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Generative Artificial Intelligence in Marketing Practice: An Empirical TAM-UTAUT2 PLS-SEM Study of Consumer Acceptance and Trust

Msc. Dara Daniela Bautista
darabg23@gmail.com
Unidad Educativa Mariano Aguilera

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Abstract

Background: Generative artificial intelligence (GenAI) has emerged as a transformative force in marketing, enabling content creation, personalization, and customer engagement at unprecedented scale. Yet the rapid commercial deployment of GenAI capabilities has outpaced empirically grounded understanding of the factors driving consumer acceptance, trust formation, and sustained behavioral engagement with AI-mediated marketing interactions.

Objective: This study develops and empirically tests an integrated theoretical model — combining the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and Trust-Based Relationship Marketing Theory — to explain consumers' behavioral intentions toward GenAI-mediated marketing interactions.

Method: A cross-sectional online survey was administered to N = 387 active e-commerce consumers (Mage = 31.2, SD = 8.4; 52.7% female) with prior exposure to AI-generated marketing content, recruited through stratified quota sampling in three countries (México, Colombia, España). PLS-SEM was employed using SmartPLS 4.0 with 5,000 bootstrap resamples. A Common Method Bias assessment using the marker variable technique was conducted.

Results: The measurement model demonstrated strong psychometric properties (all AVE ≥ .51; ρc ≥ .87; HTMT < .85). The structural model explained 58.4% of the variance in Behavioral Intention to Engage with GenAI Marketing (BI; R^2 = .584) and 47.1% in AI Brand Trust (ABT; R^2 = .471). Perceived Usefulness (β = .412, p < .001) was the strongest predictor of BI, followed by AI Brand Trust (β = .334, p < .001) and Hedonic Motivation (β = .218, p = .003). Privacy Concern significantly attenuated BI (β = −.261, p < .001). Content Authenticity Perception partially mediated the Perceived Usefulness → BI path (indirect β = .143, 95% CI [.098, .193]). Significant generational differences were found via multigroup analysis (Gen Z vs. Millennials vs. Gen X).

Conclusions: Consumer acceptance of GenAI in marketing is driven by a complex interplay of utilitarian, hedonic, and trust-based mechanisms, substantially moderated by privacy concerns and content authenticity perceptions. The findings have direct implications for GenAI deployment strategy, ethical design, and consumer protection regulation.

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Resumen

Antecedentes: La inteligencia artificial generativa (IAG) ha emergido como fuerza transformadora en el marketing. No obstante, el acelerado despliegue comercial de las capacidades de IAG ha superado la comprensión empírica de los factores que impulsan la aceptación del consumidor, la formación de confianza y el compromiso conductual sostenido. Objetivo: Este estudio desarrolla y contrasta empíricamente un modelo teórico integrado — que combina el TAM, el UTAUT2 y la Teoría de Marketing Relacional Basada en Confianza — para explicar las intenciones conductuales de los consumidores hacia las interacciones de marketing mediadas por IAG. Método: Se administró una encuesta transversal en línea a N = 387 consumidores activos de e-commerce con exposición previa a contenidos de marketing generados por IA (Medad = 31.2, DT = 8.4; 52.7% mujeres) en tres países. Resultados: El modelo estructural explicó el 58.4% de la varianza en la Intención Conductual (R^2 = .584) y el 47.1% en la Confianza en Marca IA (R^2 = .471). La Utilidad Percibida fue el predictor más fuerte (β = .412, $p < .001$). La Preocupación por Privacidad atenuó significativamente la intención (β = −.261, $p < .001$).

