correlations following (J. Hair, M. Hult, M. Ringle, 2014b) recommendation. HTMT is considered a reliable test for discriminant validity and values below 1.00 are acceptable (Henseler et al., 2014). In our study all HTMT values were under 1.00 (see Table III.) so there is no discriminant-validity problem. We assessed model fit with the standardized root mean square residual (SRMR). A value less than 0.10 is considered a good fit(Cho et al., 2020).In our study, the SRMR was 0.08 which suggests that the model has a good fit.

Table 2

Construct Factor	Factor Loading	CR	AVE	VIF
ANT	0.945	0.909	0.770	3.961
	0.845			2.155
	0.839			2.438
CV	0.821	0.895	0.741	1.691
	0.865			1.939
	0.894			2.117
ES	0.818	0.891	0.731	1.650
	0.882			2.106
	0.863			1.847
HE	0.813	0.834	0.626	1.392
	0.799			1.368
	0.761			1.347
IN	0.887	0.924	0.753	2.917
	0.884			3.021
	0.853			2.298
	0.846			2.081
INT	0.903	0.913	0.777	2.584
	0.888			2.136
	0.853			1.983
PER	0.860	0.882	0.714	1.866
	0.817			1.739
	0.858			1.622
PUR INT	0.833	0.911	0.774	2.366
	0.858			2.167
	0.944			3.819
WB	0.875	0.901	0.753	2.133
	0.883			2.220
	0.844			1.704

Table 3 Discriminant Validity

HTMT ratios	**ANT**	**CV**	**ES**	**HE**	**IN**	**INT**	**PER**	**PUR INT**	**WB**
ANT									
CV	0.674								
ES	0.503	0.900							
HE	0.755	0.833	0.626						
IN	0.604	0.657	0.656	0.606					
INT	0.792	0.837	0.767	0.771	0.748				
PER	0.611	0.710	0.666	0.649	0.895	0.849			
PUR INT	0.480	0.677	0.665	0.432	0.569	0.587	0.562		
WB	0.552	0.843	0.859	0.686	0.582	0.683	0.608	0.807	

Table 4 Discriminant validity

Fornell–Larcker Criterion	**ANT**	**CV**	**ES**	**HE**	**IN**	**INT**	**PER**	**PUR INT**	**WB**
ANT	0.877								
CV	0.565	0.861							
ES	0.420	0.741	0.855						
HE	0.581	0.636	0.476	0.791					
IN	0.527	0.563	0.557	0.479	0.867				
INT	0.679	0.711	0.642	0.602	0.653	0.882			
PER	0.516	0.587	0.548	0.500	0.762	0.711	0.845		
PUR INT	0.416	0.576	0.560	0.345	0.500	0.509	0.468	0.880	
WB	0.467	0.704	0.714	0.532	0.504	0.582	0.502	0.685	0.868

Table 5 Hypotheses Results

	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1a:IN -> CV	0.372	0.062	6.00	0.000	supported
H1b:IN -> ES	0.220	0.086	2.562	0.010	Supported
H1c:IN -> HE	0.104	0.082	1.273	0.203	Not Supported
H2a:INT -> CV	0.488	0.076	6.436	0.000	Supported
H2b:INT -> ES	0.058	0.091	0.641	0.522	Not supported
H2c:INT -> HE	0.293	0.073	4.038	0.000	Supported
H3a:PER -> CV	0.094	0.041	2.292	0.022	Supported
H3b:PER -> ES	0.058	0.091	0.641	0.522	Not supported
H3c:PER -> HE	0.172	0.058	2.96	0.0003	Supported
H4a:ANT -> CV	0.130	0.063	2.064	0.039	Supported
H4b:ANT -> ES	0.292	0.058	5.214	0.0001	Supported
H4c:ANT -> HE	0.304	0.058	5.218	0.000	Supported
H5a:CV -> WB	0.302	0.070	4.333	0.000	Supported
H5b:ES -> WB	0.424	0.063	6.718	0.000	Supported
H5c:HE -> WB	0.138	0.045	3.081	0.002	Supported
H6:WB -> PUR INT	0.685	0.034	20.222	0.000	Supported

Note: A percentile bootstrap 95% confidence interval is employed.

