Neuro-Marketing in the Age of Generative AI: Neuroscientific Responses to AI-Generated Advertising

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ABSTRACT

This study investigated whether and how AI-generated ad personalization and perceived human-likeness affect the effectiveness of AI-generated ads using consumers' neuroscientific responses and taking into account cultural context as a moderator. A quantitative cross-sectional design was used, which involved respondents from Pakistan and Gulf countries, and the model was tested using SmartPLS 4. The results revealed that personalization and perceived human-likeness had a significant impact on the neuroscientific responses and, in turn, these responses had a strong impact on advertising effectiveness. Both relationships were mediated to a significant extent by neuroscientific responses. The personalization–neuroscientific response relationship was significantly moderated by cultural context, but not the human-likeness pathway. The model was reasonably well explained and predictively good in CVPAT. The results broaden Stimulus–Organism–Response theory to the field of generative AI advertising and give implications for culturally responsive, human-like, and personalized advertising strategies throughout markets.

Keywords: Generative AI; Neuromarketing; AI-Generated Advertising; Perceived Human-Likeness; Advertising Personalization

Introduction

Generative artificial intelligence (GenAI) is transforming advertising by allowing companies to use AI to generate content, tailor messages for specific audiences, and even mimic human voice and expression (Hermann & Puntoni, 2024; Chen et al., 2024). In contrast to traditional algorithmic advertising, GenAI can generate novel multimodal content, and the perceived source, authenticity, and human-likeness of the content are more central to the assessment of the content by consumers (Kirk & Givi, 2024; Chen et al., 2024). Consumers react differently to AI-generated advertising as it is influenced by the appeal, authenticity, trust, and perceived social capabilities of the artificial agents (Chen et al., 2024; Kirk & Givi, 2024). AI-mediated interactions can also arouse privacy or exploitation concerns, while anthropomorphic cues can reduce negative trust responses, suggesting that the persuasion process with AI is a complex phenomenon that involves both cognitive and affective components (Lefkeli et al., 2024).

The development of these strong arguments justifies the integration of neuromarketing with GenAI advertising, given that it is not possible to fully measure the implicit and non-conscious reactions to marketing stimuli with the use of self-report measures alone (Bigné et al., 2025). Consumer-neuroscience techniques using electroencephalography (EEG), eye-tracking, galvanic skin response, and other neurophysiological processes can provide complementary information to the consumers' verbal attitudes and behavioral intentions regarding attention, emotional arousal, approach–withdrawal tendencies, and memory-related processing (Bigné et al., 2025). These methods thus offer a valuable methodological framework to assess whether personalisation and perceived human-likeness of AI-generated ads elicit unique neural and attentional reactions that increase advertising effectiveness (Bigné et al., 2025).

Gulf markets offer a particularly relevant context as digitally mediated consumption experiences continue to grow while trust, authenticity, social influence, and culturally congruent communication are still significant factors in technology-mediated consumption (Alboqami, 2023; Abbasi et al., 2024). Research conducted in Saudi Arabia has revealed that the dimensions of attractiveness, authenticity, and expertise, coupled with consumer–influencer congruence, are crucial when it comes to the trust placed in artificial-intelligence influencers (Alboqami, 2023). The findings from the social-media study further support the importance of cognitive and emotional processing in the Gulf consumer markets, as it shows how digital-marketing stimuli impact customer engagement and behavioral responses (Abbasi et al., 2024).

Beyond that, Pakistan can offer a theoretically relevant comparison for emerging markets, as the adoption and resistance to AI services are shaped by both the broader motivations of consumers for technology use and context-specific factors (Rasheed et al., 2023). Consumer reactions to AI-driven persuasion are not necessarily the same across culturally different markets, as indicated by these contextual differences (Rasheed et al., 2023).

While the field of GenAI research has developed rapidly, current marketing research literature has focused largely on self-reported attitudes, authenticity, trust, and behavioral intentions, with only a limited amount of research on neuroscientific evidence related to AI-driven advertising content (Hermann & Puntoni, 2024; Bigné et al., 2025). For this reason, the present study delves into the neural responses to the personalization and perceived human-likeness of AI-generated ads, and how these responses drive the efficacy of AI-based ads while keeping cultural context as another boundary condition (Chen et al., 2024; Bigné et al., 2025). This synergy of generative AI, advertising, consumer neuroscience, and cross-cultural consumer research provides an urgent pathway to understanding the cognitive and emotional processing of technologically produced persuasion in the markets of the Gulf and Pakistani consumers (Hermann & Puntoni, 2024; Rasheed et al., 2023).

Theoretical Framework

The proposed framework was based on the Stimulus – Organism – Response (S–O–R) model, which posits that external marketing stimuli generate internal cognitive and affective responses that lead to evaluative and behavioral responses; recent research using GenAI has drawn parallels between the combination of external stimuli (in this case, AI-generated marketing content) and the internal response (in this case, the cognitive and affective processes) and the subsequent evaluative and behavioral outcomes (Ali et al., 2025). AI-mediated ad personalization and perceived human-likeness are included in the framework as the stimulus component, as both of them influence the consumer's judgment regarding the content of the ad, its relevance, and social presence, as well as the persuasive power of the ad (Chen et al., 2024; Jung et al., 2025). The proposition that personalized and human-like cues influence consumers' processing of ads is supported by evidence from this experiment that suggests that ads generated by AI are processed differently based on their message characteristics and the perceived social role of AI. The human connection is crucial, as human attributes in GenAI ads boost trust and evaluations, while purely AI-driven ads can create anxiety and negative attitudes (Jung et al., 2025; Madathil, 2025).

