Accountancy Business and the Public Interest
ISSN: 1745-7718

Special Issue
Theme 2 August 2025

ARTIFICIAL AUTHENTICITY? THE IMPACT OF HUMANISED AI CONTENT ON BRAND TRUST AND CUSTOMER LOYALTY

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Abstract

The use of Artificial Intelligence (AI) in marketing has rapidly improved the interactions between brands and consumers, and at the same time has raised issues regarding the reliability of AI-generated content and how it affects brand loyalty. This study focuses on how marketing strategies that utilize AI technology require greater empathy, anthropomorphism, intelligence, and transparency to transform consumer engagement and perception of the brands. It analyzes the impact of perceived authenticity, brand trust, and their influence on customer loyalty to brands using Humanised AI content. To validate the proposed conceptual model, data was gathered from 411 respondents using a survey and analyzed through Smart PLS (PLS-SEM) with a set quantitative model. Results show that humanised AI content impacts authenticity and trust. Trust depended on the level of authenticity presented and in turn impacted loyalty to the brand. The study maintains the importance of human touch alongside automation in AI technology to create and maintain authenticity to brand relationships. This research highlights practical strategies for incorporating automated AI systems alongside human elements to strengthen trust and loyalty to the brand. Further research could focus on specific industries and the shifts in consumer sentiment over time.

Keywords: Humanised AI content, Perceived Authenticity, Brand Trust, Smart PLS, Customer Loyalty, Perceived Anthropomorphism, Perceived Intelligence, Perceived Transparency, Perceived Empathy.

INTRODUCTION

The adoption of Artificial Intelligence (AI) in marketing practices has transformed brand-consumer relationships by providing unparalleled personalization and operational efficiencies (Davenport et al., 2020). On the other hand, this technological change has also raised major issues regarding the trustworthiness of content created by AI, including its impacts on brand reputation and customer loyalty (Longoni et al., 2019). With the widespread adoption of AI-powered marketing techniques, there is more than a growing tendency to incorporate empathy, anthropomorphism, intelligence, and transparency to these interactions (Cheng et al., 2022). This investigation aims to determine the effects of humanized AI content on consumer perception and engagement, particularly focusing on perceived authenticity, brand trust, and customer loyalty. Perceived authenticity is a key construct in this research because it indicates the degree to which consumers view AI-created content as legitimate and trustworthy (Morhart et al., 2015). In a world where interactions are heavily automated, authenticity becomes extremely significant (Grayson & Martinec, 2004). Brands can strengthen emotional attachment by incorporating anthropomorphic elements and transparent communications into AI content which increases the perceived authenticity (Mende et al., 2019).

Brand trust, which is another important variable, is vital for managing consumer relationships over time (Chaudhuri & Holbrook, 2001). Trust is developed when consumers are confident a brand is looking out for them and that the brand will keep its promises (Morgan & Hunt, 1994). In AI automation marketing, trust may erode if consumers view interactions with AI as cold, robotic, or manipulative (Castelo et al., 2019). On the other hand, if AI content is anthropomorphized, it may alleviate these issues because consumers expect meaningful interactions that are genuine (van Doorn et al., 2017).

The most significant outcome variable for this study, customer loyalty, is further developed by the perceived authenticity and trust placed on the brand (Oliver, 1999). Loyal consumers tend to make repeat purchases, recommend the brand to others, and are less likely to shift to competing brands (Reichheld & Teal, 1996). In the age of AI marketing, nurturing loyalty is a challenging equilibrium between mechanization and human interaction (Huang & Rust, 2021). This study argues that anthropomorphized AI content can foster loyalty by increasing perceived authenticity and brand trust. Data was gathered from 411 individuals using a quantitative approach and evaluated through Partial Least Squares Structural Equation Modeling (PLS-SEM) to validate the proposed conceptual model. Results indicate that humanized AI content improves perceived authenticity, which increases brand trust, and in turn, enhances consumer loyalty. These findings emphasize the need to apply AI technologies with a humanistic approach to ensure authenticity and strengthen brand loyalty. This research contributes to the growing body of literature on AI in marketing by highlighting the critical role of humanization in enhancing consumer perceptions and engagement. It offers practical insights for marketers on how to design AI-driven strategies that resonate with consumers on a human level. Further research could examine the use of humanized AI marketing in particular industries and analyze the gradual changes in sentiment toward AI-generated content over time.

LITERATURE REVIEW

The adoption of AI technologies in marketing and customer service, among other domains, is transforming the field at a staggering rate. This transformation has created a gap in understanding the determinants of user adoption that AI content generation systems users interact with. This literature review aims to address gaps in studies by examining the concepts of perceived anthropomorphism, perceived empathy, perceived intelligence, perceived transparency, perceived authenticity, brand trust, and customer loyalty with respect to Zhou and Lu's (2025) interactions of AI and humans.

Perceived Anthropomorphism

Perceived anthropomorphism describes the degree to which users assign human features to AI systems (Epley et al., 2007). Unlike traditional forms of technology, AI is able to engage users on a personal level, creating a unique experience which expands with advanced anthropomorphic designs (Waytz et al., 2014). However, excessive anthropomorphism may lead to unrealistic expectations, as users might expect AI to exhibit human-like emotional understanding and responsiveness (Mende et al., 2019). Zhou and Lu (2025) emphasize that perceived anthropomorphism has a positive impact on trust in AI systems, as people are more apt to interact with systems that enact human behaviors. This trust, however, is conditional as the AI system needs to perform according to user expectations, since gaps between expectations and reality can diminish trust (Castelo et al., 2019; Cheng et al., 2022).

Perceived Empathy

Users of AI systems expect to be empathized with, which means the AI has to recognize and adequately respond to the user’s emotional needs (van Doorn et al., 2017). Empathy is imperative for the AI systems because it enables the users to connect with the technology on a deeper level and hence trust the AI systems (Mende et al., 2019). Zhou and Lu (2025) state that AI systems offering personalized, emotionally aware interactions are likely to earn trust and will be adopted by users. However, perceived empathy’s effectiveness is contingent upon the authenticity of the AI’s responses. Users are likely to dismiss empathy that appears to be emotionally scripted and insincere (Grayson & Martinec, 2004).

