Generative AI and Consumer Decision-Making: Examining the Effects of Consumer Trust, Engagement, and Purchase Behaviour Among Digital Consumers in Pakistan

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https://doi.org/10.62345/jads.2025.14.3.187

Abstract
Generative AI has changed digital marketing in a fairly short span of time. Brands can now churn out personalized captions, visuals, and short-form video at a scale and speed that would have been unthinkable for human creative teams alone, and retail, fashion, and e-commerce companies have leaned into this heavily across Instagram, TikTok, Facebook, and YouTube. But there's a catch: people don't seem to engage with AI-made marketing content the same way they engage with human-made content (Abdelfattah & Mehdi, 2025). This study looks at how generative AI-driven marketing content (GAIM) shapes consumer engagement and trust, and whether these two variables that are alone or together to help explain the link between GAIM and actual purchase behaviour. It also asks whether disclosing that content is AI-generated changes how much consumers trust it. Drawing on the Elaboration Likelihood Model, Technology Acceptance Model, and Signaling Theory, and using survey data from 314 consumers in Sialkot analysed via PLS-SEM in SmartPLS 4, the findings show GAIM has a strong effect on engagement and a smaller but real effect on trust. Engagement itself strongly predicts trust, and both feed into purchase behaviour. Interestingly, disclosing AI involvement strengthens trust rather than undermining it a useful insight for marketers and regulators navigating Pakistan's digital economy.
Keywords: Generative AI, Consumer Decision-Making, Digital Marketing, Behavioural Engagement, Consumer Trust, Purchase Behaviour, AI Disclosure Transparency.

Introduction

Generative artificial intelligence has moved quickly from an experimental technology to a routine part of marketing operations. Tools that can interpret consumer language and visual preferences, and that can predict what audiences are likely to respond to, are now used daily by advertising and content teams (Ahmed et al.). This chapter introduces how generative AI has become embedded in marketing practice, identifies the gap this study addresses, and sets out the study's objectives, research questions, and significance.

Background of the Study

Generative AI allows brands to produce advertising and marketing content quickly and at low cost, a capability that has been especially valuable for Pakistan's fast-growing base of digitally native start-ups. These tools let smaller brands produce content that looks professional and can be varied

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Compliance with ethical standards: There are no conflicts of interest (financial or non-financial). This study did not receive any funding.

at scale. At the same time, when consumers recognize that content was produced by AI rather than by people, they can become less trusting of it, a pattern researchers refer to as the AI-authorship effect (Chen et al., 2024). Other research finds the opposite: consumers often respond well to AI-made content when it is well executed and useful, and this can increase their willingness to buy.
Because Pakistani consumers are spending more time online and are becoming more selective about which brands they trust (Amin, 2025), it is important to examine directly how they respond to generative AI in marketing, rather than assuming that findings from other markets will transfer without adjustment.

Problem Statement

Generative AI is now used extensively in Pakistani advertising, but its effect on consumer trust and purchasing behaviour remains poorly understood. Most existing research on this question comes from other national contexts and may not generalize to Pakistan. This gap can be summarized in three parts.
First, little is known about how generative AI-driven marketing operates within Pakistan's specific cultural and economic context. Consumer behaviour in Pakistan differs from the Western and East Asian markets where most existing research has been conducted, and this difference has not been tested empirically (Zheng et al., 2025).
Second, no existing model captures how generative AI content affects consumer trust, behavioural engagement, and purchase behaviour together, as one connected system, rather than as separate, disconnected relationships.
Third, no combined theoretical framework has been built specifically to explain how consumers process and respond to generative AI-driven content. Existing theories of information processing and technology acceptance have not previously been brought together in a way that is tailored to this technology (Bowen & Watson, 2025).
Because of these gaps, brands and marketers operating in Pakistan currently lack the evidence they need to use generative AI in ways that support, rather than damage, the trust of their customers.