Neuroscientific responses reflect the organism (attention, arousal, memory) and reflect advertising stimuli. The value of the neurophysiological mechanisms goes beyond self-reported attitudes, as confirmed by consumer-neuroscience research that has been conducted on the impact of the advertising environment on selective attention, encoding, and recall, on the one hand, and on cortical vigilance, on the other (Mandolfo et al., 2025). The responses are expected to moderate the impact of the advertising features generated by AI on advertising effectiveness. Lastly, cultural context is suggested as a moderator, as the concepts of authenticity, humanness, trust, and persuasion with AI might differ in different contexts, which has implications for the effectiveness of GenAI advertising (Mehmood et al., 2024; Jung et al., 2025).

Hypotheses Development

AI-Generated Ad Personalization and Neuroscientific Responses

Generative AI can help advertisers personalize images, words, and the appeal in a message to the consumers' tastes in a far more sophisticated way than traditional advertising systems. A personalized ad makes the content more relevant to the viewer and boosts their cognitive engagement with the content, but over-personalized AI advertising can provoke threat and privacy concerns as well (Sun et al., 2025). Recent experiments show that moderately personalized ads are most likely to elicit good consumer reactions as consumers consider the information value and potential threat of ads (Sun et al., 2025). Personalization through AI, as a result, could have an impact on the attention, emotional arousal, and encoding processes that underpin explicit attitudes. Neuroscientific studies also give evidence for the measurable differences in attentional engagement and neurological processing of advertising stimuli, which affect advertising evaluation (Ishtiaque et al., 2025).

H1: *AI-generated ad personalization has a positive effect on consumers' neuroscientific responses.*

Perceived Human-Likeness and Neuroscientific Responses

Humans can provide the cues and signals that are growing in importance in AI-generated ads, as consumers view anthropomorphic elements as a sign of social presence, communicative competence, and interpersonal similarity. Empirical studies of the impacts of generative AI advertising in recent times have revealed that perceived humanness significantly enhances consumers' perception of advertising informativeness, entertainment, credibility, and novelty (Jung et al., 2025). Likewise, the influence of the social role attributed to AI and the extent to which the advertisement conforms to what the consumer expects from a human message determine their reaction to an AI-generated advertisement (Chen et al., 2024). The attention should therefore be drawn to the emotional and cognitive processing stimulated by human-like visual and communicative cues.

H2: *Perceived human-likeness of AI-generated advertisements has a positive effect on consumers' neuroscientific responses.*

Neuroscientific Responses and AI-Generated Advertising Effectiveness

Neuromarketing suggests that the effectiveness of advertising is due to cognitive and affective processes that can take place prior to the point of consumer conscious evaluation. Neural engagement and attentional processing, along with neural activity, have been found to discriminate consumer preference toward advertisements and can offer explanatory information in addition to traditional self-reported measures, as demonstrated in EEG-based advertising studies (Ishtiaque et al., 2025). The attention processed increases the likelihood that the advertising information will be encoded in memory, emotional arousal contributes to the motivational relevance of the advertising information, and memory encoding increases the likelihood that the encoded advertising content and brands will later be retrieved. These processes are all more relevant to AI ads since the consumer will assess the creative content as well as the tech that is driving its creation.

H3: *Consumers' neuroscientific responses have a positive effect on AI-generated advertising effectiveness.*

Mediating Role of Neuroscientific Responses

Based on the Stimulus–Organism–Response theory, the characteristics of the AI-generated ads should impact advertising outcomes based on how consumers process the stimuli cognitively and affectively. Personalization is an external stimulus of advertising, while attention, arousal, and memory are internal organismic responses that make the stimulus more likely to lead to subsequent evaluations or responses. The results of the last few years suggest that AI attributes of ads affect consumers' responses not only directly but also through intervening psychological mechanisms (Chen et al., 2024; Sun et al., 2025). Therefore, when the ads are tailored to the content of the page, and the processing of that content is stronger in terms of attention, emotions, and memory, the effectiveness of the personalized ads should increase.

H4: *Neuroscientific responses mediate the relationship between AI-generated ad personalization and AI-generated advertising effectiveness.*

Perceived human-likeness ought to function in a similar fashion. Human-like AI attributes improve perceived social quality and advertising attributes, and recent empirical research shows that perceived humanness is a key factor in consumers' assessment of the AI-generated advertising content (Jung et al., 2025). Human-like cues should therefore enhance the effectiveness of advertising to some extent due to their ability to facilitate increased internal attention, emotional involvement, and memory processing.