Perceived Intelligence

Perceived intelligence showcases the user's evaluation of the AI's task performance and information relevance (Huang & Rust, 2021). A greater level of perceived intelligence results in greater user trust. Users are more inclined to depend on AI systems that are believed to be competent and reliable (Gefen et al., 2003). Zhou and Lu (2025) argue that perceived intelligence is one of the primary factors driving user adoption, especially where AI content is used for decision making or problem solving. However, the study also notes that perceived intelligence must be balanced with transparency to avoid user skepticism about the AI's decision-making processes (Castelo et al., 2019).

Perceived Transparency

Perceived transparency means a user's understanding of the functioning of an AI system, its data sources, algorithms, and its decision-making processes (Shin, 2021). In order to have trust, the AI should reduce the uncertainty by providing information that enables the user predict its reliability (Kizilcec, 2016). Zhou and Lu (2025) state that AI systems are more likely to be accepted and trusted by the users if the users feel that they have enough control and information about the AI system which gives them knowledge about what is taking place within the AI algorithms and the actions of the AI. However, excessive transparency can overwhelm users with technical details, highlighting the need for a balanced approach (Shin, 2021).

Perceived Authenticity

Perceived authenticity captures the degree of deemed genuineness, credibility, and resonance to expectations that users hold towards an AI-generated content (Morhart et al., 2015). Authenticity is a basic construct of trust and users are much more likely to interact with content that is processed as real and trustworthy (Grayson & Martinec, 2004). Zhou and Lu (2025) argue that there must be a balance on automation and human like authenticity for an AI system to be trusted and adopted. This requires that AI-generated content be relevant, resonate emotionally, and does not manipulate the audience (Longoni et al., 2019).

Brand Trust

Brand trust is the user's confidence in a brand's reliability, integrity, and commitment to fulfilling its promises (Chaudhuri & Holbrook, 2001). In the context of AI-generated content, brand trust is influenced by the perceived anthropomorphism, empathy, intelligence, transparency, and authenticity of the AI system (Zhou & Lu, 2025). Trust is a critical mediator between user perceptions and adoption, as users are more likely to engage with brands they perceive as trustworthy (Morgan & Hunt, 1994). Zhou and Lu (2025) emphasize that building brand trust requires consistent and transparent AI practices that align with user expectations.

Customer Loyalty

Customer loyalty denotes a customer's commitment to a certain brand over a long period of time, such as repeat purchases, referrals to other customers, and brand retention (Oliver, 1999). For AI generated content, loyalty is fostered by trust, authenticity, and positive user interaction (Zhou & Lu, 2025; Cheng et al., 2022). Loyalty in this instance is also shaped by emotional attachments created by AI systems (Mende et al., 2019). According to Zhou and Lu (2025), brands in the AI field need to focus on building and maintaining user trust and brand authenticity in order to achieve loyalty. Perceived anthropomorphism, empathy, intelligence, transparency, authenticity, brand trust, and customer loyalty share interrelations that produce synergistic results which are vital in the user adoption process of AI generated content. These relationships are investigated by Zhou and Lu (2025) as they study the impact of these constructs on trust and adoption highlighting the importance to AI systems of balancing automation and humanlike features.

RESEARCH GAPS

Limited Studies in the Indian Context

The only available literature on marketing AI systems and consumer trust seems to focus on the West ignoring India's culture, language, and technology. There is a need to investigate how Indian customers form trust toward, and loyalty with, brands that use AI technologies for content creation in terms of trust and authenticity.

Perceived Authenticity: More research is required on humanized AI content and its perceived authenticity. Marketers, as well as AI developers, need a more detailed model that combines a humanized AI content and authenticity with brand trust and customer loyalty in order to take informed decisions.

HYPOTHESIS DEVELOPMENT

H1: Humanised AI Content significantly influences Brand Trust

Theoretical Basis:

- **Social Exchange Theory (SET)**: This theory posits that trust is built through repeated interactions and the fulfilment of expectations (Blau, 1964). Humanised AI content, which incorporates empathy, anthropomorphism, intelligence, and transparency, creates a sense of familiarity and reliability, fostering trust in the brand.
- **Technology Acceptance Model (TAM)**: TAM suggests that perceived usefulness and ease of use influence trust in technology (Davis, 1989). Humanised AI content enhances perceived usefulness by making interactions more relatable and intuitive, thereby increasing brand trust.
- **Anthropomorphism Theory**: When AI systems exhibit human-like traits, users are more likely to trust them, as they perceive them as more predictable and understandable (Waytz et al., 2014).

Humanised AI content, by mimicking human traits and behaviors, reduces the perceived uncertainty and risk associated with AI interactions, leading to higher brand trust.

H2: Humanised AI Content significantly influences Perceived Authenticity

Theoretical Basis:

- **Authenticity Theory**: Authenticity is perceived when an entity is seen as genuine, credible, and true to its purpose (Morhart et al., 2015). Humanised AI content, through empathetic and transparent interactions, aligns with consumer expectations of authenticity.
- **Signaling Theory**: Humanised AI content acts as a signal of the brand's commitment to creating meaningful and genuine interactions, enhancing perceived authenticity (Spence, 1973).
- **Human-Computer Interaction (HCI)**: Research in HCI suggests that systems designed to reflect human values and emotions are perceived as more authentic (Fogg, 2003).

By incorporating human-like qualities, humanised AI content signals genuineness and credibility, leading consumers to perceive the brand as more authentic.

H3: Perceived Authenticity significantly influences Brand Trust

Theoretical Basis:

- **Trust-Authenticity Framework**: Authenticity is a key antecedent of trust, as consumers are more likely to trust brands that they perceive as genuine and transparent (Grayson & Martinec, 2004).
- **Social Identity Theory**: Consumers identify with brands that reflect their values and beliefs, and authenticity strengthens this identification, fostering trust (Tajfel & Turner, 1979).
- **Relationship Marketing Theory**: Trust is built through consistent and authentic interactions, which reinforce the brand's credibility and reliability (Morgan & Hunt, 1994).

When consumers perceive a brand as authentic, they are more likely to trust its intentions and actions, leading to stronger brand trust.

