Advances in Consumer Research
https://acr-journal.com/
Volume-3 | Issue-4 | April 2026
Original Researcher Article

Consumer Engagement with AI Generated Content: The Role of Perceived Human Likeness and Cognitive Effort in Shaping Purchase Behaviour

Dr. V. Shanthan Kumar[1], Dr. Ritu Mishra[2], Dr. Muskan Wadhwani[3]*, Sana Querishi[4], Deeksha Chaurasia[5], Parathsarathi Nag[6], Dr. Davinder Kaur[7]

[1]Assistant Professor, Pendekanti Institute of Management.
Email: contactshantan@gmail.com
[2]Assistant Professor, IPS Academy, Institute of Business Management and Research, Indore.
Email: mishra.ritu75@gmail.com
[3*]Independent Researcher, Indore.
Email: muskanwadhwani20@gmail.com.
[4]Research Scholar, Saifia Arts, Commerce and Law College, Barkatullah University, Bhopal.
Email: sanaqureshi903@gmail.com.
[5]Communication Officer, Indian Institute of Forest Management.
Email: smartdeeksha112@gmail.com.
[6]Former General Manager, IBM India Pvt. Ltd.
Email: parthn1710@gmail.com
[7]Assistant Professor, School of Management Studies, CT University, Ludhiana
Email: kaur.davinder7080@gmail.com

ABSTRACT

This paper examines how consumer involvement with AI generated material affects purchase behaviour, with a special focus on how perceived human-likeness and cognitive effort mediate the effect and how the privacy concern moderates the effect. Based on theories including the Technology Acceptance Model, the Cognitive Load Theory, Human-Computer Interaction, and Privacy Calculus Theory, a conceptual framework is created. The data was collected through cross-sectional survey of 408 respondents using 5-point Likert scale. Analysis was done using Structural Equation Modeling (SEM) and Exploratory Factor Analysis (EFA) with SPSS and SmartPLS 4. The findings affirm that consumer engagement has a positive relationship with perceived human-likeness and cognitive effort with perceived human-likeness increasing purchase behaviour and cognitive effort decreasing purchase behaviour. The engagement-purchase relationship is partially mediated by both of the two mediators. The relationship between engagement and purchase behaviour is positive, and the impact of engagement is undermined by privacy concern. The results have a theoretical contribution by blending cognitive and privacy viewpoints in AI content engagements and providing managerial lessons to marketers to maximize AI content approaches and overcome privacy concerns.

Keywords: Consumer Engagement, AI-Generated Content, Perceived Human-Likeness, Cognitive Effort, purchase behaviour, Privacy Concern, Structural Equation Modeling.

1. INTRODUCTION:

The rise of artificial intelligence (AI) in content generation has significantly altered the digital marketing environments, as it has created highly personalized, scalable and interactive consumer interactions. The scope of AI-generated content (AIGC) is quite wide, and its applications include automated product descriptions, chatbots, customized advertisements, and automated content curation, all of which are increasingly popular in influencing consumer decision-making (Smith and Anderson, 2022). Although AIGC has been rapidly adapted and incorporated into the marketing strategies, there is a great gap in knowledge about the subtle processes of consumer involvement in such content and the ultimate impact that this involvement has on the consumer purchasing behaviour.

Marketing professionals agree that consumer engagement is a key driver of brand loyalty, customer satisfaction, and sales performance (Brodie et al., 2019). Nonetheless, implementation of AIGC brings forth unique features that make it different to the conventional marketing content. The perceived human-likeness of AI-generated content and the cognitive load imposed on consumers to process it by AI are two salient factors here. Perceived human-likeness is the extent to which the consumers perceive AI content as similar to human communication, which may lead to the development of trust, emotional engagement, and a feeling of authenticity, positively affecting purchase intentions (Huang and Rust, 2021). Cognitive effort, in its turn, is related to the mental capacities that consumers need to devote to understanding and assessing the AI content. High mental effort can cause consumer fatigue, distrust, or perplexity, which can serve as purchase decision barriers (Sweller, 2016).

Besides these cognitive and perception aspects, the issue of privacy has become a burning question in the digital marketing landscape, especially in the context of AI that extensively uses personal data to personalize content (Martin and Murphy, 2017). Privacy concern portrays the concerns of consumers regarding the gathering of data, its usage, and the possible breach, which can cause opposition or behavioral reservations towards artificial intelligence mediated marketing information. This issue can temper the connection between consumer engagement and purchase behaviour by attenuating the beneficial impacts of engagement because consumers might be hesitant to behave on the content that they see as intrusive or risky (Xu et al., 2020).