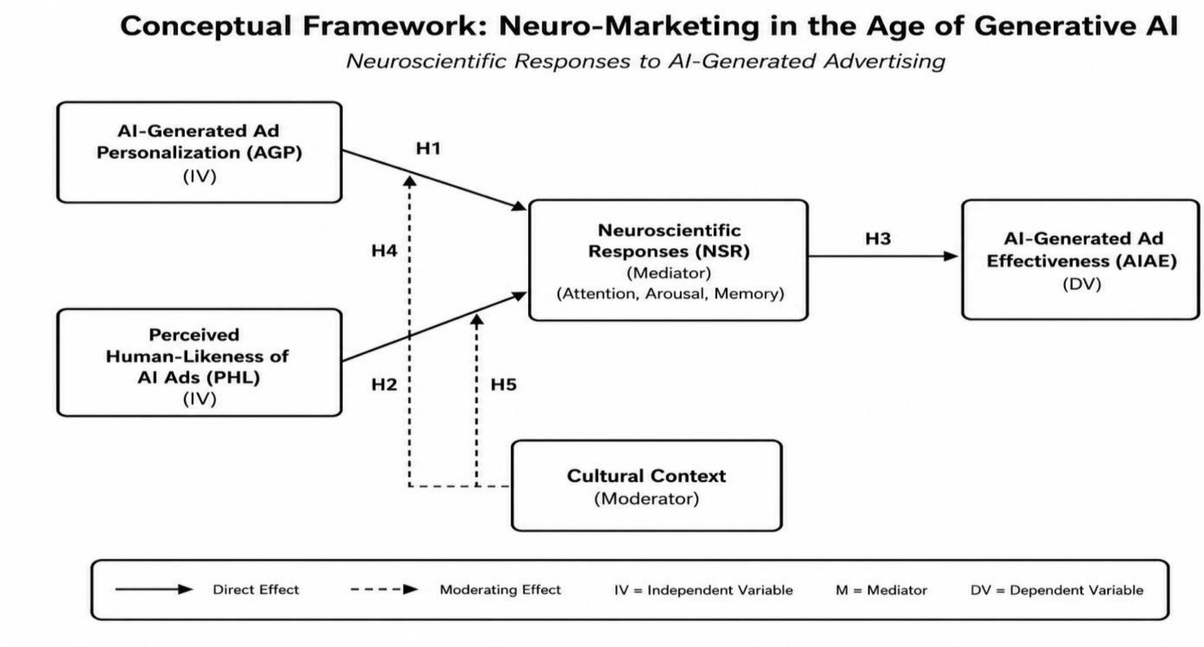
H5: *Neuroscientific responses mediate the relationship between perceived human-likeness of AI-generated advertisements and AI-generated advertising effectiveness.*

Moderating Role of Cultural Context

The meaning of AI-mediated communication is rooted in cultural and social contexts. This could result in varying reactions in culturally different consumer markets, as anthropomorphic AI cues, the process of building trust, perceived authenticity, technological familiarity, and persuasive communication can all yield different reactions. Recent studies have focused on the impact of humanness, authenticity, and technological cues on consumer evaluations (Jung et al., 2025; Grigsby et al., 2025), and findings on the effectiveness of technological cues on advertising have shown that this depends considerably on the context (Grigsby et al., 2025). These kinds of discoveries warrant the consideration of cultural context as a significant boundary condition, as opposed to assuming that the same cognitive/emotional reactions are triggered by AI-driven advertising in different markets.

H6: *Cultural context moderates the relationship between AI-generated ad personalization and neuroscientific responses, such that the strength of the relationship differs across cultural contexts.*

H7: *Cultural context moderates the relationship between perceived human-likeness of AI-generated advertisements and neuroscientific responses, such that the strength of the relationship differs across cultural contexts.*



Methodology

Research Design

This study uses a quantitative, cross-sectional, and cross-cultural research design to explore consumer reactions to AI-created ads. The conceptual model contained four first-order latent constructs: AI-Generated Ad Personalization (AAP), Perceived Human-Likeness (PHL), Neuroscientific Response (NR), and AI-Generated Advertising Effectiveness (AAE). No higher-order construct was proposed. Culture was considered an observed grouping variable (Pakistan and Gulf countries). The study adopted a prediction-oriented perspective and was therefore appropriate for the use of partial least squares structural equation modelling (PLS-SEM) for the simultaneous estimation of direct, mediating, and cross-cultural effects. PLS-SEM is especially suitable for studies that focus on explanation and prediction and in which the latent-variable scores and predictive assessment are of importance (Richter & Tudoran, 2024; Vaithilingam et al., 2024).

Population and Sample

The target audience included consumers aged 18 or older who regularly used social media platforms and who were aware of digital advertising. Respondents were selected from the population of Pakistan and Gulf Cooperation Council (GCC) countries such as Saudi Arabia, U.A.E., Qatar, Kuwait, Bahrain, and Oman. A sample size of about 400 was set, and around 200 were received from Pakistan and 200 from Gulf countries. A purposive sampling method was used as the participants needed to be familiar with digital and AI-driven advertising. An AI-advertisement-exposure screen was added to verify that participants had seen some ads that were made or supported by AI.

Respondents were first presented with a pre-made advertisement for a fictional consumer brand created by AI. An unfamiliar brand minimized possible contamination due to previous brand familiarity, loyalty, and/or established brand attitude. Experimental studies in recent years have shown that the attributes of AI-powered ads impact consumer evaluation, social perception, and advertising effectiveness (Chen et al., 2024; Jung et al., 2025).

Measurement Instrument

The variables in the conceptual framework were measured using a structured questionnaire. The instrument used included substantive construct measures, cultural-context questions, screening questions, and demographic information. All substantive latent constructs were formulated as first-order reflective constructs and were measured across seven-point Likert scales ranging from 1 = strongly disagree to 7 = strongly agree. The wording of existing measurement scales was modified to make them more applicable to the context of AI-generated advertising without changing the meaning of the scales.

AI-Generated Ad Personalization (AAP) was assessed with four constructs (AAP1–AAP4) previously used to assess perceived personalization in digital advertising and recently in AI-generated ad personalization (De Keyzer et al., 2024). The responses were evaluated based on their perceived personalization of the ad, level of congruence with personal preferences, relevance to their personal needs, and the specific target audience of the ad. Scores were higher for greater perceptions of personalization of the AI-generated advertisement to the individual consumer.

Perceived Human-Likeness (PHL) was assessed through four items (PHL1–PHL4), adapted from previous research that investigated the perceived human-likeness in AI-generated advertising (Jung et al., 2025). The questions asked whether the audience perceived the AI-generated ad as human, as natural (as opposed to mechanical), as more like a human-made advertisement, and as creating an illusion of a human presence. The importance of perceived humanness in generative-AI advertising has grown significantly, as consumers not only assess the content of the ads but also how well the AI-generated communication matches human communication (Jung et al., 2025).