H4: Perceived Authenticity significantly influences Customer Loyalty

Theoretical Basis:

- **Commitment-Trust Theory**: Trust and authenticity are critical drivers of customer loyalty, as they foster emotional commitment to the brand (Morgan & Hunt, 1994).
- **Customer Loyalty Theory**: Authenticity enhances emotional attachment and satisfaction, which are key predictors of loyalty (Oliver, 1999).
- **Brand Relationship Theory**: Authentic brands create deeper emotional connections with consumers, leading to long-term loyalty (Fournier, 1998).

Perceived authenticity strengthens emotional bonds between consumers and brands, increasing the likelihood of repeat purchases and positive word-of-mouth, thereby enhancing customer loyalty.

H5: Brand Trust significantly influences Customer Loyalty

Theoretical Basis:

- **Commitment-Trust Theory**: Trust is a foundational element of customer loyalty, as it reduces perceived risk and fosters long-term relationships (Morgan & Hunt, 1994).
- **Relationship Marketing Theory**: Trust enhances customer satisfaction and commitment, which are critical for loyalty (Berry, 1995).
- **Consumer Behavior Theory**: Trust reduces uncertainty and increases confidence in the brand, leading to repeat purchases and loyalty (Chaudhuri & Holbrook, 2001).

When consumers trust a brand, they are more likely to remain loyal, as trust reduces the perceived risk of switching to competitors and reinforces positive brand associations.

RESEARCH METHOD

With the help of Structural Equation Modeling (SEM) and Smart PLS, this research assesses the impacts of humanized AI content on perceived authenticity, brand trust, and customer loyalty through a quantitative lens. The sample of 411 respondents is adequate for testing SEM, offering sufficient statistical power and reliability, while combining convenience and snowball sampling increases accessibility and inclusiveness. SEM allows for the simultaneous examination of multiple relationships, and Smart PLS is chosen for its ability to handle smaller sample sizes and non-normal data, emphasizing predictive accuracy. The use of validated instruments in structured surveys enhances the reliability of the data and enables the determination of how humanized AI content impacts consumer perception and behavior. This methodology ensures a robust and comprehensive analysis, offering valuable insights for both academia and industry.

DATA COLLECTION

The study uses a structured questionnaire with a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree). Humanised AI Content is a second-order construct comprising four dimensions: Perceived Anthropomorphism, Perceived Empathy, Perceived Intelligence, and Perceived Transparency.

Construct	Dimensions/Items	Source
Humanised AI Content	Second-order construct with 4 LOC	
1. Perceived Anthropomorphism		Waytz, Cacioppo, & Epley (2010)
PAN1	This brand’s AI-driven systems make data-informed decisions with clear intentions.	
PAN2	This brand’s AI operates autonomously within set parameters to enhance customer experience.	
PAN3	This brand’s AI personalizes interactions in a way that mimics human-like emotions.	
PAN4	This brand’s AI is conscious in improving customer engagement.	
PAN5	This brand’s AI adapts to situations proving that it has a mind of its own.	
2. Perceived Empathy		Parasuraman, Berry, & Zeithaml (2002); Azize, Cemal, & Hakanb (2012)
PE1	I receive content from this brand that feels personalized to my preferences.	
PE2	I engage with this brand through AI-driven chatbots.	
PE3	The brand’s chatbots provide accurate responses to my queries.	
PE4	I benefit from this brand’s AI-driven loyalty programs.	
PE5	I feel that this brand uses AI to understand my needs.	
PE6	I find that this brand’s AI-driven recommendations provide good value.	
3. Perceived Intelligence		Priya & Sharma (2023)
PI1	This brand’s AI is capable of completing the tasks submitted by users.	
PI2	This brand’s AI has extensive knowledge to provide accurate information.	
PI3	This brand’s AI is smart.	
4. Perceived Transparency		Calderon, James, & Lowry (2023)
PT1	This brand’s AI provides transparency in how it creates content.	

Construct	Dimensions/Items	Source
PT2	This brand’s AI explains how it personalizes content for users.	
PT3	This brand’s AI makes its processes clear for the users to understand.	
GSV	Overall, the content is clear, thoughtful, and consumer-friendly.	
Perceived Authenticity		Bui et al., 2024; Bruhn, Schoenmüller, Schäfer, & Heinrich (2012)
PAUTH1	The brand’s AI-generated content feels natural.	
PAUTH2	The tone used in the brand’s AI-generated content seems genuine.	
PAUTH3	The brand’s AI-generated content does not feel artificial.	
PAUTH4	The brand’s AI-generated content is consistent with its overall messaging.	
PAUTH5	The brand’s AI-generated content aligns with my previous interactions with the brand.	
Brand Trust		Chaudhuri & Holbrook (2001); Koschate-Fischer & Gartner (2015)
BT1	This is an honest brand.	
BT2	I am confident in this brand’s ability to perform well.	
BT3	I can trust this brand.	
BT4	This brand is reliable.	
BT5	This brand’s products make me feel safe.	
BT6	This brand delivers what it promises.	
Consumer Loyalty		Ismail & Spinelli (2012); Carroll & Ahuvia (2006)
CL1	I intend to continue purchasing from this brand in the future.	
CL2	I would recommend this brand to friends and family.	
CL3	I prefer this brand over its competitors.	
CL4	I feel a strong sense of loyalty toward this brand.	

ANALYSIS

Common Method Bias

Common Method Bias (CMB) is a potential threat to research validity, occurring when variance in data is attributed to the measurement method rather than the constructs being studied. It can lead to spurious relationships and inaccurate conclusions (Podsakoff et al., 2003).

To check for CMB, Harman's Single Factor Test is used. If a single factor explains more than 50% of the variance, CMB is present (Harman, 1976). In this study, the test was conducted on 32 items, and the total variance extracted by one factor was 32.286%, which is below the 50% threshold. Thus, there is no evidence of CMB in the data.