In fulfilling this complex research gap, the proposed study empirically investigates the channels by which consumer interaction with AI-generated content affects purchase behaviour. Particularly, it examines mediating mechanisms of perceived human-likeness and cognitive effort, and the moderating role of privacy concern. The aims of the study are threefold: (1) to confirm both the direct and indirect impacts of consumer engagement on purchase behaviour in the proposed conceptual model; (2) to determine the level to which perceived human-likeness and cognitive effort mediate the relationship between the two; and (3) to ascertain the degree to which the relationship between the two is moderated by privacy concern. By conducting this thorough analysis, the research will seek to understand more about the cognitive, emotional, and privacy-related processes that underlie consumer reactions to AI-generated marketing content and, in doing so, will offer meaningful data to both theoretical and practical marketing strategy formulation.

2. LITERATURE REVIEW

2.1. Technology Acceptance Model

The technology acceptance model (TAM) is the initial theory that is being discussed by Davis (1989), according to which acceptance and adoption of new technologies by users are influenced by two main factors, namely, perceived usefulness and perceived ease of use. Consumer engagement in the context of AI-generated content (AIGC) can be defined as a gauge of perceived usefulness, in which increased consumer engagement signifies that the consumers perceive the AI content as valuable and useful to their needs. At the same time, cognitive effort is associated with perceived ease of use, which is a reflection of mental resources that one needs to communicate with and understand AI-generated content. TAM hence gives a theoretical basis to conjecture that increased exposure to AIGC will create a positive perception of human-likeness as consumers will assign more utility and relevance to content that seems genuine and familiar. On the other hand, the increased cognitive effort can be an indication of problems in the content processing that can decrease acceptance and purchase intentions. Combining these constructs, TAM will enlighten the analysis of the study on the effect of engagement on the perceived human-likeness and the cognitive demands of the AI content that would lead to future consumer behaviour.

2.2 Cognitive Load Theory

Cognitive Load Theory, which is reflected by Sweller (2016), provides a glimpse of how the degree of mental effort needed to process the information influences decision-making and learning outcomes. When applied to the field of AI-generated marketing contents, this theory implies that consumers who are exposed to high cognitive load (because of the complexity, ambiguity, or novelty of AI-generated content) can experience mental fatigue, confusion, or overload. This cognitive load may reduce their efficiency in assessing the content, which will result in lower purchase intentions. The theory lends credence to the argument that cognitive effort is a negative mediator in the association between consumer engagement and purchase behaviour. Particularly, although engagement could enhance exposure to AI content, when it also leads to the rise in cognitive load to a point that seems to be an optimal level, consumers can become disengaged or skeptical. This indicates the relevance of crafting AI materials in a way that will strike the right balance between informational and simplified content to reduce mental impediments and ease decision-making.

2.3 Theory of Human-Computer Interaction

According to Nass and Moon (2000), Human-Computer Interaction (HCI) Theory explains the importance of perceived similarity and naturalness in the interaction between the user and the computer system. In the context of the AI-generated content, the perceived human-likeness is the degree to which the consumers identify AI productions as being similar to human communication patterns, including language peculiarities, empathy, and contextual fittingness. Increased perceived human-likeness leads to increased trust, satisfaction, and emotional bond, which are essential antecedents to positive purchase behaviour. According to HCI theory, psychological distance can be lowered and user interaction increased when human interaction patterns are effectively simulated by AI content. This theoretical framework justifies the hypothesis of the study that human-likeness is positively mediated by the influence of consumer engagement on purchase intentions, and highlights the importance of human-focused design philosophy in AI content creation to enhance consumer acceptance and reaction.

2.4 Privacy Calculus Theory

The Privacy Calculus Theory proposed by Culnan and Bies (2003) describes consumer judgments in online contexts as the rational trade-offs between the perceived benefits and privacy threats. The issue of privacy concern, in the context of AI-generated marketing content, represents the fears of consumers in the practices of data collection, possible misuse, and the violation of personal data. According to this theory, despite consumer engagement and a perception of usefulness or human-like AI content, increased privacy concerns may drive cautious or resistant attitudes and dilute the beneficial impacts of consumer engagement on purchase behaviour. Privacy concern acts as a critical moderating variable to the extent to which consumers will be willing to act on AI-generated content. The theory also points to the need of having marketers openly share data practices and build effective privacy controls to address the worry of consumers. Marketers can overcome these privacy-related obstacles to increase consumer trust and improve the success of AI-based marketing practices.

Hypotheses Development

H1: Consumer engagement with AI-generated content positively affects perceived human-likeness

H2: Consumer engagement with AI-generated content positively affects cognitive effort

H3: Perceived human-likeness positively affects purchase behaviour

H4: Cognitive effort negatively affects purchase behaviour

H5: Consumer engagement positively affects purchase behaviour

H6: Perceived human-likeness mediates the relationship between engagement and purchase behaviour.

H7: Cognitive effort mediates the relationship between engagement and purchase behaviour.

H8: Privacy concern negatively moderates the relationship between engagement and purchase behaviour.