The six items of Neuroscientific Response were operationalized as a single first-order construct (NR). These items were designed and adapted from the literature of consumer neuroscience focusing on attention, affective activation, cognitive engagement, and memory as key internal reactions to advertising messages (Bigné et al., 2025). The six items measured whether the ad captured immediate attention, held attention during exposure, elicited a strong emotional response, stimulated mental processing, was easily recalled in memory, and whether the main message of the ad was remembered. Since all six indicators were directly assigned to one NR construct in SmartPLS 4, no second-order or higher-order construct was used. The measures were not directly collected from EEG, fMRI, GSR, or eye-tracking equipment but were instead based on respondents' perceptions of their neurocognitive responses to the ads generated by AI.

The AI-Generated Advertising Effectiveness (AAE) was captured by five items (AAE1–AAE5) that were adapted from the recent AI-generated advertising research focusing on consumers' advertising evaluations, persuasion, brand responses, and behavioral intentions (Chen et al., 2024; Jung et al., 2025). The five items measured the effectiveness and persuasiveness of the ad, its positive impact on the advertised brand, its positive impact on interest in the advertised product/service, and its positive impact on purchase consideration. Higher scores thus indicated a higher perceived effectiveness of the AI-generated advertisement.

A total of 19 substantive measurement items were used for the four main latent constructs: AI-Generated Ad Personalization (4 items), Perceived Human-Likeness (4 items), Neuroscientific Response (6 items), and AI-Generated Advertising Effectiveness (5 items).

Cultural Context (CC) was included in the structural model as the moderating variable. Cultural context was coded as a categorical variable, 0 = Pakistan and 1 = Gulf, and represented respondents' main cultural context. To facilitate accurate cultural classification, six additional background questions were added. The questions that were used recorded their nationality (CC1), country of residence (CC2), length of time spent in the country in which they currently reside (CC3), country where they spent the majority of the previous decade (CC4), main language spoken in everyday life (CC5), and feelings of belonging to the cultural values and social norms of the country in which they reside (CC6). These questions were used as screening and cultural-verification questions only, and were not added together to form an artificial reflective cultural scale.

In the structural model of SmartPLS analysis, the binary CULTURE variable was directly included in the model as an observed moderator. The moderating effects were estimated in terms of creating the interaction terms AAP × CULTURE → NR and PHL × CULTURE → NR. The two-stage approach was chosen for SmartPLS 4 estimations as it is appropriate for moderation by a latent predictor construct and an observed moderator. If an interaction coefficient was statistically significant, it was interpreted as meaning that the correlation of the respective AI-advertising characteristic with the neuroscientific reaction was different in the different cultural contexts.

Pilot Testing and Data Collection

The questionnaire was content valid, clear, and relevant as it was reviewed by experts in marketing, consumer behaviour, and quantitative research. About 30-40 respondents were then included in a pilot study. Any items with poor or unclear preliminary reliability were revised prior to the primary data collection. To ensure the semantic equivalence between the different cultural groups, the questionnaire was translated into Urdu and Arabic as needed using forward and reverse translation processes.

The participants were first presented with the screening and cultural background questions and then the standardized AI-generated ad. Immediately after exposure, they responded to the 19 substantive measurement items and demographic questions. Participation was voluntary, informed consent was obtained, and responses were anonymous.

Data Analysis Using SmartPLS 4

The data were initially checked in SPSS 23 for missing values, incomplete questionnaires, outliers, descriptive statistics, and demographic characteristics. The hypothesized model was then tested using SmartPLS 4 software. The primary aims were the identification of key drivers that affect the effectiveness of advertising created by AI and the estimation of mediation effects, as well as the assessment of the model's predictive power, which led to the selection of PLS-SEM. Recent methodological studies highlight the advantages of PLS-SEM for prediction-oriented business research and also suggest comprehensive robustness and predictive evaluations by Vaithilingam et al (2024) and Richter & Tudoran (2024).

The measurement model was evaluated using outer loadings, Cronbach's alpha, rho_A, composite reliability, and average variance extracted (AVE). Indicator loadings of about 0.708 or higher were preferred, as well as Cronbach's alpha, rho_A, and composite reliability values of 0.70 or higher. Convergent validity was established if the AVE value was above 0.50. The heterotrait-monotrait ratio (HTMT) was used to test discriminant validity.

The structural model was then assessed with the inner VIF, standardized path coefficients, R square and f-squared values. Direct and indirect effects were estimated using 5,000 bootstrap subsamples. Specifically, the main direct pathways were AAP → NR and PHL → NR, and the indirect pathways AAP → NR → AAE and PHL → NR → AAE were investigated and examined for the presence of the indirect effect of neuroscientific response.

The out-of-sample predictive assessment of the model was carried out using PLSpredict and CVPAT to complement the model's explanatory results. In recent years, predictive evaluation and robustness have become the major concerns in PLS-SEM rather than the mere R^2 and significance (Vaithilingam et al., 2024; Sharma et al., 2024).