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.331	32.286	32.286	10.331	**32.286**	**32.286**
2	3.251	10.159	42.445			
3	1.548	4.838	47.283			
4	1.360	4.249	51.532			
5	1.184	3.699	55.231			
6	1.016	3.175	58.406			
7	.959	2.997	61.404			
8	.779	2.434	63.837			
9	.699	2.185	66.022			
10	.676	2.113	68.135			
11	.651	2.035	70.170			
12	.640	2.001	72.171			
13	.614	1.919	74.089			
14	.593	1.852	75.942			
15	.583	1.823	77.765			
16	.549	1.715	79.479			
17	.533	1.666	81.146			
18	.515	1.609	82.755			
19	.488	1.525	84.280			
20	.486	1.519	85.800			
21	.462	1.444	87.243			
22	.452	1.413	88.657			
23	.439	1.373	90.030			
24	.429	1.340	91.371			
25	.400	1.250	92.621			
26	.383	1.197	93.817			
27	.381	1.191	95.009			
28	.349	1.091	96.099			
29	.340	1.062	97.161			
30	.326	1.017	98.178			
31	.307	.959	99.138			
32	.276	.862	100.000			
Extraction Method: Principal Component Analysis.						

ANALYSIS OF HIGHER ORDER CONSTRUCTS:

The Disjoint Two-Stage Approach is an alternative to the repeated indicators method for analyzing higher-order constructs (Wetzels et al., 2009). It involves:

1. Stage 1: Lower-Order Components (LOCs)
   - Make a model only with the LOCs (e.g., Perceived Anthropomorphism, Perceived Transparency, Perceived Intelligence, Perceived Empathy).
   - Generate and save latent variable scores for LOCs.
2. Stage 2: Higher-Order Construct (HOC)
   - Use latent variable scores from Stage 1 to model the HOC (e.g., Humanised AI Content).
   - Link the HOC to other constructs to test theoretical relationships.

Validation of Higher-Order Constructs (Chin, 2010):

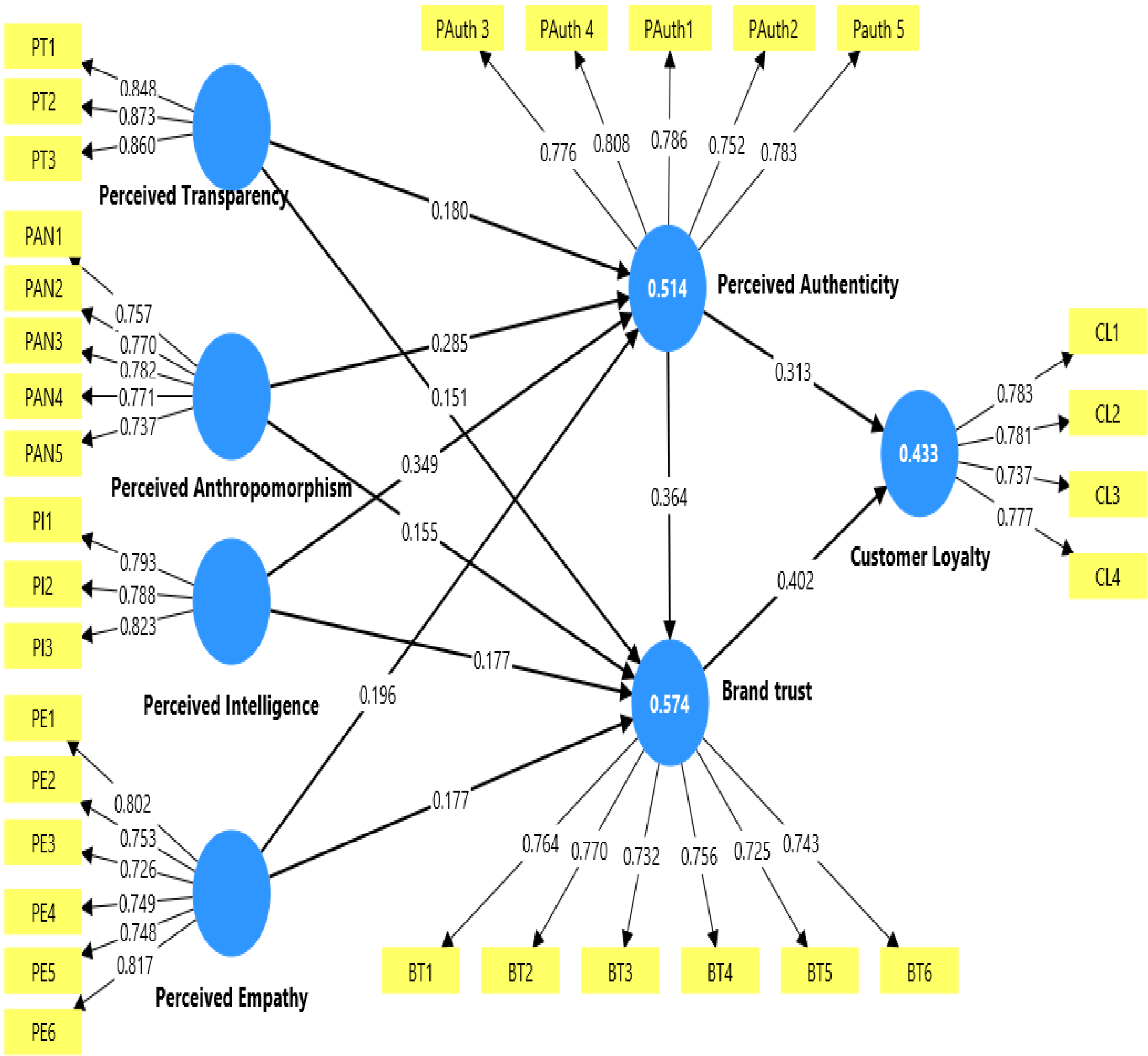
- Stage 1: Assess internal consistency and convergent validity of LOCs using PLS-SEM criteria.
- Stage 2: Evaluate path coefficients for convergent validity (≥ 0.700; Hair et al., 2017), collinearity (VIF), outer loadings, weights, and significance of LOCs. Validate structural model results using path significance, Q^2, and PLS Predict metrics.

Application to Humanised AI Content (HAC):

- Stage 1: Analyze LOCs and their relationships with dependent variables.
- Stage 2: Use latent variable scores to estimate HAC and test its relationships with dependent variables.