Significance of the Study

This study offers value on both theoretical and practical fronts. Theoretically, it introduces a combined framework that draws together the Elaboration Likelihood Model, the Technology Acceptance Model, and signaling Theory, and tests their combined explanatory power using field data (Bhuiyan et al., 2025). By treating consumer trust and behavioural engagement as parallel and sequential structural pathways, the study extends existing work on the AI-authorship effect and offers a more complete account of how machine-made persuasion operates. In terms of context, this research contributes empirical evidence from Pakistan, establishing a baseline for South Asian consumer psychology research in an increasingly automated marketing environment.
Practically, the findings are intended to provide clear guidance for brand managers, visual designers, and e-commerce agencies across Pakistan. They help identify the operational balance between creative automation and human authenticity signals, so that fast, AI-driven marketing campaigns do not damage customer relationships (Cervi, 2021).

Research Objectives

- To evaluate the direct effect of generative AI-driven marketing content on consumer behavioural engagement among digital consumers in Pakistan.
- To examine the direct effect of generative AI-driven marketing content on consumer trust.

- To examine the relationship between consumer behavioural engagement and consumer trust.
- To evaluate the effect of consumer trust on purchase behaviour.
- To evaluate the effect of consumer behavioural engagement on purchase behaviour.
- To examine whether consumer behavioural engagement and consumer trust mediate the relationship between generative AI-driven marketing content and purchase behaviour, individually and in sequence.
- To examine whether AI disclosure transparency moderates the relationship between generative AI-driven marketing content and consumer trust.

Literature Review

This chapter reviews the existing literature on generative AI-driven marketing content and its effect on consumer decision-making. It covers five areas relevant to this study: generative AI-driven marketing content (GAIM), consumer trust, behavioural engagement, purchase behavior, and the digital consumer behaviour of Pakistani audiences. It then presents the theoretical framework, explains why the three chosen theories were combined, develops the study's seven hypotheses, and closes with the conceptual framework, described in words and in a diagram.

Generative AI-Driven Marketing Content (GAIM)

Generative AI-driven marketing content refers to promotional material, including brand copywriting, visual graphics, interface designs, packaging layouts, and short-form video, produced by deep-learning systems rather than through direct, manual human effort (Johnsen, 2024). Brands increasingly rely on these tools because they support hyper-personalization at scale and allow content to be generated immediately, at a fraction of the cost of manual production.

Academic findings on how consumers respond to AI-generated media remain divided. One line of research documents algorithm aversion, or AI-authorship devaluation: when consumers recognize that an advertisement or brand asset was produced by an automated system, they can penalize the brand for what feels like a lack of genuine effort or empathy. Other studies find the opposite pattern: when generative AI produces visually strong, highly targeted content, consumers respond favourably, sometimes matching or exceeding the engagement levels seen with human-made creative work (Darmawan, 2025).

Consumer Trust

In digital and social-media-driven marketing, trust functions as a way of reducing perceived risk, which matters most in categories where consumers cannot physically inspect a product before buying (Eze, 2025).

Within automated marketing specifically, trust appears to form differently. Emerging research suggests that transparency signals, such as clear disclosure that content was AI-generated, can meaningfully change how trust develops. Abrupt or poorly worded AI disclosures can raise consumer suspicion, while clear, well-framed, and ethically presented disclosures can act as an integrity signal that reinforces long-term credibility.

Behavioural Engagement

Behavioural engagement captures a consumer's measurable interaction with a brand's content, including clicks, shares, comments, and other forms of participation. In generative AI contexts, engagement often reflects an immediate response to how vivid and personalized the content feels.

Generative AI is particularly effective at driving early engagement, since it can analyze user data and produce optimized, highly relevant content variations in real time. A continuing debate in the literature is whether this early engagement translates into durable brand trust, or whether it simply reflects short-lived curiosity (Connolly et al., 2023).

Purchase Behaviour

Purchase behaviour is the final outcome in most consumer decision-making models, captured empirically through a consumer's stated commitment or willingness to buy a brand's products or services. It depends heavily on how effectively earlier steps in the communication process have reduced perceived risk and increased perceived usefulness.