Finding and Analysis

Measurement Model

The measurement model was generally reliable, convergent, and had no significant multicollinearity within the constructs. Indicator reliability was good, with all indicator loadings above the suggested level of 0.70, ranging from 0.778 for CC2_RESIDENCE_CODE to 0.933 for AAP1. The AI-Generated Ad Personalization exhibited good measurement quality, with loadings ranging from 0.885 to 0.933, Cronbach's alpha of 0.935, composite reliability of 0.953, and AVE of 0.836. AI-Generated Advertising Effectiveness also showed high internal consistency (α = 0.929; CR = 0.947) and good convergent validity (AVE = 0.780). Neuroscientific Response showed good reliability (α = 0.935, CR = 0.949, and AVE = 0.755), and all loadings were over 0.837. The perceived Human-Likeness also had high α (0.917), high CR (0.942), and AVE (0.802). Cultural Context had acceptable convergent validity (AVE = 0.720) and composite reliability (CR = 0.836), although Cronbach's alpha (0.626) was below the recommended level of 0.70 and should thus be considered with caution. VIF values ranged from 1.261 to 4.314. There was no serious multicollinearity as all values were below 5.0, but there were comparatively higher values for AAP1 and AAP3. The overall measurement model has satisfactory evidence of indicator reliability, internal consistency, convergent validity, and acceptable collinearity, and extends to assessing discriminant and structural models. The findings, thus, indicate that the indicators chosen for measurement reflect the constructs they are supposed to measure well. However, it should be noted that the lower reliability of Cultural Context requires consideration prior to hypothesis testing, especially when it is kept as a reflective construct in the SmartPLS specification.

Table 1: Reliability and Validity

Construct	**Indicator**	**Loading**	**VIF**	**Cronbach's Alpha**	**CR**	**AVE**
AI-Generated Advertising Effectiveness (AAE)	AAE1	0.872	2.824	0.929	0.947	0.780
	AAE2	0.875	2.901			
	AAE3	0.874	2.808			
	AAE4	0.910	3.679			
	AAE5	0.883	2.987			
AI-Generated Ad Personalization (AAP)	AAP1	0.933	4.314	0.935	0.953	0.836
	AAP2	0.885	2.917			
	AAP3	0.929	4.070			
	AAP4	0.911	3.424			
Cultural Context (CC)	CC2_RESIDENCE_CODE	0.778	1.261	0.626	0.836	0.720
	CC5_LANGUAGE_CODE	0.914	1.261			

Construct	Indicator	Loading	VIF	Cronbach's Alpha	CR	AVE
Neuroscientific Response (NR)	NR1	0.887	3.306	0.935	0.949	0.755
	NR2	0.893	3.496			
	NR3	0.889	3.346			
	NR4	0.837	2.455			
	NR5	0.864	2.868			
	NR6	0.841	2.496			
Perceived Human-Likeness (PHL)	PHL1	0.883	2.776	0.917	0.942	0.802
	PHL2	0.904	3.081			
	PHL3	0.918	3.531			
	PHL4	0.875	2.603			

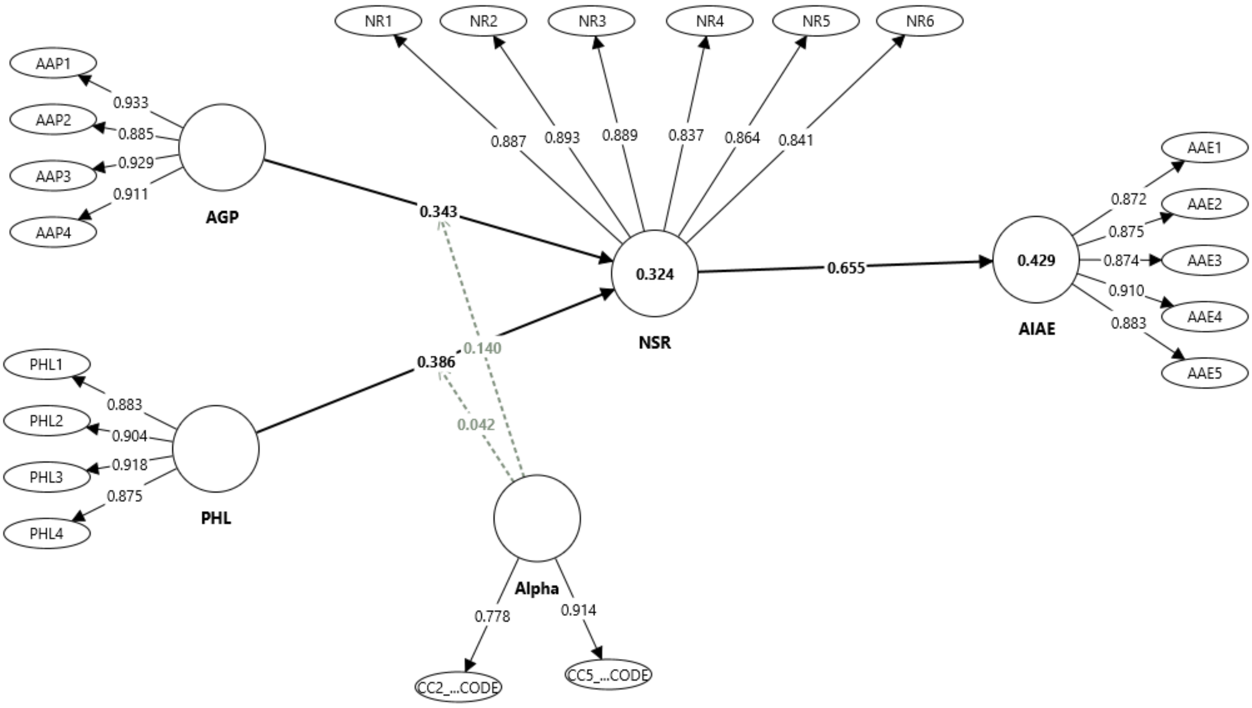


Figure 2: Measurement Model

Discriminant Validity

The HTMT results showed good discriminant validity for all constructs used in the measurement model. All the HTMT values were below the conservative level of 0.85 and the more liberal level of 0.90 proposed for determining discriminant validity. The strongest conceptual link was found between AIAE and NSR with an HTMT score of 0.701. However, this value was well below the recommended value, thus providing evidence for the empirical distinction between the two constructs. The association between NSR and PHL was found to be moderate (HTMT = 0.459) and acceptable (AGP = 0.423), respectively.