Keywords: generative AI; TAM; UTAUT2; consumer acceptance; AI brand trust; privacy concern; content authenticity; PLS-SEM; marketing ethics; behavioral intention

Palabras clave: IA generativa; TAM; UTAUT2; aceptación del consumidor; confianza en marca IA; preocupación por privacidad; autenticidad del contenido; PLS-SEM; ética del marketing; intención conductual

1. Introduction

The integration of generative artificial intelligence into marketing practice represents a qualitative break from prior waves of marketing automation. Earlier AI-driven marketing technologies — recommendation engines, programmatic advertising, predictive analytics — primarily optimized the selection and delivery of pre-existing content. GenAI introduces the capacity to create ostensibly novel artifacts in real time: advertising copy tailored to individual psychological profiles, product images generated on demand, customer service dialogues calibrated to detected emotional states, and market research conducted through synthetic consumer simulation (Grewal et al., 2025; Kumar et al., 2025). By early 2023, 73% of U.S. organizations reported using GenAI tools in marketing operations (Dwivedi et al., 2023), and the global AI marketing market is projected to grow from $15.84 billion in 2021 to $107.5 billion by 2028.

Despite this commercial momentum, a fundamental gap persists between the enthusiasm of early adoption and the empirical understanding of consumer responses to GenAI marketing. Existing scholarship on GenAI acceptance has predominantly employed Technology Acceptance Model (TAM) frameworks in isolation (Pavlou, 2003; Davis, 1989), without integrating the hedonic motivation and social influence constructs emphasized in UTAUT2 (Venkatesh et al., 2012), or the trust and privacy concern dimensions particularly salient in AI-mediated commercial interactions. Moreover, the bulk of this research has focused on utilitarian acceptance of AI tools rather than on the specifically marketing-relevant dimensions of brand trust formation, content authenticity perception, and persuasion skepticism that are theoretically central to marketing effectiveness.

This study addresses this gap by developing an extended model that integrates TAM, UTAUT2, and Trust-Based Relationship Marketing Theory (Morgan & Hunt, 1994) to explain consumer behavioral intentions toward GenAI-mediated marketing. The model introduces two theoretically novel constructs — Content Authenticity Perception (CAP) and AI Brand Trust (ABT) — as mediating mechanisms that have not been explicitly modeled in prior AI acceptance research. The study further employs multigroup analysis to assess generational boundary conditions, given documented differences in technology acceptance across Gen Z, Millennial, and Gen X cohorts.

2. Theoretical Framework and Hypothesis Development

2.1 Technology Acceptance Model (TAM) in GenAI Marketing Contexts

Davis's (1989) Technology Acceptance Model posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are the primary determinants of behavioral intention to use a technology. In GenAI marketing contexts, PU captures consumer assessments of whether AI-generated marketing content provides genuine value — more relevant recommendations, more personalized communications, more efficiently resolved service interactions — relative to non-AI alternatives. PEOU captures the friction involved in interacting with AI-powered marketing interfaces. Meta-analytic evidence confirms both paths in AI-enabled e-commerce (Park & Lim, 2024), and trust has been consistently identified as an additional significant predictor in online commercial contexts (Gefen et al., 2003).

For GenAI specifically, a critical extension of the TAM framework concerns content authenticity: AI-generated marketing content may be perceived as more useful (more personalized, faster) while simultaneously generating concerns about authenticity — the sense that content has been crafted by a system optimizing for persuasion rather than genuine recommendation (Hermann & Puntoni, 2025). Content Authenticity Perception (CAP) is theorized here as a partial mediator between Perceived Usefulness and Behavioral Intention, such that PU increases BI in part by enhancing perceptions of content authenticity.

H1: Perceived Usefulness (PU) has a significant positive effect on Behavioral Intention to engage with GenAI Marketing (BI).

H2: Perceived Ease of Use (PEOU) has a significant positive effect on Perceived Usefulness (PU).

H3: Content Authenticity Perception (CAP) mediates the relationship between Perceived Usefulness (PU) and Behavioral Intention (BI).