Under generative AI marketing, purchase decisions appear to follow two related paths. One is utility-driven: a well-designed, AI-customized offer can prompt a purchase directly because of its convenience and fit. The other is trust-driven: the purchase depends on whether the AI-mediated interaction feels authentic and credible (Gkourla & Schafraad, 2024).

Pakistan's Digital Consumer Behaviour

Pakistan's digital marketplace is growing quickly, supported by a large and expanding smartphone user base and heavy consumer activity on platforms such as Instagram, TikTok, and YouTube. Pakistani consumer behaviour combines strong collectivist cultural values and reliance on interpersonal recommendation with a fast-growing appetite for digital convenience.

Local e-commerce and direct-to-consumer brands face particular trust challenges, since Pakistani consumers frequently encounter inconsistent service, shipping delays, and misleading advertising. As a result, domestic consumers tend to be highly sensitive to signals of brand credibility and authenticity. While local businesses are adopting generative AI quickly to produce low-cost, high-frequency content, there is almost no localized empirical evidence on how Pakistani consumers actually process this kind of automated marketing, a gap this study addresses directly.

Theoretical Framework

This study draws on three theoretical perspectives, each explaining a different part of how consumers process and respond to generative AI-driven marketing content: the Elaboration Likelihood Model (ELM), the Technology Acceptance Model (TAM), and Signaling Theory.

The Elaboration Likelihood Model holds that consumers process persuasive messages through one of two routes: a central route, involving careful, effortful evaluation, or a peripheral route, involving quick judgments based on surface-level cues (Pan, 2024). In generative AI marketing, peripheral cues such as visual quality, perceived automation, and transparency labels are especially influential during low-involvement browsing. ELM grounds the part of this study that explains how automated content and disclosure cues shape consumer evaluations.

The Technology Acceptance Model explains that people accept new technology based on how useful and how easy to use they find it. TAM explains why high-quality, personalized generative AI content can stimulate engagement and purchase behaviour directly, simply because it meets a consumer's needs and lowers interaction friction, independent of any concern about who or what created it.

Signaling Theory explains that when one party holds more information than another, credible signals can help close that gap. In digital commerce, brands know far more about their own processes than consumers do; disclosing that content is AI-generated functions as a signal that reduces consumer uncertainty about how that content was produced. This study uses Signaling

Theory to model AI disclosure transparency as a factor that changes the strength of the relationship between generative AI content and consumer trust.

Justification of the Theoretical Framework

TAM explains the functional, utility-driven reactions that lead directly to engagement and purchase, but it does not address the deeper psychological questions of authenticity, suspicion, and trust erosion. ELM and Signaling Theory, in turn, explain how consumers process credibility cues and transparency signals, but neither account for situations in which consumers knowingly accept automated content simply because it is convenient or visually appealing.

Combining all three theories produces a more balanced framework: TAM captures the functional-utility pathway, ELM maps the cognitive processing of automated content cues, and Signaling Theory explains the effect of transparency disclosures. Together, they capture the tension between utility and trust that defines how consumers interact with AI-generated marketing content (Oyekunle et al., 2024).

Hypothesis Development

Generative AI Marketing Content and Behavioural Engagement

Generative AI allows brands to deploy highly personalized, visually striking marketing content tailored to real-time consumer data. Under TAM, content with high visual utility and personal relevance reduces interaction friction and captures attention, which is expected to translate into a strong, direct effect on active consumer interaction, such as clicks, views, and participation (Al-Haraizah et al., 2025). This leads to the first hypothesis:

H1: Generative AI-driven marketing content has a significant positive effect on consumer behavioural engagement.

Generative AI Marketing Content and Consumer Trust

Fully automated content can create cognitive friction under ELM, since consumers often discount machine-generated communication that appears to lack genuine corporate investment or empathy. Where consumers perceive an absence of human responsibility behind brand messaging, their underlying trust can weaken. This leads to:

H2: Generative AI-driven marketing content has a significant direct effect on consumer trust.