This approach ensures rigorous validation of both LOCs and HOC, supporting robust model estimation and validity.

Step 1: All Lower order constructs



Statistical results of the measurements model.

CONSTRUCT	LOADINGS	CRONBACH ALPHA	CR	AVE
HUMANISED AI CONTENT				
Perceived Anthropomorphism		0.822	0.875	0.583
PAN 1	0.757			
PAN 2	0.770			
PAN 3	0.782			
PAN 4	0.771			
PAN 5	0.737			
Perceived Transparency		0.824	0.895	0.740
PT 1	0.848			
PT 2	0.873			
PT 3	0.860			
Perceived Intelligence		0.721	0.843	0.642
PI 1	0.793			
PI 2	0.788			
PI 3	0.823			
Perceived Empathy		0.860	0.895	0.587
PE 1	0.802			
PE 2	0.753			
PE 3	0.726			
PE 4	0.749			
PE 5	0.748			
PE 6	0.817			
PERCEIVED AUTHENTICITY		0.84	0.887	0.610
PAUTH 1	0.786			
PAUTH 2	0.752			
PAUTH 3	0.776			
PAUTH 4	0.808			
PAUTH 5	0.783			
BRAND TRUST		0.843	0.884	0.560
BT 1	0.764			
BT 2	0.770			
BT 3	0.732			
BT 4	0.756			
BT 5	0.725			
BT 6	0.743			
CUSTOMER LOYALTY		0.771	0.853	0.593
CL1	0.783			
CL2	0.781			
CL3	0.737			
CL4	0.777			

Measurement Model Evaluation

Outer Loadings:

All outer loadings surpass the threshold of 0.70, indicating significance and confirming construct validity.

Reliability of Lower-Order Constructs:

Reliability was assessed using Cronbach's Alpha and Composite Reliability (CR), both exceeding the 0.70 threshold (Hair et al., 2011). This ensures the constructs are stable, consistent, and internally reliable.

Construct Validity of Lower-Order Constructs:

- Convergent Validity: Achieved with Average Variance Extracted (AVE) values above 0.50 for all constructs, confirming sufficient convergence (Fornell & Larcker, 1981).

Indicator Multicollinearity (VIF):

Variance Inflation Factor (VIF) values are below the conservative threshold of 3 (Hair et al., 2016), indicating no significant multicollinearity issues.

Outer VIF

	VIF
BT1	1.683
BT2	1.767
BT3	1.585
BT4	1.675
BT5	1.541
BT6	1.633
CL1	1.565
CL2	1.584
CL3	1.370
CL4	1.513
PAN1	1.662
PAN2	1.582
PAN3	1.609
PAN4	1.696
PAN5	1.563
PAuth1	1.757
PAuth2	1.580
PAuth 3	1.676
PAuth 4	1.847
Pauth 5	1.756
PE1	1.852
PE2	1.751
PE3	1.609
PE4	1.712
PE5	1.653
PE6	2.020
PI1	1.392
PI2	1.380
PI3	1.506
PT1	1.767
PT2	1.992
PT3	1.864

Inner VIF

	VIF
Brand trust -> Customer Loyalty	1.890
Perceived Anthropomorphism -> Brand trust	1.532
Perceived Anthropomorphism -> Perceived Authenticity	1.365
Perceived Authenticity -> Brand trust	2.057
Perceived Authenticity -> Customer Loyalty	1.890
Perceived Empathy -> Brand trust	1.153
Perceived Empathy -> Perceived Authenticity	1.074
Perceived Intelligence -> Brand trust	1.595
Perceived Intelligence -> Perceived Authenticity	1.345
Perceived Transparency -> Brand trust	1.459
Perceived Transparency -> Perceived Authenticity	1.392

Discriminant Validity: HTMT, Fornell-Larcker, and Cross Loadings

Discriminant validity ensures that measures of distinct constructs are unique and not overly correlated (Bagozzi et al., 1991). This study evaluates it using three methods:

1. Heterotrait-Monotrait Ratio (HTMT):

HTMT ratios are below the conservative threshold of 0.85 (Kline, 2011) and the liberal threshold of 0.90 (Teo et al., 2008), confirming discriminant validity.

	Brand trust	Customer Loyalty	Perceived Anthropomorphism	Perceived Authenticity	Perceived Empathy	Perceived Intelligence	Perceived Transparency
Brand trust							
Customer Loyalty	0.765						
Perceived Anthropomorphism	0.607	0.662					
Perceived Authenticity	0.815	0.732	0.634				
Perceived Empathy	0.454	0.196	0.129	0.404			
Perceived Intelligence	0.716	0.635	0.532	0.754	0.292		
Perceived Transparency	0.615	0.568	0.550	0.595	0.243		

2. Fornell-Larcker Criterion (for lower-order constructs)

Discriminant validity is confirmed if the square root of the AVE for each construct is greater than its correlations with other constructs (Fornell & Larcker, 1981). This study meets this criterion, demonstrating robust discriminant validity.

	Brand trust	Customer Loyalty	Perceived Anthropomorphism	Perceived Authenticity	Perceived Empathy	Perceived Intelligence	Perceived Transparency
Brand trust	0.748						
Customer Loyalty	0.617	0.770					
Perceived Anthropomorphism	0.510	0.529	0.764				
Perceived Authenticity	0.686	0.589	0.532	0.781			
Perceived Empathy	0.392	0.162	0.108	0.345	0.766		
Perceived Intelligence	0.558	0.474	0.411	0.587	0.232	0.801	
Perceived Transparency	0.512	0.453	0.455	0.496			