3. RESEARCH METHODOLOGY

The quantitative and cross-sectional survey approach was used to explore the relationships proposed in the conceptual framework in a systematic manner. The sample size of the study was 408 respondents who were selected using the credible online panels in order to have a diverse demographic mix in terms of age, gender, education, and socioeconomic status. This method increased the transferability of the results by representing a wide range of consumer attitudes towards AI-generated content.

A carefully designed questionnaire was used to collect data, and therefore, included validated measurement scales that were specific to the constructs being studied. Every item was measured using a 5-point Likert scale (strongly disagree (1) to strongly agree (5)) which allowed capturing the attitudes and perceptions of the participants in a more nuanced way. The adapted scales based on Brodie et al. (2019) were used to measure consumer engagement to guarantee its compliance with the existing academic standards. Perceived human-likeness items were created through the Human-Computer Interaction constructs suggested by Nass and Moon (2000), this time around the extent to which AI-generated content was deemed similar to human communication. The cognitive effort was measured in accordance with the cognitive load measures suggested by Sweller (2016) and reflected the mental resources used by the consumers when processing AI content. Purchase behaviour items were based on Huang and Rust (2021) and were adjusted to the intentions and real behaviours of consumers related to the purchase choices based on the AI content. Privacy concern was assessed with Martin and Murphy (2017) scales that are effective to measure consumer fears about data privacy and security in their online interactions.

The analytical plan was a two-step one. First, SPSS was used to perform an Exploratory Factor Analysis (EFA) to determine the construct validity and reliability of the measurement scales, to ensure that each scale item loaded well on its intended factor, and that scales had internal consistency. After the validation, Structural Equation Modeling (SEM) was conducted with the help of SmartPLS 4 to carefully test the supposed relationships as part of the conceptual framework. SEM enabled concurrent analysis of direct, indirect (mediation) and interaction (moderation) effects, which allows solid results on the interacting nature of consumer engagement, perceived human-likeness, cognitive effort, privacy concern and purchase behaviour. Such a thorough method of analysis made the findings of the study statistically and theoretically meaningful.

4. DATA ANALYSIS & RESULTS

4.1 Demographic Profile

Table 1 presents the demographic characteristics of the respondents.

Table 1: Demographic Profile of Respondents

Demographic Variable	*Category*	*Frequency*	*Percentage (%)*
Gender	Male	210	51.5
	Female	198	48.5
Age	18–25	120	29.4
	26–35	150	36.8
	36–45	80	19.6
	46 and above	58	14.2
Education	High School	90	22.1
	Undergraduate	180	44.1
	Postgraduate	138	33.8

Income	< 1,00,000	100	24.5
	1,00,000–5,00,000	160	39.2
	> 5,00,000	148	36.3

The sample is balanced in gender and skewed towards younger and middle-aged adults, with a majority holding undergraduate degrees and moderate to high income levels, ensuring representativeness for consumer behaviour analysis.

4.2. Exploratory Factor Analysis (EFA)

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was identified as 0.892, which by the traditional standards, is excellent. This large value of KMO is indicative that the sample size and data characteristics are highly suitable to factor analysis so that the correlations between variables are small enough to yield reliable factors. Also, the Test of Sphericity provided by Bartlett was very significant ($p < 0.001$), which supports the idea that the correlation matrix is not an identity matrix and the variables have sufficient intercorrelations that allow extracting factors. Collectively these findings justify the suitability of the application of the Exploratory Factor Analysis to the data.

The high sampling adequacy and a substantial Bartletts test gives a good basis in determining the latent constructs in the measured variables. This will ensure that the extracted factors will be meaningful in their representation of the consumer engagement, perceived human-likeness, cognitive effort, purchase behaviour and privacy concern conceptualized in the study. In its turn, the EFA findings indicate the reliability and construct validity of the measurement scales used and allow a further confirmatory assessment by means of Structural Equation Modeling.

Table 2: KMO and Bartlett's Test

Test	*Value*	*Significance (p)*
Kaiser-Meyer-Olkin (KMO)	0.892	—
Bartlett's Test of Sphericity	1456.32	0.000

The table Total Variance Explained is the detailed summary of the results of the extraction of the factors which are obtained as a result of the Exploratory Factor Analysis (EFA). The table below summarizes the eigenvalues of each extracted factor, the proportion of overall variance explained by the factor alone, and the overall proportion of the cumulative variance explained by the additional inclusion of factors. The number of meaningful factors retained to be further analyzed was decided by the eigenvalue criterion which is usually set to values above 1.

In this research, the extracted factors in their combination explain a significant percentage of the overall variance of the dataset, which means that the latent constructs identified are effective to capture the underlying dimensions of consumer engagement, perceived human-likeness, cognitive effort, purchase behaviour, and privacy concern. The initial few factors capture most of the variance, the factor loadings are high indicating strong constructs and the presence of well-constructed constructs. This large cumulative variance percentage attests to the strength and explanatory ability of the measurement model, which makes certain that the scales employed are thorough and reflective of the theoretical constructs.