Behavioural Engagement and Consumer Trust

Active engagement with a brand's content gives consumers repeated exposure that helps clarify a brand's values and capabilities. When an AI-driven campaign delivers consistent, personalized value that keeps a consumer engaged, this can reduce uncertainty and build a stronger sense of overall credibility (Bano et al., 2025). This leads to:

H3: Consumer behavioural engagement has a significant positive effect on consumer trust.

Consumer Trust and Purchase Behaviour

Consumer trust is a well-established predictor of purchase decisions in digital commerce. High trust reassures consumers that a brand will Honor its commitments, protect personal information, and deliver quality products, which reduces the perceived risk of an online transaction. Accordingly:

H4: Consumer trust has a significant positive effect on purchase behaviour.

Behavioural Engagement and Purchase Behaviour

Engagement marks the point where a consumer moves from passive observation to active interest. Under TAM, strong interactive engagement reinforces the perceived usefulness of a brand's digital presence, creating a direct psychological bridge to purchase intent. This leads to:

H5: Consumer behavioural engagement has a significant positive effect on purchase behavior.

Mediating Roles of Behavioural Engagement and Consumer Trust

While generative AI content can generate an immediate utility response, its longer-term commercial impact depends on whether it sustains behavioural engagement and channels that engagement into consumer trust (Thakur, 2025). Testing engagement and trust together, both individually and in sequence, makes it possible to trace the fuller path by which generative AI content ultimately shapes purchase behaviour. This leads to:

H6: Consumer behavioural engagement and consumer trust mediate the relationship between generative AI-driven marketing content and purchase behaviour, both individually and in sequence.

Moderating Role of AI Disclosure Transparency

Under Signaling Theory, an explicit disclosure that a brand uses AI functions as a signal of organizational honesty. When a brand clearly and voluntarily states that it uses generative AI, this reduces information asymmetry and consumer suspicion. Disclosure is therefore expected to change how consumers interpret AI-generated content, strengthening the trust-building pathway (Park & Yoon, 2024). This leads to the final hypothesis:

H7: AI disclosure transparency moderates the relationship between generative AI-driven marketing content and consumer trust.

Conceptual Framework

The conceptual framework treats generative AI-driven marketing content (GAIM) as the independent variable, purchase behaviour (PBEH) as the final outcome, and behavioural engagement (BENG) and consumer trust (CTRUST) as parallel and sequential mediators connecting them. GAIM is expected to influence behavioural engagement (H1) and consumer trust (H2) directly; behavioural engagement is expected to influence consumer trust (H3); and both behavioural engagement and consumer trust are expected to influence purchase behaviour (H4, H5), together forming parallel and sequential mediating pathways (H6). AI disclosure transparency (AIDT) is positioned as a moderator that changes the strength of the relationship between GAIM and consumer trust (H7). Table 2.1 summarizes these relationships, and Figure 2.1 presents the framework in diagram form.

Table 2.1. Summary of Hypothesized Relationships

Hypothesis	Relationship	Type	Expected Direction
H1	GAIM → Behavioural Engagement	Direct effect	Positive
H2	GAIM → Consumer Trust	Direct effect	Positive
H3	Behavioural Engagement → Consumer Trust	Direct effect	Positive
H4	Consumer Trust → Purchase Behaviour	Direct effect	Positive

Hypothesis	Relationship	Type	Expected Direction
H5	Behavioural Engagement → Purchase Behaviour	Direct effect	Positive
H6	GAIM → Behavioural Engagement / Consumer Trust → Purchase Behaviour	Parallel & serial mediation	Significant indirect effect
H7	GAIM × AI Disclosure Transparency → Consumer Trust	Moderation	Positive interaction