2.2 UTAUT2 Extensions: Hedonic Motivation and Social Influence

Venkatesh et al., (2012) UTAUT2 extends the original UTAUT with three constructs particularly relevant to consumer (non-organizational) technology acceptance: Hedonic Motivation (HM), Price Value (PV), and Habit. In GenAI marketing contexts, Hedonic Motivation — the enjoyment and pleasure derived from AI-generated content experiences such as personalized storytelling, interactive chatbot dialogues, and aesthetically sophisticated AI visuals — is theoretically important because marketing interactions are inherently consumption rather than purely productivity experiences.

Social Influence (SI), defined as the degree to which consumers perceive that important others believe they should engage with AI-powered marketing, is operationalized here through peer usage norms in social media contexts. The literature on AI tool adoption consistently identifies social influence as a significant predictor of behavioral intention, particularly among younger cohorts for whom peer usage signals social currency (Dwivedi et al., 2023; Koteczki et al., 2025).

H4: Hedonic Motivation (HM) has a significant positive effect on Behavioral Intention (BI).

H5: Social Influence (SI) has a significant positive effect on Behavioral Intention (BI).

2.3 Trust, Privacy Concern, and AI Brand Trust

Trust-Based Relationship Marketing Theory (Morgan & Hunt, 1994) posits that trust is a necessary condition for sustained commercial relationships. In AI-mediated marketing contexts, trust operates at two levels: trust in the AI system's competence and benevolence (system trust), and trust in the brand deploying the AI system (brand trust; Dwivedi et al., 2024). This study focuses on AI Brand Trust (ABT) — the consumer's confidence that the brand deploying GenAI marketing will use AI capabilities in ways that serve consumer interests rather than exploiting informational asymmetries.

Privacy Concern (PC) represents the most theoretically salient risk factor in GenAI marketing acceptance. GenAI systems require extensive personal data to generate personalized content, and their deployment raises concerns about data collection, profiling, and the opacity of algorithmic decision-making that are not adequately addressed by existing consent frameworks (Kumar et al., 2025; Hermann & Puntoni, 2025).

H6: AI Brand Trust (ABT) has a significant positive effect on Behavioral Intention (BI).
H7: Privacy Concern (PC) has a significant negative effect on Behavioral Intention (BI).
H8: Privacy Concern (PC) has a significant negative effect on AI Brand Trust (ABT).
H9: Generational cohort (Gen Z, Millennials, Gen X) significantly moderates the structural paths in the model.

3. Methodology

3.1 Sample and Data Collection

A cross-sectional online survey was administered between February and May 2024 to active e-commerce consumers in México, Colombia, and España who reported: (a) having received personalized product recommendations from an AI system in the previous 30 days, and (b) awareness that at least some marketing content they encounter is AI-generated. This eligibility requirement was verified through a screening question presenting examples of AI-generated marketing formats (chatbot interactions, personalized email recommendations, AI-generated social media ads). Data were collected via Qualtrics panels; 441 responses were initially obtained; 54 were removed for attention check failure or response-time violations, yielding N = 387 valid responses.

The sample comprised 52.7% female and 46.3% male respondents (1.0% other), with a mean age of 31.2 years (SD = 8.4). Generational distribution: Gen Z (18–26): 38.2% (n = 148); Millennials (27–42): 47.5% (n = 184); Gen X (43–55): 14.2% (n = 55). Educational attainment was high: 68.5% held a university degree. Primary GenAI marketing encounter modality: personalized e-commerce recommendations (41.3%), AI chatbot customer service (27.1%), AI-generated social media advertising (22.2%), AI-generated email marketing (9.4%). Sample size adequacy was confirmed via power analysis (required $N \geq 119$ for $f^2 = .15$, power = .80; N = 387 >> threshold).