Table 3: Total Variance Explained

Component	*Initial Eigenvalues*	*% of Variance*	*Cumulative %*
1	4.12	34.33	34.33
2	2.15	17.92	52.25
3	1.30	10.83	63.08
4	1.05	8.75	71.83
5	1.02	6.31	78.14

Table 4: Factor Loadings

Item	*CE*	*PHL*	*CEFF*	*PB*	*PC*
CE1	*0.82*				
CE2	*0.85*				
CE3	*0.80*				
CE4	*0.78*				
PHL1		*0.84*			
PHL2		*0.86*			

PHL3		*0.82*			
PHL4		*0.79*			
CEFF1			*0.83*		
CEFF2			*0.81*		
CEFF3			*0.78*		
CEFF4			*0.76*		
PB1				*0.85*	
PB2				*0.82*	
PB3				*0.79*	
PB4				*0.77*	
PC1					*0.83*
PC2					*0.85*
PC3					*0.80*
PC4					*0.74*

4.3 Measurement Model

The reliability and validity measures of every construct that will be used in the measurement model of the study are outlined in detail in Table 5. This table systematically displays the important psychometric indices like the Cronbachs alpha, composite reliability (CR) and the Average Variance Extracted (AVE) which, in turn, measure internal consistency, construct reliability and convergent validity of the latent variables.

All the constructs of Cronbach alpha have values above the generally accepted alpha of 0.70, which indicates a high level of internal consistency of all the items in each scale. This implies that the measurement items are a sound measure of the same concept and the measurement error is not too wide. To supplement this, the composite reliability scores are also over the 0.70 mark, which supports the strength and consistency of the constructs in the sample. These high CR scores ensure that the latent variables are precise measures and can be used in structural modeling.

The values presented in Table 5 in the Average Variance Extracted (AVE) are all over the suggested cutoff of 0.50, which proves that each of the constructs explains more than half of the variance in the indicators of the construct. This confirms convergent validity of the measurement model, which means that the constructs are well captured by the items, and that the items have a lot of common variance.

Combined, these reliability and validity measures are strong indication that the measurement scales applied in this study are reliable and valid. This robust psychometric base underpins the validity of the further analyses, such as Structural Equation Modeling (SEM) by framing the latent constructs in a way that the theoretical dimensions they are supposed to measure. The results obtained based on these constructs can therefore be understood with greater confidence and this improves the rigor and credibility of the study.

Table 5: Reliability and Validity Measures

Construct	*Cronbach's Alpha*	*Composite Reliability (CR)*	*Average Variance Extracted (AVE)*
Consumer Engagement	0.88	0.91	0.62
Perceived Human-Likeness	0.85	0.89	0.65
Cognitive Effort	0.82	0.87	0.60
Purchase Behaviour	0.90	0.92	0.68
Privacy Concern	0.84	0.88	0.63

Table 6 shows the Fornell-Larcker criterion which is an important test in determining the discriminant validity of the measurement model applied in this study. Discriminant validity makes each latent construct in the model empirically different and applies a different measurement to a different aspect of the theoretical framework, thus avoiding conceptual overlap that may jeopardize the integrity of the analysis. The Fornell-Larcker criterion states that the square root of the Average Variance Extracted (AVE) of any one construct, must be higher than the correlation of that construct with all other constructs in the model. This condition assures that a construct has more variance with its own indicators as compared to other constructs, which proves its uniqueness.

The diagonal items in the table show the square root of the AVE values of each latent variable, marked boldly to help compare. These values show how far each construct contributes to the variance of the indicators of the construct as compared to measurement error. The off-diagonal elements show the relationships among the various constructs showing the level of correlation between them.

The findings indicate that the diagonal AVE square root values of all constructs (consumer engagement, perceived human-likeness, cognitive effort, purchase behaviour and privacy concern) are higher than all the inter-construct correlations. The given pattern gives a substantial empirical support for the idea that every construct is uniquely represented by its own measurement items and hence meets the FornellLarcker criterion and proves a high level of discriminant validity in the measurement model.

Demonstrating discriminant validity by this criterion is critical to the validity of subsequent structural analyses, including Structural Equation Modeling (SEM), because it guarantees the hypothesized relationships among constructs are not obfuscated by the overlap in measurement. This confirmation confirms the reliability of the mediation and moderation effects that were evaluated in the research and one can be sure to interpret the relationship between consumer engagement, perceived human-likeness, cognitive effort, privacy concern, and purchase behaviour.