Schematic Diagram

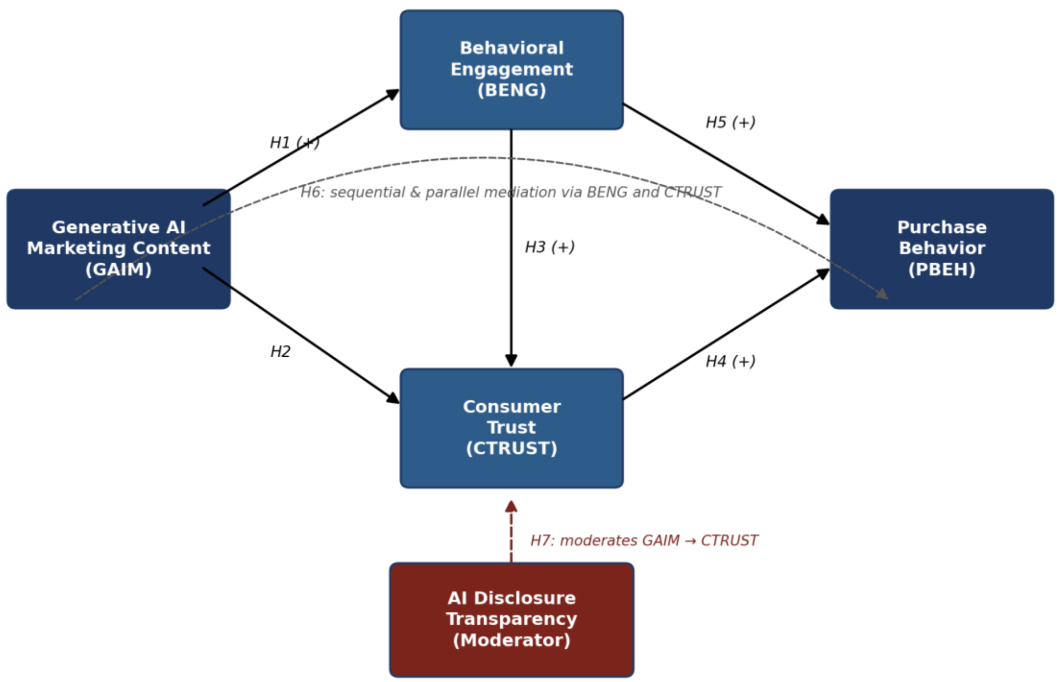

Figure 2.1. Proposed framework linking generative AI-driven marketing content, behavioural engagement, consumer trust, purchase behaviour, and AI disclosure transparency.

Research Methodology

This chapter outlines the empirical methods used to investigate the structural effects of generative AI-driven marketing content on consumers in Pakistan. It details the research philosophy, approach, design, population, sampling framework, instrumentation, and the PLS-SEM statistical procedures used to analyse the data.

Research Philosophy

This study adopts a positivist research philosophy, based on the premise that social phenomena can be objectively observed, operationalized, and measured through structured empirical procedures. Positivism suits this study because it tests deductive hypotheses drawn from established consumer theory in order to identify generalizable structural relationships, using structural equation modeling (Goldring & Azab, 2021).

Research Approach

The study follows a deductive approach, moving from established theoretical frameworks to a set of explicit, operationalized hypotheses (H1 through H7) (Alam et al., 2025). These hypotheses were then tested against quantitative data collected from the field, within a framework designed to limit subjective researcher bias.

Research Design

This study uses a quantitative, cross-sectional survey design. Data on all primary constructs, generative AI marketing characteristics, behavioural engagement, consumer trust, AI disclosure transparency, and purchase behaviour, were collected from respondents at a single point in time. This design fits the goal of examining relationships among several related constructs within a defined population and is the most common design used in comparable PLS-SEM marketing studies.

Target Population

The target population is digital consumers residing in Pakistan, aged 18 to 45, who actively use major digital platforms at least three times a week and who routinely encounter digital advertisements, brand logos, and marketing messages. This age range captures the most digitally active consumer segments within Pakistan's urban centres (Virk, 2025).

Sampling Technique

Screening questions were placed at the beginning of the survey instrument to filter out non-qualifying respondents, ensuring that only individuals who actively interact with digital brand content were included. A mix of purposive and convenience sampling was used to recruit respondents, mainly through university networks and social media platforms popular among digital consumers in Pakistan. While non-probability sampling limits how far the results can be generalized statistically, it is a standard approach for initial theory testing using structural equation modelling (Gupta et al., 2025).