The other relationships showed relatively low levels of HTMT. AIAE/AI and PHL/AI recorded 0.403, while AGP/AI and AIAE/AI recorded 0.313. These low values were the ones that were found between CC and the other constructs, ranging from 0.031 to 0.138, which shows strong empirical distinctiveness. Similarly, the HTMT value between AGP and PHL was only 0.135. None of the construct pairs reached the critical cut-off for discriminant validity. As such, the findings reflected that each construct represented a different conceptual and statistical construct in the proposed model. Based on this, the measurement model met the criterion of discriminant validity in accordance with the criteria for proceeding to assess the structural model, including the direct relationship, mediating relationship, and mediating relationship was considered appropriate.

Table 2: HTMT Criteria

Construct	AGP	AIAE	CC	NSR	PHL
AGP	—	—	—	—	—
AIAE	0.313	—	—	—	—
CC	0.031	0.138	—	—	—
NSR	0.423	0.701	0.067	—	—
PHL	0.135	0.403	0.031	0.459	—

Structural Model

Most of the proposed relationships were well supported by the results of the structural model. AI-generated ad personalization significantly and positively influenced consumers' neuroscientific response ($t = 8.260$, $\beta = 0.343$, $p < 0.001$), suggesting that the more personal the ads were, the stronger the effect on consumers' cognitive and affective response to the AI-generated ads was. Finally, perceived human-likeness had a significant positive effect on neuroscientific response ($\beta = 0.386$, $t = 10.102$, $p < 0.001$), and this effect was slightly greater than that of personalisation. The strongest direct relationship according to the neuroscientific response was found in this model, which greatly influenced the advertising effectiveness generated by the AI ($\beta = 0.655$, $t = 22.397$, $p < 0.001$), demonstrating that a greater internal response of the consumer significantly boosted the effectiveness of the advertising.

The association between personalization and neuroscientific response was significantly moderated by cultural context, with a β of 0.140 ($t = 2.236$; $p = 0.025$). This suggests that cultural context has an impact on the effect of personalization on neuroscientific response. An interaction between culture and the relationship between human-likeness and neuroscientific response was not substantial ($\beta = 0.042$, $t = 1.072$, $p = 0.284$), indicating that culture did not significantly modify the human-likeness–neuroscientific response relationship. The mediation outcomes also had ramifications. The perceived human-likeness of the ads had a strong positive association with advertising effectiveness via the neuroscientific response ($\beta = 0.253$, $t = 8.773$, $p < 0.001$), and the personalization of advertising had a similarly strong positive association with advertising effectiveness via the neuroscientific response ($\beta = 0.225$, $t = 7.695$, $p < 0.001$). The results broadly supported the central mediating effect of neuroscientific reaction and showed that cultural context was a selective, not universal, moderator

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Table 3: Path coefficients

Relationship	Beta	Sample Mean (M)	STDEV	T Value	P Value	Decision
AGP → NSR	0.343	0.346	0.042	8.260	0.000	Supported
NSR → AIAE	0.655	0.655	0.029	22.397	0.000	Supported
PHL → NSR	0.386	0.387	0.038	10.102	0.000	Supported
CC × AGP → NSR	0.140	0.128	0.063	2.236	0.025	Supported
CC × PHL → NSR	0.042	0.037	0.039	1.072	0.284	Not Supported
PHL → NSR → AIAE	0.253	0.254	0.029	8.773	0.000	Supported
AGP → NSR → AIAE	0.225	0.227	0.029	7.695	0.000	Supported