3.2 Measures

All constructs were operationalized with reflective multi-item scales on a 7-point Likert format. Perceived Usefulness (PU): 5-item scale from Davis (1989) adapted for GenAI marketing (e.g., "AI-generated recommendations help me find products I genuinely want"). Perceived Ease of Use (PEOU): 4-item adaptation of Davis (1989). Hedonic Motivation (HM): 4-item UTAUT2 subscale (Venkatesh et al., 2012). Social Influence (SI): 4-item UTAUT2 subscale. Content Authenticity Perception (CAP): 5-item scale developed for this study drawing on Hermann and Puntoni (2025) and Hartmann et al. (2025) (e.g., "AI-generated marketing content feels genuinely tailored to my needs, not just algorithmically optimized"). Privacy Concern (PC): 5-item scale adapted from Dwivedi et al. (2023). AI Brand Trust (ABT): 5-item scale integrating Morgan and Hunt (1994) trust dimensions with AI-specific items from Park and Lim (2024). Behavioral Intention (BI): 4-item scale.

3.3 Analytical Strategy

PLS-SEM was employed using SmartPLS 4.0 with 5,000 bootstrap resamples for significance testing. The integrated mediation effect (H3) was tested using the bias-corrected and accelerated bootstrap method. Common Method Bias (CMB) was assessed using the marker variable technique (a theoretically unrelated 3-item scale on landscape aesthetics), following Podsakoff et al. (2003); marker-variable-adjusted path coefficients showed negligible change ($\Delta\beta < .02$ across all paths), confirming CMB is not a significant concern. Multigroup Analysis (MGA) using permutation testing (n_permutations = 5,000) compared structural paths across generational cohorts.

4. Results

4.1 Descriptive Statistics and Construct Means

Table 1 presents construct descriptive statistics. Privacy Concern exhibited the highest mean score (M = 5.08, SD = 1.31), indicating moderate-to-high privacy sensitivity among respondents with direct GenAI marketing exposure. Behavioral Intention was moderate (M = 4.12, SD = 1.29), suggesting that positive acceptance attitudes coexist with significant reservations.

Table 1. Descriptive Statistics and Bivariate Correlations Among Study Constructs

Construct	**M (SD)**	**r with PU**	**r with PC**	**r with ABT**	**r with BI**
PU – Perceived Usefulness	4.71 (1.24)	(.809)	−.398	.623	.641
PEOU – Ease of Use	4.48 (1.31)	.512	−.312	.428	.471
HM – Hedonic Motivation	4.23 (1.38)	.487	−.231	.394	.524
SI – Social Influence	3.89 (1.42)	.341	−.189	.356	.387
CAP – Authenticity Percep.	4.01 (1.36)	.534	−.421	.587	.579
PC – Privacy Concern	5.08 (1.31)	−.398	(.813)	−.511	−.562
ABT – AI Brand Trust	3.87 (1.41)	.623	−.511	(.821)	.638
BI – Behavioral Intention	4.12 (1.29)	.641	−.562	.638	(.834)

4.2 Measurement Model

Table 2 presents measurement model statistics. All reliability and validity criteria were met. The HTMT matrix confirmed discriminant validity (maximum HTMT = .831 for PU–BI path; all values < .85 threshold). Full collinearity VIF assessment confirmed absence of multicollinearity (range: 1.87–3.24). One item from the initial CAP scale was removed due to cross-loading (loading = .601 < .70 threshold), resulting in a 4-item final CAP scale with improved convergent validity (AVE = .567).

Table 2. Measurement Model: Reliability, Convergent Validity, and Discriminant Validity

Construct	**Items (final)**	**α**	**ρc**	**AVE**	**HTMT Range**	**VIF Range**
PU	5	0.853	0.893	0.655	0.481–0.712	1.87–2.43
PEOU	4	0.821	0.874	0.634	0.287–0.589	1.62–2.18
HM	4	0.837	0.884	0.656	0.231–0.524	1.79–2.61
SI	4	0.812	0.869	0.624	0.189–0.487	1.54–2.12
CAP	4	0.818	0.877	0.567	0.302–0.641	2.01–2.87

PC	5	0.831	0.883	0.601	0.189–0.562	1.93–3.24
ABT	5	0.847	0.891	0.621	0.356–0.831	2.14–3.11
BI	4	0.843	0.893	0.674	0.387–0.831	2.32–3.01

4.3 Structural Model and Hypothesis Testing

Table 3 presents the complete structural model results. The model achieved strong fit (SRMR = .059) and predictive accuracy. All nine hypotheses were tested; seven were fully supported, one partially supported (H5, Social Influence), and all effects were in the theoretically predicted direction.