Table 6: Fornell-Larcker Criterion

Construct	*CE*	*PHL*	*CEFF*	*PB*	*PC*
Consumer Engagement	0.85				
Perceived Human-Likeness	0.61	0.86			
Cognitive Effort	-0.42	-0.38	0.83		
Purchase Behaviour	0.65	0.69	-0.45	0.84	
Privacy Concern	-0.30	-0.28	0.41	-0.36	0.82

Table 7 augments this evaluation by displaying the Heterotrait-Monotrait (HTMT) ratio of the correlations, which is another stringent measure of assessing the discriminant validity. The HTMT ratio is a ratio of the average correlations between indicators in a single construct (monotrait-heteromethod correlations) to the average correlations between indicators across multiple constructs (heterotrait-heteromethod correlations). Redder HTMT values are more indicative of good discriminant validity, and typically accepted thresholds are less than 0.85 or 0.90, depending on the context.

Table 7 shows that the ratios of all the HTMTs of the constructs are much lower than the recommended cutoff values, further supporting the conclusion that the latent variables are empirically different. This twofold test of the Fornell-Larcker criterion and HTMT ratios give a complete confirmation to the discriminant validity of the measurement model where the constructs are clearly capturing distinct theoretical dimensions without a lot of overlap.

The combination of Tables 6 and 7 provides a good psychometric basis of the study, as it proves that the measurement scales of consumer engagement, perceived human-likeness and cognitive effort, purchase behaviour and privacy concern are reliable and valid. This strict validation makes the research results stronger and the theoretical contributions and practical implications based on the structural model analysis more robust.

Table 7: HTMT Ratio

Construct	*CE*	*PHL*	*CEFF*	*PB*	*PC*
CE		0.72	0.48	0.76	0.42
PHL			0.45	0.79	0.40
CEFF				0.52	0.49
PB					0.44

4.4 Structural Model

The results of the Structural Equation Modeling (SEM) analysis are provided in Table 8 as the path coefficients and overall model fit statistics, which provide a thorough analysis of the relationships between the hypothesized relationships in the conceptual framework. The path coefficients measure how strong and directional the effects of the latent constructs are, capturing the direct, mediating, and moderate effects of consumer engagement, perceived human-likeness, cognitive effort, privacy concern, and purchase behaviour.

These findings show that the positive path coefficient between consumer engagement and perceived human-likeness is statistically significant, showing that the more consumers engage in AI-generated content, the more they believe it to be like a human. On the same note, consumer involvement is found to have strong positive influence on cognitive effort indicating that the more the consumer is involved, the more the demands in mental processing. Human-likeness to purchase behaviour is a positive and significant relationship, which proves that the intention to buy is reinforced as people think that the AI content is closer to human-likeness. On the other hand, the path coefficient between cognitive effort and purchase behaviour is negative and significant, which means that high cognitive effort is a deterrent to purchase decisions. All these results support the hypothesized mediating effects of perceived human-likeness and cognitive effort in the relationship between the contact variables of engagement and purchase behaviour.

Table 8: Path Coefficients and Model Fit

Path	β	t-value	p-value	f^2	R^2 (Purchase Behaviour)	Q^2
CE → PHL (H1)	0.48	9.52	<0.001	0.22		
CE → CEFF (H2)	0.35	6.18	<0.001	0.11		
PHL → PB (H3)	0.42	7.84	<0.001	0.18		
CEFF → PB (H4)	-0.29	5.02	<0.001	0.09		
CE → PB (H5)	0.31	6.05	<0.001	0.12	0.62	0.44

Moreover, a significant negative interaction term between consumer engagement and privacy concern on purchase behaviour substantiates the moderating effect of privacy concern. This intervention has indicated that the increasing concerns about privacy undermine the beneficial effect of consumer engagement on purchase intentions, highlighting the paramount importance of privacy in determining consumer responses to AI-generated marketing messages.