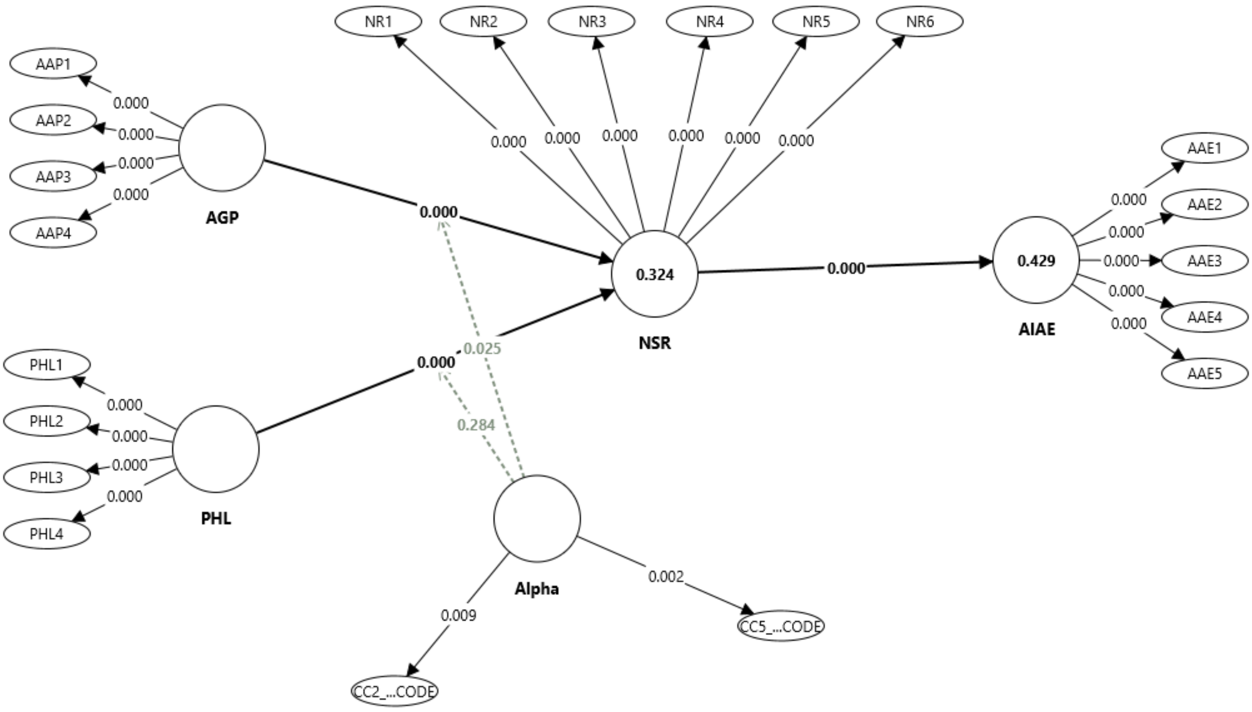

Figure 3: Structural Model (alpha=Cultural Context "CC")

R-Square and f-Square Assessment

The results of the coefficient of determination showed that the structural model has satisfactory explanatory power. AI-generated advertising effectiveness (AIAE) had an R^2 value of 0.429, and the adjusted R^2 value of 0.427, which means that about 42.9% of the variance in advertising effectiveness is accounted for by its predictor in the model. There was little difference between R^2 and adjusted R^2, indicating that the model's explanatory power was not drastically changed by including the number of predictors. Likewise, the

R^2 value of 0.324 and adjusted R^2 value of 0.315 for the neuroscientific response (NSR) indicated that about 32.4% of the variance was accounted for by AI-generated ad personalization, perceived human-likeness, cultural context, and the corresponding moderation effects.

The relative contribution of individual predictors was also significantly different, as shown by the magnitude of the f^2 results. The strongest effect, exceeding the 0.35 threshold for a large effect, was found for NSR, which established the central role that consumers' neuroscientific responses play in advertising effectiveness. The f^2 value for PHL → NSR was 0.216, which amounts to a medium f^2 value and an average contribution, whereas the f^2 value for AGP → NSR was 0.171, which is also a medium f^2 value and an average contribution. The direct effect of cultural context on NSR, however, was small ($f^2 = 0.003$). This weak direct effect should not be interpreted as an attack on the ability of culture to moderate the strength of another relationship, but not mean that culture itself has a direct predictive effect on NSR. Overall, the model had an acceptable level of explanatory power, and NSR turned out to be the most important predictor of advertising effectiveness.

Table 4: R-Square and f-Square

Metric Type	Construct / Relationship	R-square	R-square Adjusted	f^2	Interpretation
Coefficient of Determination	AIAE	0.429	0.427	—	Moderate explanatory power
Coefficient of Determination	NSR	0.324	0.315	—	Moderate explanatory power
Effect Size	AGP → NSR	—	—	0.171	Medium effect
Effect Size	CC → NSR	—	—	0.003	Negligible effect
Effect Size	NSR → AIAE	—	—	0.750	Large effect
Effect Size	PHL → NSR	—	—	0.216	Medium effect

PLS Predict/CVPAT analysis

The results of the Cross-Validated Predictive Ability Test (CVPAT) indicated that the PLS-SEM model had higher predictive power than the Indicator Average (IA) model set-up as a benchmark. For AI-Generated Advertising Effectiveness (AIAE), the PLS loss was 3.064, which is lower than the IA loss of 3.609, resulting in a highly significant average loss difference of -0.545 ($t = 6.121$, $p < 0.001$). Likewise, Neuroscientific Response (NSR) posted a loss of PLS 2.897, compared to the loss of PLS 3.761 posted by IA. The difference in loss was statistically significant ($t = 6.932$, $p < 0.001$), with a particularly good predictive ability for NSR in this case (corresponding loss difference of -0.864). At the overall model level, the PLS loss was 2.973 compared with an IA loss of 3.692, resulting in a significant difference of -0.719 ($t = 7.504$, $p < 0.001$). The loss differences were consistently negative and statistically significant, which supports the superiority of the proposed PLS-SEM model in making more accurate out-of-sample predictions, as lower loss values indicate better predictive performance. In summary, the results of the CVPAT gave good evidence of the model's predictive validity, and they also supported the explanatory results of R^2

and path coefficients, as well as the results of the measure of effect size.

Table 4 CVPAT analysis

Construct	PLS Loss	IA Loss	Average Difference	Loss t Value	p Value	Interpretation
AIAE	3.064	3.609	-0.545	6.121	0.000	PLS significantly outperforms IA
NSR	2.897	3.761	-0.864	6.932	0.000	PLS significantly outperforms IA
Overall	2.973	3.692	-0.719	7.504	0.000	Strong overall predictive superiority

Discussion

The results confirmed that the Stimulus–Organism–Response logic underlying this study was effective, as AI-generated ad personalization and the perceived human-likeness significantly increased consumers' neurocognitive reactions. Personalization had a positive impact on neuroscientific response ($p<0.001$, $\beta=0.343$), highlighting that the AI-generated content that was personally relevant generated greater attention, emotional engagement, and memory-related processing. It is consistent with previous research findings on the impact of personalization on the perceived relevance of ads and on the cognitive processing of AI advertising (Sun et al., 2025). The perceived human likeness had a greater impact on the neuroscientific response ($\beta = 0.386$, $p <0.001$), corroborating previous findings that human-like AI communication fosters social presence and consumer assessments (Chen et al., 2024; Jung et al., 2025).