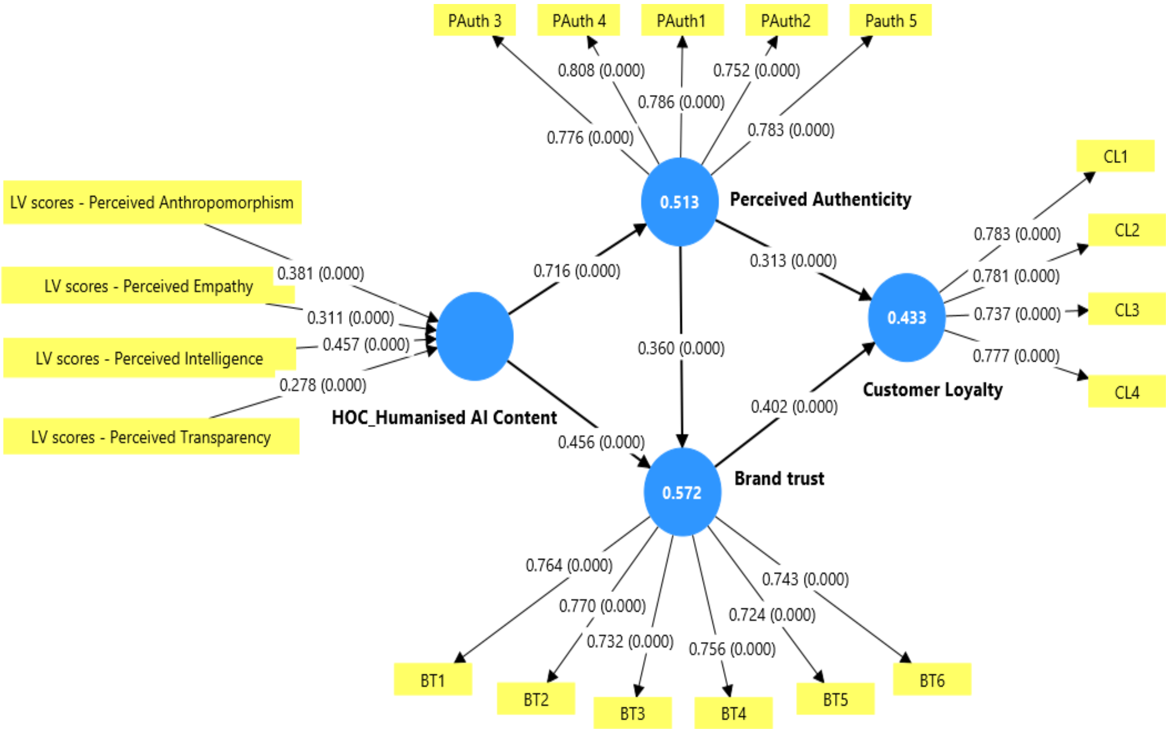
3. **Cross Loadings**

As per Wasko and Faraj (2005), indicators should load higher on their intended constructs than on others. This study confirms that all indicators meet this criterion, further supporting discriminant validity.

	Brand trust	Customer Loyalty	Perceived Anthropomorphism	Perceived Authenticity	Perceived Empathy	Perceived Intelligence	Perceived Transparency
BT1	0.764	0.487	0.403	0.546	0.309	0.441	0.367
BT2	0.770	0.426	0.408	0.517	0.306	0.417	0.379
BT3	0.732	0.481	0.344	0.480	0.261	0.396	0.377
BT4	0.756	0.484	0.365	0.531	0.273	0.424	0.387
BT5	0.725	0.441	0.379	0.508	0.339	0.393	0.408
BT6	0.743	0.451	0.389	0.496	0.272	0.433	0.383
CL1	0.467	0.783	0.405	0.467	0.111	0.375	0.311
CL2	0.470	0.781	0.375	0.434	0.119	0.341	0.372
CL3	0.469	0.737	0.404	0.474	0.118	0.397	0.366
CL4	0.493	0.777	0.443	0.439	0.149	0.345	0.346
PAN1	0.374	0.399	0.757	0.341	0.119	0.292	0.333
PAN2	0.420	0.434	0.770	0.443	0.088	0.307	0.389
PAN3	0.438	0.423	0.782	0.464	0.115	0.345	0.355
PAN4	0.362	0.373	0.771	0.398	0.040	0.340	0.340
PAN5	0.335	0.385	0.737	0.366	0.046	0.281	0.312
PAuth1	0.548	0.437	0.409	0.786	0.286	0.455	0.361
PAuth2	0.516	0.456	0.410	0.752	0.273	0.444	0.400
PAuth3	0.541	0.461	0.439	0.776	0.246	0.457	0.436
PAuth4	0.558	0.488	0.405	0.808	0.309	0.465	0.386
PAuth5	0.517	0.458	0.416	0.783	0.233	0.472	0.352
PE1	0.378	0.142	0.112	0.287	0.802	0.191	0.196
PE2	0.251	0.072	0.096	0.238	0.753	0.137	0.143
PE3	0.248	0.150	0.070	0.248	0.726	0.173	0.158
PE4	0.276	0.107	0.128	0.250	0.749	0.172	0.183
PE5	0.301	0.104	0.028	0.268	0.748	0.153	0.126
PE6	0.323	0.160	0.066	0.289	0.817	0.232	0.135
PI1	0.433	0.428	0.359	0.485	0.173	0.793	0.313
PI2	0.457	0.346	0.304	0.456	0.191	0.788	0.312
PI3	0.453	0.365	0.325	0.470	0.193	0.823	0.374
PT1	0.429	0.369	0.359	0.432	0.207	0.373	0.848
PT2	0.428	0.393	0.398	0.439	0.165	0.356	0.873
PT3	0.465	0.406	0.417	0.408	0.157	0.344	0.860

Step 2: Validating Higher-Order Constructs

The higher-order construct- ‘Humanised AI Content’ is formed by four lower-order constructs: Perceived anthropomorphism, perceived intelligence, perceived transparency and perceived empathy. Validation includes evaluating outer weights, outer loadings, and Variance Inflation Factor (VIF).