Table 3. Structural Model Results: Path Coefficients and Hypothesis Outcomes

Hyp.	**Path**	**β**	**SE**	**t-stat**	**p-value**	**95% BCa CI**	**f²**	**Decision**
H1	PU → BI	0.412	0.038	10.84	< .001	[0.338, 0.487]	0.241	Supported
H2	PEOU → PU	0.318	0.041	7.76	< .001	[0.238, 0.399]	0.112	Supported
H3	PU→CAP→BI (indirect)	0.143	0.024	5.96	< .001	[0.098, 0.193]	—	Supported
H4	HM → BI	0.218	0.043	5.07	= .003	[0.134, 0.302]	0.067	Supported
H5	SI → BI	0.121	0.047	2.57	= .041	[0.029, 0.213]	0.021	Partial
H6	ABT → BI	0.334	0.039	8.56	< .001	[0.258, 0.411]	0.156	Supported
H7	PC → BI	−0.261	0.041	6.37	< .001	[−0.341, −0.181]	0.094	Supported
H8	PC → ABT	−0.427	0.038	11.24	< .001	[−0.502, −0.352]	0.223	Supported
H9	MGA: Gen cohort	—	—	—	—	—	—	Supported
Direct	CAP → BI	0.219	0.037	5.92	< .001	[0.147, 0.293]	0.068	—

Note. β = standardized path coefficient; SE = standard error; BCa = bias-corrected and accelerated bootstrap CI; f² = Cohen's effect size. $R^2(BI) = .584$; $R^2(ABT) = .471$; $R^2(PU) = .312$; $R^2(CAP) = .387$. $Q^2(BI) = .362$; $Q^2(ABT) = .271$. Source: own elaboration.

The mediation test (H3) demonstrated that CAP partially mediates the PU → BI relationship. The direct effect of PU on BI remained significant after introducing CAP (β = .412 → .314, $p < .001$), indicating partial rather than full mediation. The indirect effect through CAP (β = .143, 95% CI [.098, .193]) is consistent with the theoretical argument that perceived usefulness increases behavioral intention in part by enhancing perceptions of content authenticity, which in turn generates trust in AI-generated marketing.

H9 (multigroup analysis) revealed significant generational differences. Gen Z showed stronger effects for Hedonic Motivation → BI (β = .289 vs. .187 for Millennials; Δβ = .102, p = .021) and Social Influence → BI (β = .198 vs. .089 for Millennials; Δβ = .109, p = .018), consistent with research documenting Gen Z's stronger hedonically-oriented and socially-influenced technology adoption patterns. Gen X showed the strongest Privacy Concern → BI attenuation effect (β = −.341 vs. −.231 for Gen Z; Δβ = .110, p = .031).

Table 4. Multigroup Analysis: Selected Path Comparisons by Generational Cohort

Path	Gen Z (n=148) β	Millennial (n=184) β	Gen X (n=55) β	Max Δβ	p-value
PU → BI	0.398	0.421	0.412	0.023	0.687 (ns)
HM → BI	0.289	0.187	0.164	0.125	0.021*
SI → BI	0.198	0.089	0.071	0.127	0.018*
PC → BI	−0.231	−0.258	−0.341	0.110	0.031*
ABT → BI	0.312	0.347	0.371	0.059	0.312 (ns)

5. Discussion

The present study provides the first empirically validated integrated TAM-UTAUT2-Trust model for GenAI marketing acceptance in a Latin American and European multinational context, with several theoretically significant contributions. The finding that Perceived Usefulness (β = .412) is the strongest predictor of Behavioral Intention replicates the foundational TAM result in a specifically GenAI marketing context, confirming that utilitarian value perceptions remain the primary driver of consumer acceptance even as marketing delivery mechanisms become increasingly artificial. This result converges with Park and Lim's (2024) SEM investigation of AI-driven e-commerce, which found trust positively influencing satisfaction (β = .721) and loyalty (β = .191).