The structural model results reveal a differentiated pattern of effects across the proposed hypotheses. (Table V) shows that among the informativeness paths, H1a ($\beta = 0.372$, $p < 0.001$) and H1b ($\beta = 0.220$, $p = 0.010$) were supported demonstrating that informative AI influencer cues significantly elevate both cognitive value and emotional satisfaction. But H1c was not supported ($\beta = 0.104$, $p = 0.203$) indicating that informativeness does not enhance hedonic enjoyment. For interactivity H2a ($\beta = 0.488$, $p < 0.01$) and H2c ($\beta = 0.293$, $p < 0.01$) were supported, showing strong positive effects on cognitive value and hedonic enjoyment respectively, while H2b was not supported ($\beta = 0.058$, $p = 0.522$), suggesting interactivity alone does not enhance emotional satisfaction. In the case of personalization, H3a ($\beta = 0.094$, $p<0.05$) and H3c ($\beta = 0.172$, $p < 0.01$) were supported, indicating significant contributions to cognitive value and hedonic enjoyment, whereas H3b was not supported ($\beta = 0.058$, $p = 0.522$), showing no effect on emotional satisfaction. Anthropomorphism displayed consistent significance across all three experiential dimensions, supporting H4a ($\beta = 0.130$, $p <0.05$), H4b ($\beta = 0.292$, $p < 0.001$), and H4c ($\beta = 0.304$, $p < 0.01$), confirming its strong role in enhancing cognitive value, emotional satisfaction, and hedonic enjoyment. Regarding well-being outcomes, H5a ($\beta = 0.302$, $p < 0.001$), H5b ($\beta = 0.424$, $p < 0.001$), and H5c ($\beta = 0.138$, $p<0.01$) were all supported, demonstrating that cognitive value, emotional satisfaction, and hedonic enjoyment significantly enhance consumer well-being, with emotional satisfaction exerting the strongest influence. Finally, H6 was strongly supported ($\beta = 0.685$, $p < 0.01$), confirming that consumer well-being is a powerful predictor of purchase intention.

DISCUSSION

Findings of the overall model

Informativeness positively influenced cognitive value (H1a) and emotional satisfaction (H1b). Clear and accurate information helps viewers process product details more effectively and increases emotional satisfaction when informative messages make shopping experience feel trustworthy and emotionally comforting (Lou and Yuan, 2019d). However, H1c was not supported, indicating that informativeness does not contribute to hedonic enjoyment. This result suggests that informational content is perceived as utilitarian rather than entertaining, as consumers may prioritize social presence and enjoyment over factual detail in experiential settings (Lee and Theokary, 2021).The effect of interactivity on cognitive value(H2a) and hedonic enjoyment(H2c) were also significant. Interactive features appear to stimulate active information processing and create a lively, immersive experience, enhancing both understanding and enjoyment(Tedjakusuma et al., 2025; Wang et al., 2023). In contrast, (H2b) was not supported indicating that interactivity alone does not enhance emotional satisfaction. This finding suggests that while interactivity improves engagement, it may lack the emotional depth required to generate feelings of warmth or personal connection without stronger affective cues (Lee and Kim, 2024; Mao, 2022). Personalization positively influenced cognitive value and hedonic enjoyment, supporting (H3a) and (H3c). Personalised suggestions made the offerings feel more relevant, meaningful, and emotionally engaging for consumers, leading to more favorable cognitive evaluations and pleasurable experiences. However, (H3b) was not supported, indicating no effect on emotional satisfaction. This may occur because viewers perceive personalized recommendations as algorithm-driven marketing rather than genuine care or authentic connection, limiting emotional satisfaction. These findings align with (Kim and Baek, 2024; Liu, 2025).Anthropomorphism emerged as the most consistent predictor across experiential dimensions, with H4a, H4b, and H4c all supported. Their human-like appearance and emotional expressions enhance perceived credibility, emotional connections and enjoyment, thereby deepening consumer experiences. These findings highlight anthropomorphism as a critical mechanism through which virtual influencers simulate social interaction and enrich experiential consumption. Regarding outcome variables, cognitive value, emotional satisfaction, and hedonic enjoyment all significantly enhanced consumer well-being, supporting H5a,H5b and H5c. Among these, emotional satisfaction exerted the strongest influence, underscoring the central role of affective fulfillment in shaping overall well-being. Finally, H6 was strongly supported, confirming that consumer well-being is a powerful predictor of purchase intention. This finding reinforces the view that positive experiential states translate into favourable behavioural outcomes in AI-mediated influencer marketing contexts.