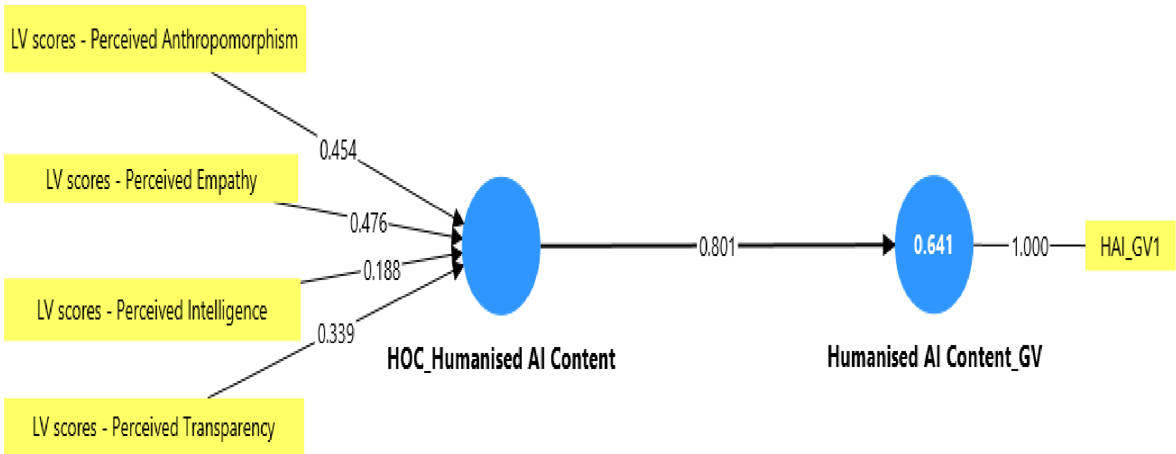


Validating higher order construct: Humanised AI Content

HOC	LOC	Outer weight		T statistic	P values	Outer loadings		T statistic	P value	VIF
		Original Sample	Sample mean			Original Sample	Sample mean			
Humanised AI Content	PAN	0.381	0.380	4.564	0.000	0.729	0.721	9.367	0.000	1.365
	PT	0.278	0.276	4.073	0.000	0.705	0.699	10.153	0.000	1.392
	PE	0.311	0.309	4.279	0.000	0.516	0.512	5.558	0.000	1.074
	PI	0.457	0.451	5.865	0.000	0.801	0.793	13.505	0.000	1.345

All outer loadings (> 0.500) and outer weights are significant, with VIF values below 3, indicating no multicollinearity (Hair et al., 2016; Sarstedt et al., 2019). These results confirm the validity of the higher-order construct.

Validating Higher Order ‘Humanised AI Content’ Construct (Reflective-Formative)



1. **Convergent Validity:** Redundancy analysis showed a path coefficient of 0.801, exceeding the threshold of 0.708, confirming convergent validity (Chin, 1998; Cheah et al., 2019; Hair et al., 2022).
2. **Collinearity Assessment:** VIF values were below 3, indicating no collinearity issues (Hair et al., 2022).
3. **Outer Weights:** Significant outer weights confirmed the relevance of the lower-order constructs (Hair et al., 2016).
4. **Outer Loadings:** All outer loadings exceeded 0.50 and were significant, supporting validity (Sarstedt et al., 2019).

The Humanised AI Content (HAC) construct met all criteria, establishing its validity.

Step 3: Run the structural model

The next step in structural equation modelling is assessment of the hypothesized relationship to substantiate the proposed hypotheses.

	Endogenous	Exogeneous	Path Coeff	Standard error	T stats	P values	R sq	Remark	f sq	Remark	Overall Remark
Humanised AI -> Brand trust	Humanised AI	Brand Trust	0.461	0.066	6.898	0.000	0.576	Moderate to substantial power	0.248	Medium effect size	Supported
Humanised AI -> Perceived Authenticity	Humanised AI	Perceived Authencity	0.719	0.043	16.747	0.000	0.519	Moderate power	1.052	Large effect size	Supported
Brand Trust-> Customer Loyalty	Brand Trust	Customer Loyalty	0.402	0.069	5.850	0.000	0.437	Moderate power	0.159	Medium effect size	Supported
Perceived Authenticity -> Brand Trust	Perceived Authenticity	Brand Trust	0.353	0.078	4.637	0.000	0.576	Moderate power to substantial power	0.152	Medium effect size	Supported
Perceived Authenticity -> Customer Loyalty	Perceived Authenticity	Customer Loyalty	0.312	0.070	4.473	0.000	0.437	Moderate power	0.098	Medium effect size	Supported

- **R^2 (Coefficient of Determination):** Measures the model's predictive accuracy. Thresholds are:
  - Substantial (~75%)
  - Moderate (~50%)
  - Weak (~25%) (Hair et al., 2011; Henseler et al., 2014).

This study shows moderate to substantial R^2 values for all constructs.

- **f^2 (Effect Size):** Evaluates the impact of independent variables on dependent variables. Thresholds are:
  - Large (≥0.35)
  - Medium (≥0.15)
  - Small (≥0.02) (Cohen, 1988).

All constructs in this study have meaningful effects, with f^2 values exceeding 0.03.

Together, R^2 and f^2 confirm the structural model's validity.

Hypothesis Testing Results:

- H1: Humanised AI Content significantly influences Brand Trust ($\beta = 0.461$, $t = 6.898$, $p = 0.000$). Supported.
- H2: Humanised AI Content significantly influences Perceived Authenticity ($\beta = 0.719$, $t = 16.747$, $p = 0.000$). Supported.
- H3: Perceived Authenticity significantly influences Brand Trust ($\beta = 0.353$, $t = 4.637$, $p = 0.000$). Supported.
- H4: Perceived Authenticity significantly influences Customer Loyalty ($\beta = 0.312$, $t = 4.473$, $p = 0.000$). Supported.
- H5: Brand Trust significantly influences Customer Loyalty ($\beta = 0.402$, $t = 5.850$, $p = 0.000$). Supported.

These findings validate the proposed model and confirm significant relationships among key constructs.

Predictive Relevance Q square:

	Q^2predict	Remark	RMSE	MAE
Brand trust	0.494	Strong predictive power	0.722	0.458
Customer Loyalty	0.335	Moderate predictive power	0.825	0.529
Perceived Authenticity	0.494	Strong predictive power	0.720	0.450

Structural Model Evaluation: R^2, Q^2, and CVPAT

1. **R^2 Value**: Measures in-sample predictive accuracy, with higher values indicating better prediction.
2. **Stone-Geisser's Q^2 Value**: Evaluates out-of-sample predictive relevance (Geisser, 1974; Stone, 1974). Thresholds:
   - Weak: 2–15%
   - Moderate: 15–35%
   - Strong: Above 35%

This study depicts strong to moderate predictive power.