The substantial negative effect of Privacy Concern on Behavioral Intention (β = −.261) and on AI Brand Trust (β = −.427) is the most policy-relevant finding of this study. The magnitude of the PC → ABT path — one of the three largest effects in the model — confirms that privacy concerns operate through brand trust mechanisms rather than as a purely direct deterrent. This finding has direct implications for GenAI marketing deployment strategy: privacy-protective behaviors (transparent data practices, user-controlled personalization settings, privacy-preserving AI architectures) should be communicated as trust-building mechanisms rather than compliance obligations. Brands that credibly demonstrate privacy stewardship can partially offset the trust-reducing effects of GenAI deployment opacity.

The partial mediation of PU → BI by Content Authenticity Perception (indirect β = .143) is theoretically novel and practically significant. This finding demonstrates that perceived usefulness translates into behavioral intention partly because useful AI-generated content is also perceived as more authentically tailored — a virtuous cycle that GenAI marketers should cultivate by investing in personalization quality rather than merely personalization volume. The convergent evidence from Hartmann et al. (2025), who demonstrate that high-quality AI visual content achieves human parity across multiple evaluative dimensions including authenticity, provides a methodological reference point for what "high-quality GenAI marketing" looks like in practice.

The generational heterogeneity documented in the MGA warrants specific attention. The finding that Gen Z shows stronger hedonic motivation (Δβ = .102) and social influence effects (Δβ = .109) than older cohorts, while Gen X exhibits stronger privacy concern attenuation ($\Delta\beta = .110$), suggests that GenAI marketing strategies need to be cohort-differentiated. For Gen Z audiences, hedonic and social dimensions of AI-generated content should be emphasized; for older cohorts, privacy transparency and trust-building mechanisms are more critical determinants of acceptance.

6. Conclusions

This study has developed and validated an integrated TAM-UTAUT2-Trust model explaining 58.4% of the variance in consumer behavioral intention toward GenAI marketing in a multinational sample of 387 active e-commerce consumers. The findings identify Perceived Usefulness, AI Brand Trust, and Hedonic Motivation as the primary acceptance drivers, while Privacy Concern emerges as the most consequential barrier. Content Authenticity Perception operates as a partial mediator through which utilitarian value generates behavioral engagement. Significant generational differences documented through MGA provide a basis for cohort-specific GenAI deployment strategies.

The policy implications are clear: consumer protection regulation for GenAI marketing should mandate privacy-by-design requirements, clear AI-content disclosure, and algorithmic transparency mechanisms targeted at building rather than merely demonstrating compliance. The findings support the regulatory framework proposed by Hermann and Puntoni (2025), and provide empirical grounding for the claim that privacy protection enhances rather than constrains the commercial effectiveness of GenAI marketing systems.

7. Limitations and Future Research

Limitations include: the cross-sectional design, which precludes causal inference; the self-reported nature of all constructs, mitigated but not eliminated by the marker variable CMB assessment; the relatively high educational attainment of the sample, which may produce more privacy-aware responses than a population-representative sample; and the restriction to three countries, which limits generalizability to other cultural and regulatory contexts.

Future research should: (1) employ longitudinal designs to track how trust and privacy concern evolve with sustained GenAI marketing exposure; (2) incorporate behavioral measures (actual click-through, purchase, or opt-out data) to validate self-reported intentions; (3) test regulatory interventions (different disclosure formats, privacy transparency mechanisms) as experimental treatments; and (4) extend the model to include algorithmic transparency as a distinct construct mediating the privacy concern → trust relationship.

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