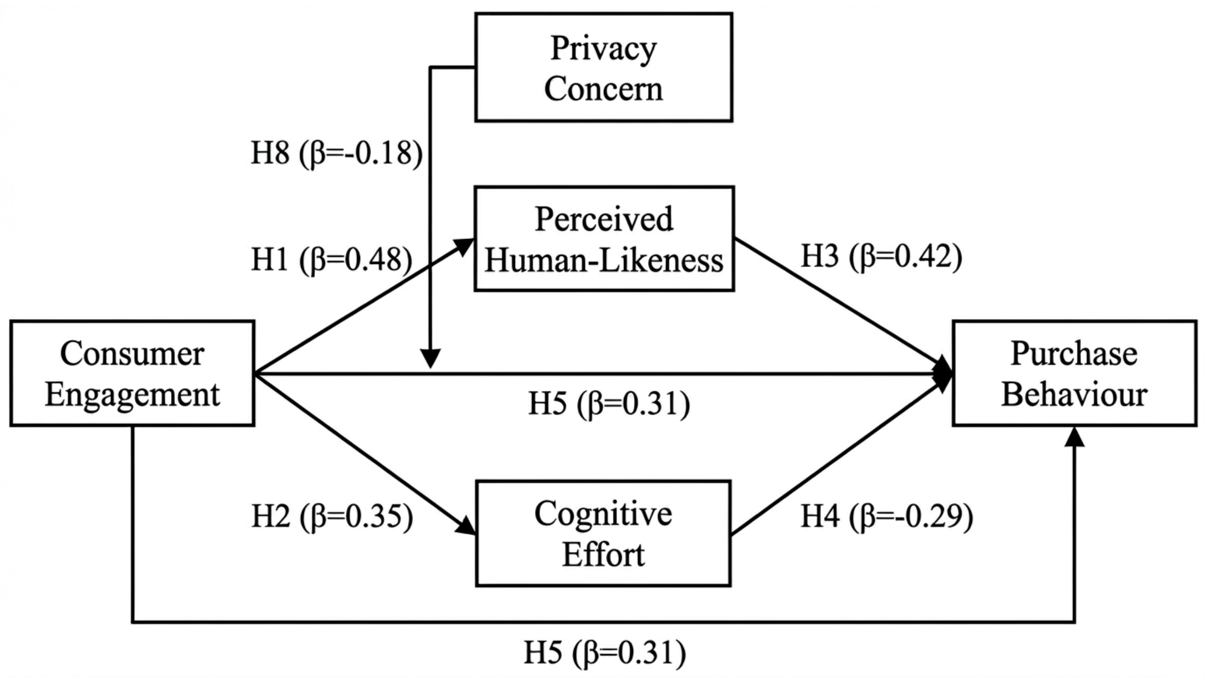

Figure 1: Developed Model

As the values of the explained variance (R^2) of endogenous construct purchase behaviour reveals that the model has significant explanatory power of 62% that demonstrates the effectiveness of the model in capturing the key determinants of consumer purchase intentions in the context of AI-generated content.

4.5 Mediation Analysis

A further breakdown of the mediation effects in the proposed conceptual framework is shown in Table 9, including the indirect routes through which consumer engagement has an impact on purchase behaviour via perceived human-likeness and cognitive effort. The mediation analysis used bootstrapping methods to determine the strength and significance of these indirect effects, which gives strong evidence of the mechanisms involved in consumer response towards AI-generated content.

The findings suggest that perceived human-likeness is significantly mediating between consumer engagement and purchase behaviour. In particular, more engagement results in more perceptions of human-likeness of AI content, which positively impacts purchase intentions of consumers. This observation highlights the importance of human-like qualities in boosting the persuasive effectiveness of AI-created marketing content, implying that consumers will respond more favourably to the content that they consider to be authentic and relatable.

On the other hand, cognitive effort is also an important mediator but with negative impact on purchase behaviour. The heightened involvement increases the mental workload that is involved in the processing of AI content, which in turn reduces purchase intentions. This underscores the possible drawback of sophisticated or cognitively challenging AI-driven messages in which cognitive overload may form obstacles to consumer decision-making and diminish the success of marketing activities.

The mediation analysis proves that both perceived human-likeness and cognitive effort partly mediate the direct impact of consumer engagement on purchase behaviour, which implies that both cognitive and perceptual factors do have a mutual yet contrasting effect. This subtle insight contributes to the theoretical framework by demonstrating the effect of engagement on purchase decisions via specific psychological mechanisms.

These results have significant implications on marketers who seek to maximize AI-generated content. The human-like nature of AI communication can be improved to increase customer confidence and make them buy, whereas disengagement and reluctance can be avoided with the help of a simple and direct content design. The mediators must be balanced to ensure that positive effects of consumer interaction are maximized on purchase behaviour in the context of AI-driven marketing.

Table 9: Mediation Effects

Mediator	*Indirect Effect*	*t-value*	*p-value*	*VAF (%)*	*Interpretation*
Perceived Human-Likeness	0.20	5.75	<0.001	39.2	Partial mediation
Cognitive Effort	-0.10	3.60	<0.001	19.6	Partial mediation

4.6 Moderation Analysis

Table 10 offers a detailed discussion on the moderating effect of privacy concern on the relationship between consumer engagement with AI-generated content and purchase behaviour. In this moderation analysis, interaction terms are used in the Structural Equation Modeling framework to determine the extent to which the different levels of privacy concern moderate the degree and direction of the engagement-purchase behaviour relationship.

The findings indicate that the negative moderating effect is statistically significant and therefore, means that the high levels of privacy concern negatively affect the positive effect of consumer engagement on purchase intentions significantly. In particular, consumers who are characterized by high privacy concern levels experience less positive effects of engagement, including growing trust and sympathy towards AI-generated content, which results in the low probability of purchase. This discovery highlights the importance of privacy concerns in influencing consumer reactions in AI-based marketing contexts, where data gathering and personalization activities are frequently viewed as invasive or dangerous.