3. **CVPAT (Cross-Validated Predictive Ability Test)**: Compares the PLS-SEM model's prediction error to the Indicator Averages (IA) benchmark (Liengaard et al., 2021; Sharma et al., 2023). A negative difference in average loss values indicates superior predictive performance.

Together, these metrics provide a comprehensive evaluation of the structural model's in-sample and out-of-sample predictive accuracy.

CVPAT LV Summary- PLS Sem Vs Indicator Average

	PLS loss	IA loss	Average loss difference	t value	p value
Brand trust	0.811	1.118	-0.307	4.478	0.000
Customer Loyalty	0.975	1.213	-0.238	3.689	0.000
Perceived Authenticity	0.887	1.263	-0.377	4.154	0.000
Overall	0.880	1.192	-0.312	4.489	0.000

In this study, SmartPLS demonstrates superior performance as the average loss difference is negative and significant, confirming it as a better modeling approach.

Model Fit:

1. **Normed Fit Index (NFI):**
   - Compares the chi-square value of the proposed model to a null model.
   - Values >0.90 indicate good fit (Bentler & Bonett, 1980).
   - In this study, NFI values for both saturated and estimated models are close to 1, confirming good fit.
2. **Standardized Root Mean Square Residual (SRMR):**
   - Measures residual differences, with thresholds <0.10 indicating good fit (Hu & Bentler, 1998).
   - SRMR values are 0.051 (saturated model) and 0.053 (estimated model), both within acceptable limits, confirming model fit (Henseler et al., 2014).

The model meets all criteria, demonstrating strong fit for PLS-SEM analysis.

	Saturated model	Estimated model
SRMR	0.051	0.053
d_ULS	0.504	0.542
d_G	0.144	0.149
Chi-square	419.713	428.934
NFI	0.899	0.897

FINDINGS AND DISCUSSION

The study reveals significant insights into the relationships between humanised AI content, perceived authenticity, brand trust, and customer loyalty. The findings are as follows:

1. Humanised AI Content and Brand Trust (H1):

   Humanised AI content significantly influences brand trust ($\beta = 0.461$, $t = 6.898$, $p = 0.000$). This aligns with Social Exchange theory and Anthropomorphism theory, suggesting that AI systems mimicking human traits reduce perceived uncertainty and foster trust. The findings emphasize the importance of incorporating empathy, anthropomorphism, intelligence, and transparency in AI-driven interactions to build consumer trust.

2. Humanised AI Content and Perceived Authenticity (H2):

   Humanised AI content significantly impacts perceived authenticity ($\beta = 0.719$, $t = 16.747$, $p = 0.000$). This supports Authenticity theory and Signaling theory, indicating that human-like qualities in AI content signal genuineness and credibility, enhancing consumer perceptions of authenticity.

3. Perceived Authenticity and Brand Trust (H3):

   Perceived authenticity significantly influences brand trust ($\beta = 0.353$, $t = 4.637$, $p = 0.000$). This finding is consistent with the Trust-Authenticity Framework, highlighting that authenticity strengthens consumer trust by aligning with their expectations of genuine and transparent brand interactions.

4. Perceived Authenticity and Customer Loyalty (H4):

   Perceived authenticity significantly impacts customer loyalty ($\beta = 0.312$, $t = 4.473$, $p = 0.000$). This supports Commitment-Trust theory and Customer Loyalty theory, suggesting that authentic AI-driven interactions foster emotional bonds, leading to repeat purchases and positive word-of-mouth.

5. Brand Trust and Customer Loyalty (H5):

   Brand trust significantly influences customer loyalty ($\beta = 0.402$, $t = 5.850$, $p = 0.000$). This aligns with Relationship Marketing theory, emphasizing that trust reduces perceived risk and reinforces positive brand associations, driving long-term loyalty.

The moderate to substantial R^2 values (ranging from 0.437 to 0.576) and medium to large effect sizes (f^2) confirm the predictive accuracy and relevance of the model. The Stone-Geisser's Q^2 values indicate strong predictive power for brand trust and perceived authenticity, and moderate predictive power for customer loyalty. The CVPAT results further validate the model's superiority, with negative and significant average loss differences.

The model fit indices (SRMR = 0.051, NFI = 0.899) confirm the robustness of the PLS-SEM analysis, demonstrating strong alignment with the proposed theoretical framework.

CONCLUSION

This research emphasizes the impact humanized AI content has on the perceived authenticity, brand trust, and customer loyalty of a brand. Incorporating empathy, anthropomorphism, intelligence, and transparency allows brands to foster higher trust and loyalty from customers during AI interactions. Maintaining a balance between automation and human touch is crucial for authenticity and strong brand relationships.

AI technology in marketing has been further investigated considering the effects humanized AI content has on consumer behavior. It offers actionable insights for marketers to design AI-driven strategies that resonate with consumers on a human level, fostering trust and loyalty.

Limitations of the Study

1. Geographical Limitation: The focus of the research is on a selected sample that includes urban areas. This is likely to limit the general acceptance of the findings in other locations or cultures.

2. Cross-Sectional Data: The study relies on cross-sectional data, which restricts the ability to infer causal relationships or observe long-term effects.
3. Industry-Specific Focus: The study employed data from a general consumer sample which may not fully represent specific aspects of the industry.

Future Scope

1. Industry-Specific Studies: Humanized AI content can be studied and analyzed in segments such as e-commerce, healthcare, or finance for understanding industry specific humanized AI dynamics.
2. Longitudinal Studies: Trust and loyalty towards a brand and its consumers would be better understood through longitudinal studies centered on humanized AI content.
3. Cultural Contexts: Investigating the impact of humanised AI content in diverse cultural settings, would enhance the generalizability of findings.
4. Ethical Considerations: Exploring the ethical issues surrounding humanized AI content such as data exposure, privacy issues, and consumer deception can be better addressed in subsequent studies.
5. Advanced Analytical Techniques: Consumer related perceptions and behaviors can be better understood by incorporating some advanced analytical techniques like machine learning or sentiment analysis.

By addressing these limitations and exploring future research directions, scholars and practitioners can further advance the understanding of AI-driven marketing strategies and their impact on consumer relationships.

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