Neuroscientific response was significantly correlated with advertising effectiveness generated by AI ($\beta = 0.655$, $p < 0.001$) and mediated both personalization and human-likeness effects, indicating that internal cognitive-affective processing is a key mechanism that drives AI advertising effectiveness. In general, the cultural condition of the personalization–response relationship was found to be significant, whereas the cultural condition of the human-likeness–response relationship was not. This suggests that AI persuasion is culturally conditioned. The model also has moderate explanatory power and good predictive power with significantly lower PLS prediction losses than the IA benchmark, CVPAT.

Theoretical Implications

The study extends the Stimulus–Organism–Response model framework into the domain of generative-AI advertising, adding to the theoretical contributions. The organismic mechanism that connected external stimuli (AI-generated personalization and perceived human-likeness) with the advertising effect was the consumers' neurocognitive responses. This serves as empirical evidence for the theoretical framework outlined in the manuscript, in which personalization/human-likeness was considered to be an AI stimulus and neurocognitive response the mediating organismic state.

The second contribution is showing that the effect of personalization was mediated by the effect of neurocognitive response, as was the effect of human-likeness, extending the study of neurocognitive response in the context of AI advertising. It also helps establish a cross-cultural theory of AI advertising by revealing that cultural context is a selective boundary condition, as it enhanced or modified the personalization pathway, but did not substantially modify the human-likeness pathway. This discovery implies that the effect of culture might be different across various forms of AI-mediated persuasion and does not consistently impact every kind.

Practical Implications

The results offer actionable advice for organizations deploying generative AI to create digital advertising campaigns. Advertisers should focus on meaningful personalization, as personalised AI-generated ads elicited more neurocognitive responses, which in turn led to better advertising effectiveness. Personalization should be around truly relevant needs of consumers; however, it should not be too much, as previous studies have identified a potential balance between the utility of personalization and the perceived threat (Sun et al., 2025).

This is because the greater the perceived human likeness, the more impactful the ad. Because of this, AI-generated ads must include natural language, realistic communication styles, expressions that can be easily understood, and human-centered storytelling. These features can enhance engagement, emotional involvement, and retention of the message. The findings from the mediation also suggest that campaign effectiveness should be measured beyond clicks or even purchase intention, but also through attention, engagement, emotional reactions, and recall. Personalized advertising, especially when used in the context of different markets, requires cultural adaptation, as the relationship between personalization and response was quite different in different cultures. However, the human-like communication seems to be relatively stable across contexts, which means that some anthropomorphic advertising principles may be more easily translatable to culturally diverse markets.

Managerial Implications

The concept of personalisation should be viewed as part of, but not a replacement for, human-likeness in GenAI marketing campaigns. The direct effect was greater with perceived human-likeness compared to personalization, which also had a significant medium-sized contribution. Managers need, therefore, to invest in AI systems that can generate content that is both relevant to each consumer and natural to communicate with them. A neuroscientific response to advertising had a large effect on advertising effectiveness ($f^2 = 0.750$), implying that ads should not only be creative and cheap, but should also be designed to capture attention, induce emotion, engage the mind, and promote retention of the message.

It is also important that managers don't apply the same personalization strategies to culturally different markets. The personalization pathway was strongly moderated by cultural context; therefore, personally relevant message content, culturally relevant language, social norms, and customer data should be used to tailor campaigns. However, the minimal cultural moderation of human-likeness indicates that managers could potentially use some of the principles of human communication with AI more effectively across markets. Last, the model's predictive ability establishes the relevance of applying PLS-based analytics to offer valuable insights into which features of AI advertisements are most likely to elicit beneficial consumer reactions.

Limitations and Future Research Recommendations

There are a number of caveats to be noted. The study used a cross-sectional design, limiting the ability to make causal inferences and to evaluate the impact of the AI-generated advertising over time. Longitudinal or controlled experimental designs should be used for future studies. Secondly, instead of physiological measures like EEG, eye tracking, GSR, or fMRI, the study used self-reported measures of neurocognition. Further research should integrate the survey measures with actual neurophysiological measures to enhance the contribution of neuromarketing.

Thirdly, the study was conducted with consumers in Pakistan and Gulf countries, and this may make the findings less generalizable to other contexts, such as Western countries, East Asian countries, or African countries. The framework should be replicated in other cultural contexts in the future. Fourth, it was operationalised using mainly background and classification indicators, which would facilitate future studies to include cultural dimensions such as collectivism, uncertainty avoidance, or power distance. Lastly, other AI-advertising traits, such as disclosure, authenticity, creativity, perceived manipulation, privacy concern, and AI literacy, could be incorporated into subsequent models for the explanation of a larger portion of neurocognitive response and advertising effectiveness.

Conclusion

This study investigated the influence of AI-generated ad personalization and perceived human-likeness on advertising effectiveness based on consumers' neurocognitive response, and tested cultural context as a moderator. The results reveal that personalization and human-likeness were both significantly positively associated with neurocognitive response, and that the neurocognitive response was strongly associated with the effectiveness of the AI-generated advertising. Moreover, both relationships were significantly mediated by neurocognitive response, highlighting that ads produced by AI that captured higher levels of attention, emotion, cognitive processing, and memory were more effective.

While personalization had a significant moderating effect on the effect of the neurocognitive response, the cultural effect on the human-likeness relationship was not significant, suggesting that the cultural effect is selective, not universal. The model accounted for 42.9% of the variation in advertising effectiveness and 32.4% of the variation in neuroscientific response, and the results of the CVPAT further validated the model's out-of-sample predictive performance. Overall, the study contributes to the study of GenAI advertising as it brings together personalization, human-likeness, neurocognitive processing, advertising effectiveness, and cultural context in one predictive model.

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