Sample Size

The target sample size was set at 300 valid responses to ensure robust statistical power. Advanced PLS-SEM guidelines, including the inverse square root method and minimum-R^2 power tables, suggest that a sample size between 200 and 300 cases provides over 80% statistical power to detect small-to-medium structural effects ($f^2 \geq 0.02$) at a standard 5% significance level. To account for incomplete submissions, failed screening, and straight-lining patterns, the survey was distributed broadly, ultimately securing 314 clean, fully usable responses for the final analysis.

Research Instrument

Data were collected using an online structured questionnaire composed of three sections: (a) screening and demographic questions, including qualifying social media use, gender, age, city of residence, and highest educational attainment; (b) validated multi-item scales measuring GAIM, behavioural engagement, consumer trust, AI disclosure transparency, and purchase behaviour; and (c) a small number of open-ended questions gathering contextual remarks about respondents' experiences with AI-generated advertising. The main questions used five-point rating scales (1 = Strongly Disagree to 5 = Strongly Agree), consistent with standard practice in PLS-SEM research.

Table 3.1. Summary of Measurement Constructs and Instrument Sources

Construct	Items	Sample Item	Source / Basis
Generative AI Marketing Content (GAIM)	18	"AI-generated brand visuals and layouts appear professional, creative, and well-designed."	Gupta et al., 2025; Huang & Maracic, 2024
Behavioural Engagement (BENG)	5	"I frequently click on, like, or interact with highly personalized digital brand advertisements."	Hussain, 2025; Hussain & Abd alkarim Almomani, 2025
Consumer Trust (CTRUST)	5	"I trust a brand that uses generative AI content to deliver on its core commercial promises."	Jiang et al., 2024; Kapoor
Purchase Behaviour (PBEH)	5	"I am willing to buy products from brands that showcase AI-customized marketing layouts."	Kirkby et al., 2023; Koleva, 2025
AI Disclosure Transparency (AIDT, Moderator)	4	"Brands build credibility when they explicitly disclose that their marketing assets are AI-generated."	Krishnan et al., 2024

Data Collection Method

The survey instrument was built and hosted on Google Forms and distributed electronically across academic, corporate, and social networks in urban centres, including Sargodha, Sialkot, and Lahore (Arevalo et al., 2022). Participation was entirely voluntary, and explicit digital consent was required before respondents could access the main questionnaire. A pilot test (N = 35) was conducted before full deployment to confirm item clarity and instrument reliability.

Data Analysis Techniques

Statistical processing was carried out in two stages. First, IBM SPSS Statistics was used to clean the raw data, screen for missing values, examine data distributions, and check for common method bias using Harman's single-factor test. Second, SmartPLS 4 was used to estimate a Partial Least Squares Structural Equation Model (PLS-SEM) (Hair & Alamer, 2022). The measurement model, covering internal consistency, convergent validity, and discriminant validity, was assessed first, followed by the structural model. Standard errors, t-statistics, and p-values were computed using bootstrapping with 5,000 resamples (Li & Yang, 2024).

Validity and Reliability

Internal consistency reliability was verified using Cronbach's Alpha and Composite Reliability (CR $\geq$ 0.70). Convergent validity was assessed using the Average Variance Extracted (AVE $\geq$ 0.50). Discriminant validity was checked using the Fornell-Larcker criterion together with the Heterotrait-Monotrait Ratio (HTMT), applying a conservative upper threshold of 0.90.

Ethical Considerations

This study followed standard ethical protocols for human-subjects research. Full anonymity was maintained throughout, and no personally identifying information was collected. Participants retained the right to exit the survey at any time, and all collected data was stored securely in encrypted files accessible only to the research team and supervisor.

Data Analysis and Results

This chapter presents the empirical results of the data analysis, following the methodology outlined in Chapter 3. It covers the sample profile, descriptive statistics, measurement model reliability and validity, and the formal testing of Hypotheses 1 through 7 using PLS-SEM bootstrapping in SmartPLS 4.