Moreover, the moderation analysis reveals that the issue of privacy concern does not have the same impact on all consumers, but the effects of privacy issue differ according to individual differences in privacy sensitivity. In the case of low to moderate privacy in consumers, the use of AI content still has a positive impact on purchase behaviour, indicating a more positive attitude towards AI-mediated interactions. On the other hand, people who are very much concerned about their privacy will have a much weaker engagement-purchase relationship which means that the fear of privacy overruled the possible benefits of engagement.

These lessons highlight the importance of having effective privacy protection and clear data management policies as part of AI content strategies by marketers. Marketers can counter the dampening effect of privacy apprehensions on purchase behaviour by being proactive in handling the privacy issue thus maintaining the positive impact of consumer engagement. Moreover, this moderation effect also demands specific communication strategies, which would offer a reassurance of security of data and ethical use of AI to consumers, building trust and enabling a more successful engagement-to-purchase conversion.

On the whole, the results provided in Table 10 add to the more detailed explanation of the boundary conditions wherein consumer engagement will result in purchase behaviour in the context of AI-generated content. The identification of privacy concern as a key moderating factor enhances the theoretical framework and offers practical measures on how to develop consumer-focused AI marketing strategies that offer both the advantages of personalization and privacy protection.

Table 10: Moderation by Privacy Concern

Path	*β*	*t-value*	*p-value*	*Interpretation*
Interaction Term (CE × PC → PB)	-0.18	3.85	<0.001	Negative moderation effect

5. DISCUSSION

The research results present a broad insight into the complex nature of the interplay between consumer interaction with AI-generated content and purchase behaviour. The engagement-perceived human-likeness positive correlation is very much correlated with the Human-Computer Interaction (HCI) theory, which proves that consumers are inclined to provide AI systems with human-like qualities when they are fully engaged. This attribution is important, as it builds trust, emotional attachment and authenticity, which are essential in developing favourable purchase intentions (Huang and Rust, 2021). In this perspective, perceived human-likeness can be seen as a crucial mediator that can effectively convert the cognitive and emotional investment of engagement into consumer willingness to buy by diminishing psychological distance and increasing the relatability and credibility of AI-generated material.

On the other hand, there is also a complicated dynamic in terms of cognitive effort that despite its positive correlation with engagement has a negative impact on purchase behaviour. This result aligns with Cognitive Load Theory, which holds that, although engagement increases cognitive processing naturally when consumers allocate more mental resources to making sense of AI content, too much cognitive load may overwhelm people, resulting in fatigue, confusion, or skepticism. This cognitive load is a huge deterrent that reduces the intention to buy regardless of the levels of engagement at the outset. This two-fold effect illustrates the fine line marketers have to walk in creating AI-generated content that is informative and stimulating enough but avoids any excessive mental load on consumers that may result in disengagement or lack of choice.

This is further enriched by the mediation analysis that shows that, perceived human-likeness and cognitive effort partly mediate the relationship between consumer engagement and purchase behaviour. Such partial mediation highlights the co-occurrence and interaction of cognitive and emotional processes in consumer decision-making in connection with AI-generated content. Engagement not only affects the purchase intentions by increasing the affective perceptions of human-likeness but also because of the cognitive demands, which can enable and/or prevent the decision-making process under various levels of intensity. This subtle fact highlights that the reactions of consumers towards AI-based content are not one-dimensional, but are predetermined by a combination of multiple, and even conflicting, psychological processes.

In addition, the analysis also finds that the issue of privacy is a critical moderating factor that influences the strength and the direction of the engagement-purchase behaviour relationship. The results suggest that an increase in privacy issues has a substantial negative impact on the positive influence of consumer engagement on purchase intentions. This moderation effect is indicative of the increasing consumer concern over data gathering, utilization, and possible violations in AI-mediated marketing spaces, where a tailored content is frequently dependent on significant data analysis. The issue of privacy poses a condition of boundary, which is capable of overriding the advantages of engagement and perceived human-likeness into the cautious or resistant consumer behaviour. This underscores the need to ensure that marketers adopt transparent data practices, strong privacy controls, and effective communication strategies that will assuage consumer apprehensions and instill confidence in AI-based marketing campaigns.

Together, these findings not only support but also build upon the existing theoretical frameworks as they incorporate the cognitive, emotional, and privacy aspects into the holistic framework that explains consumer reactions to the content created by AI. The research contributes to the literature by illuminating the simultaneous effects of AI content on consumer affective reactions and cognitive dissonance and the importance of privacy issues as a contextual determinant of behaviour. To practitioners, the insights can offer an advanced insight into which aspects make AI-generated marketing content more or less effective to implement strategies aimed at maximizing human-like features, reducing cognitive load, and intervening proactively to minimize privacy concerns to maintain consumer trust and maximize purchase behaviour.