IMPLICATIONS

Theoretical implications

Our study extends foundational theories of influencer marketing and consumer experience by conceptualizing AI-driven virtual influencers (VIs) as marketing stimuli in a classic S–O–R framework. Each VI attribute is treated as a stimulus that evokes internal cognitive, affective, and hedonic reactions, consistent with experiential consumption theory. Experiential theory posits that consumption involves cognitive, emotional, and hedonic dimensions. for example, hedonic experiences (like entertainment) are known to boost subjective well-being (Guevarra and Howell, 2015), while informative content improves understanding and trust (Hanaysha, 2022) ,By mapping each VI feature to cognitive value, emotional satisfaction, and hedonic enjoyment, we explain when and why VI marketing may enhance consumers overall well-being and purchase intentions, thereby extending source credibility and experiential value theories into the age of virtual personalities. The findings of the study broaden the theoretical discourse on influencer marketing by integrating cognitive and emotional experiences. They demonstrate that virtual influencers influence consumers via diverse internal routes rather than solely through emotional appeal (Li and Huang, 2024). By linking experiential outcomes to consumer well-being and purchase intention, we show that marketing stimuli can impact broader aspects of consumers quality of life. This aligns with studies indicating that credible, informative content builds trust and drives purchase behaviours (Ducoffe, 1996).Theoretically, this calls for models of influencer effects that fully integrate both cognitive judgments and emotional experiences and invites future research on how these internal states interact over time and across cultures. In sum, our research extends the S–O–R framework and experiential consumption theory into the realm of AI-driven virtual influencers by clarifying which attributes trigger specific internal responses.

Practical implications

This study offers clear and actionable insights for brands and marketers using AI-driven virtual influencers. First, marketers should prioritize informative content such as tutorials, specifications, or comparisons to build trust and perceive usefulness. However, informativeness alone does not enhance enjoyment, brands might pair information with engaging storytelling, visuals and multimedia elements to create a more enjoyable experience. Brands should check which type of information customers like the most by looking at engagement data (comments, likes, watch time). For example, Indian e-tailers like Nykaa and Myntra could implement AI influencers that use analytics to deliver highly informative yet engaging guides on Instagram and YouTube. Second, interactive features such as responsive chatbots, product quizzes, and live Q&A sessions should be integrated into AI influencer campaigns to stimulate engagement and enjoyment. As interactivity alone may not generate emotional satisfaction, brands should embed social cues or empathetic language to make interactions feel warmer and more personal (Gan et al., 2025).Third, personalization should be used responsibly to increase relevance and enjoyment while avoiding overly mechanical communication. Adding a human tone to personalized messages can strengthen emotional connection and improve the overall experience. Fourth, anthropomorphism emerged as a key driver of consumer experience. Brands should design virtual influencers with relatable personalities, natural language, and expressive cues to enhance enjoyment, emotional comfort, and trust. However, highly realistic designs may create discomfort and weaken user confidence (Barari et al., 2025b).Finally, as consumer well-being emerged as the strongest driver of purchase intention, brands should design AI influencer content that reduces decision anxiety, increases emotional comfort, and offers fun, ensuring that sessions feel both helpful and uplifting.

CONCLUSION

This study provides actionable guidance for brands deploying AI-driven virtual influencers in social media marketing. First, informativeness should be positioned as a trust-building and decision-support mechanism, not as a source of entertainment. Product tutorials, specifications, and comparisons are effective in enhancing perceived usefulness and emotional reassurance; however, such content should be embedded within storytelling or visually rich formats, as informativeness alone does not generate enjoyment. Social media managers should therefore monitor engagement metrics such as watch time and comments to identify which informational formats resonate most with their audiences. Second, interactive features—including live Q&A sessions, quizzes, and chatbot-based responses—can enhance engagement and enjoyment by encouraging active participation. However, because interactivity alone does not foster emotional satisfaction, campaign designers should integrate empathetic language, social cues, and conversational warmth to create a sense of personal connection. Third, personalization should be applied strategically to enhance relevance and enjoyment while avoiding overly mechanical or algorithmic communication. Adding a human tone to personalized recommendations can help mitigate perceptions of artificiality and strengthen emotional responses. Most importantly, anthropomorphism emerged as the strongest experiential driver. Brands should therefore invest in designing virtual influencers with relatable personalities, expressive communication styles, and natural language interactions. At the same time, overly realistic designs should be avoided, as excessive human-likeness may create discomfort and undermine trust. Finally, as consumer well-being was found to be a strong predictor of purchase intention, marketers should design virtual influencer interactions that reduce decision anxiety, provide emotional comfort, and deliver enjoyable experiences, thereby supporting both commercial outcomes and consumer welfare.

LIMITATIONS AND FUTURE RESEARCH

The present study has several limitations that should be acknowledged. The study focused exclusively on Indian consumers. Therefore, cross-cultural research is needed to assess the generalizability of these findings across different cultural and market contexts. Future studies could adopt experimental or longitudinal approaches to better capture causal relationships and examine how consumer responses to virtual influencers evolve over time. Virtual influencers vary widely in design like 2D vs.3D, realistic vs. stylized and interaction capability like pre-scripted vs. real-time AI. The current study did not differentiate these variations. Future research could explore how different levels of realism and AI sophistication affect consumer response.

USE OF ARTIFICIAL INTELLIGENCE:

Generative artificial intelligence tools were employed solely for linguistic editing and manuscript refinement. The study’s conceptual framework, data analysis, interpretation, and final conclusions were entirely developed and validated by the authors.

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