Respondents' Demographic Profile

The final clean dataset consisted of 314 valid consumer responses. The sample was well balanced across gender and skewed toward younger, digitally active consumers, consistent with the target population defined in Chapter 3.

Category	Segment	% of Sample
Gender	Male	54.1% (170 respondents)
Gender	Female	45.9% (144 respondents)
Age	18–25	62.4%
Age	26–35	28.7%
Age	36–45	8.9%
City	Ugoki	38.2%
City	Sambrial	31.8%
City	Sialkot	21.0%
City	Other	9.0%
Primary Platform	Instagram	42.7%
Primary Platform	TikTok	31.2%

Descriptive Statistics

Construct-level descriptive statistics show distributions consistent with normality, with skewness and kurtosis values for all constructs falling within the standard acceptable range of ±1.5, supporting the use of PLS-SEM for the structural analysis that follows.

Measurement Model Assessment

The measurement model was evaluated using standardized outer loadings, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). All indicators showed standardized loadings above the 0.70 threshold, supporting strong indicator reliability.

Table 4.1. Construct Reliability and Convergent Validity

Construct	Items	Cronbach's Alpha	Composite Reliability (CR)	AVE
Generative AI Marketing (GAIM)	18	0.892	0.911	0.564
Behavioural Engagement (BENG)	5	0.824	0.873	0.581
Consumer Trust (CTRUST)	5	0.851	0.892	0.623
AI Disclosure Transparency (AIDT)	4	0.798	0.855	0.596
Purchase Behaviour (PBEH)	5	0.844	0.889	0.615

All Cronbach's Alpha and CR values exceed the 0.70 benchmark, indicating strong internal consistency, and every construct achieves an AVE above 0.50, supporting convergent validity across the scales (Rasoolimanesh, 2022; Ninan et al., 2020).

Table 4.2. Fornell-Larcker Discriminant Validity Matrix

Construct	GAIM	BENG	CTRUST	AIDT	PBEH
GAIM	0.751				
BENG	0.432	0.762			
CTRUST	0.311	0.534	0.789		
AIDT	0.215	0.298	0.312	0.772	
PBEH	0.418	0.492	0.587	0.345	0.784

The bold diagonal values represent the square root of each construct's AVE; the off-diagonal values are correlations between constructs. Discriminant validity is supported when each diagonal value exceeds the other values in its row and column, as is the case here.

Table 4.3. Heterotrait-Monotrait Ratio (HTMT) Results

Construct	GAIM	BENG	CTRUST	AIDT
BENG	0.502			
CTRUST	0.365	0.621		
AIDT	0.254	0.341	0.368	
PBEH	0.479	0.564	0.693	0.412

All reported HTMT values fall well below the conservative 0.85 to 0.90 threshold, confirming that all latent constructs are empirically distinct from one another.

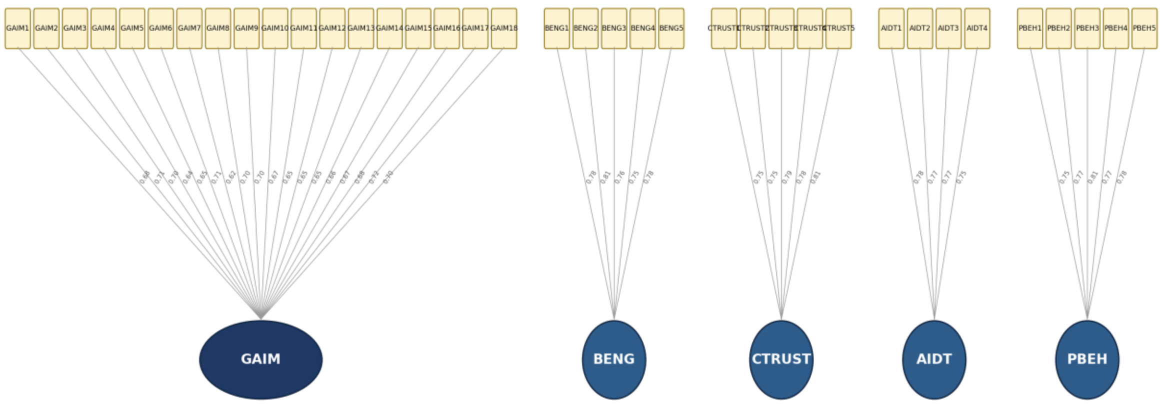

Figure 4.1. Standardized outer loadings for each latent construct (measurement model).