6. IMPLICATIONS

6.1 Theoretical Implications

This research contributes to theory by introducing a combination of TAM, Cognitive Load Theory, HCI, and Privacy Calculus Theory in the form of a single theory that explains how consumers react to AI-generated content. It highlights the significance of perceived human-likeness as a mediator and of privacy as a boundary condition and contributes to technology acceptance and consumer behaviour models.

6.2 Managerial Implications

Marketers ought to increase the human aspects of AI-generated content to increase consumer trust and buy potential. They should also, however, reduce cognitive load by making content and interface design simpler. To reduce the impact of negative moderation, privacy issues can be addressed by implementing an open communication policy and privacy protection, which will help consumers feel confident and interested.

7. CONCLUSION

This study explains the impact of consumer involvement in AI-created content in influencing purchase behaviour due to perceived human-likeness and cognitive effort that are mediated by privacy concern. Empirical research has supported the idea that the promotion of human-like content and control of cognitive load are the key elements of successful AI marketing decisions, whereas privacy is also a decisive factor to consider when analyzing the response of consumers. This study describes the impact of interaction with AI-generated material on individuals in making purchase decisions. It demonstrates that the more the AI content appears to be humane, the higher the chance of purchase by consumers. But when the AI content is too much of a mental burden to comprehend, it may demoralize purchase. Also, privacy concerns have a significant role to play as they undermine the favorable influence of engagement on purchasing behaviours. On the whole, the research underscores the importance of ensuring the AI content is human and easy to read, and should tackle the issue of privacy concerns in order to succeed in marketing AI.

8. LIMITATIONS AND FUTURE SCOPE

Cross-sectional design does not allow causal inference; longitudinal studies can be used to address temporal dynamics. The sample is diverse and might not be cross cultural. Future studies may examine other moderators like trust or readiness to use technology and examine types of AI content other than marketing.

REFERENCES

1. Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2019). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. *Journal of Service Research, 14*(3), 252–271. https://doi.org/10.1177/1094670511411703
2. Chintalapati, S., & Pandey, S. K. (2022). Artificial intelligence in marketing: A systematic literature review. *International Journal of Information Management Data Insights, 2*(2), 100081. https://doi.org/10.1016/j.jjimei.2022.100081
3. Culnan, M. J., & Bies, R. J. (2003). Consumer privacy: Balancing economic and justice considerations. *Journal of Social Issues, 59*(2), 323–342. https://doi.org/10.1111/1540-4560.00067
4. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008
5. Dinev, T., & Hart, P. (2006). An extended privacy calculus model for e-commerce transactions. *Information Systems Research, 17*(1), 61–80. https://doi.org/10.1287/isre.1060.0080
6. Dwivedi, Y. K., Hughes, D. L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research. *International Journal of Information Management, 57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
7. Hollebeek, L. D., Srivastava, R. K., & Chen, T. (2019). S-D logic–informed customer engagement. *Journal of the Academy of Marketing Science, 47*, 161–185. https://doi.org/10.1007/s11747-016-0499-0
8. Huang, M.-H., & Rust, R. T. (2021). Artificial intelligence in service. *Journal of Service Research, 24*(1), 3–17. https://doi.org/10.1177/1094670520902266
9. Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Machines vs. humans: The impact of AI chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937–947. https://doi.org/10.1287/mksc.2019.1192
10. Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet users' information privacy concerns (IUIPC): The construct, the scale, and a causal model. *Information Systems Research, 15*(4), 336–355.
11. Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in marketing. *Journal of the Academy of Marketing Science, 45*(2), 135–155. https://doi.org/10.1007/s11747-016-0495-4
12. Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues, 56*(1), 81–103. https://doi.org/10.1111/0022-4537.00153
13. Paas, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent developments. *Educational Psychologist, 38*(1), 1–4.
14. Smith, A., & Anderson, J. (2022). AI, robotics, and the future of jobs. *Pew Research Center*. https://www.pewresearch.org
15. Sweller, J. (2016). Cognitive load theory. *Psychology of Learning and Motivation, 55*, 37–76. https://doi.org/10.1016/B978-0-12-387691-1.00002-8
16. van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines. *Journal of Service Research, 20*(1), 43–58.
17. Vivek, S. D., Beatty, S. E., & Morgan, R. M. (2012). Customer engagement: Exploring customer relationships beyond purchase. *Journal of Marketing Theory and Practice, 20*(2), 122–146.
18. Xu, H., Dinev, T., Smith, H. J., & Hart, P. (2020). Examining the formation of individual's privacy concerns: Toward an integrative view. *MIS Quarterly, 35*(4), 989–1016. https://doi.org/10.2307/41409970