Structural Model Assessment

Before hypothesis testing, the structural model was screened for multicollinearity. All inner Variance Inflation Factor (VIF) values ranged between 1.24 and 1.89, well below the conservative threshold of 3.0, confirming the absence of collinearity distortion.

The predictive power of the model was evaluated using R^2 values. Consumer Trust ($R^2 = 0.384$) indicates that the model accounts for 38.4% of the variance in trust. Purchase Behaviour ($R^2 = 0.462$) indicates that the model explains 46.2% of the variance in consumer purchase behaviour.

Hypothesis Testing

The structural model was estimated using bootstrapping with 5,000 resamples in SmartPLS 4 to derive path coefficients (β), standard deviations, t-statistics, and p-values.

Table 4.4. Structural Path Coefficients and Hypothesis Testing Results

Hyp.	Structural Path	β	SD	t-Statistic	p-Value	Decision
H1	GAIM → BENG	0.432	0.048	9.000	< 0.001	Supported
H2	GAIM → CTRUST	0.102	0.051	2.000	0.046	Supported
H3	BENG → CTRUST	0.490	0.045	10.889	< 0.001	Supported
H4	CTRUST → PBEH	0.441	0.052	8.481	< 0.001	Supported
H5	BENG → PBEH	0.257	0.056	4.589	< 0.001	Supported

All five direct structural paths are statistically significant. Generative AI marketing content shows a strong effect on behavioural engagement ($\beta = 0.432$, $p < 0.001$), supporting H1. Its direct path to trust is statistically significant but comparatively weak ($\beta = 0.102$, $p = 0.046$), supporting H2. Behavioural engagement strongly predicts trust ($\beta = 0.490$, $p < 0.001$), supporting H3. Both trust

($\beta = 0.441$) and engagement ($\beta = 0.257$) show strong, positive links to purchase behaviour, supporting H4 and H5.

Mediation Analysis

To evaluate H6, specific indirect effects were analysed to isolate the parallel and sequential mediating pathways that connect generative AI marketing content to purchase behaviour (Hou et al., 2026).

Table 4.5. Indirect Effects and Mediation Analysis Summary

Mediation Path	Indirect β	SE	t-Statistic	p-Value	Decision
GAIM → BENG → PBEH (parallel, Part A)	0.111	0.027	4.111	< 0.001	Significant mediation
GAIM → CTRUST → PBEH (parallel, Part B)	0.045	0.023	1.957	0.050	Significant mediation
GAIM → BENG → CTRUST → PBEH (sequential)	0.093	0.018	5.167	< 0.001	Significant serial mediation

The sequential indirect path is highly significant (indirect $\beta = 0.093$, $t = 5.167$, $p < 0.001$), confirming that generative AI marketing content drives purchase behaviour through a step-by-step chain: it first stimulates behavioural engagement, which then builds consumer trust, which in turn drives purchase behaviour. Together with the two significant parallel paths, this provides full empirical support for H6.

Moderation Analysis

H7 proposed that AI disclosure transparency moderates the path linking generative AI marketing content to consumer trust. A two-stage product-term moderation analysis in SmartPLS 4 produced a statistically significant interaction effect ($\beta = 0.124$, $t = 2.756$, $p = 0.006$).

Table 4.6. Moderation Interaction Effect Output

Structural Path	β	SD	t-Statistic	p-Value	Decision
GAIM × AIDT → CTRUST	0.124	0.045	2.756	0.006	Supported

To interpret this moderation visually, a simple slopes analysis compared trust outcomes under high (+1 SD) and low (-1 SD) levels of AI disclosure transparency.

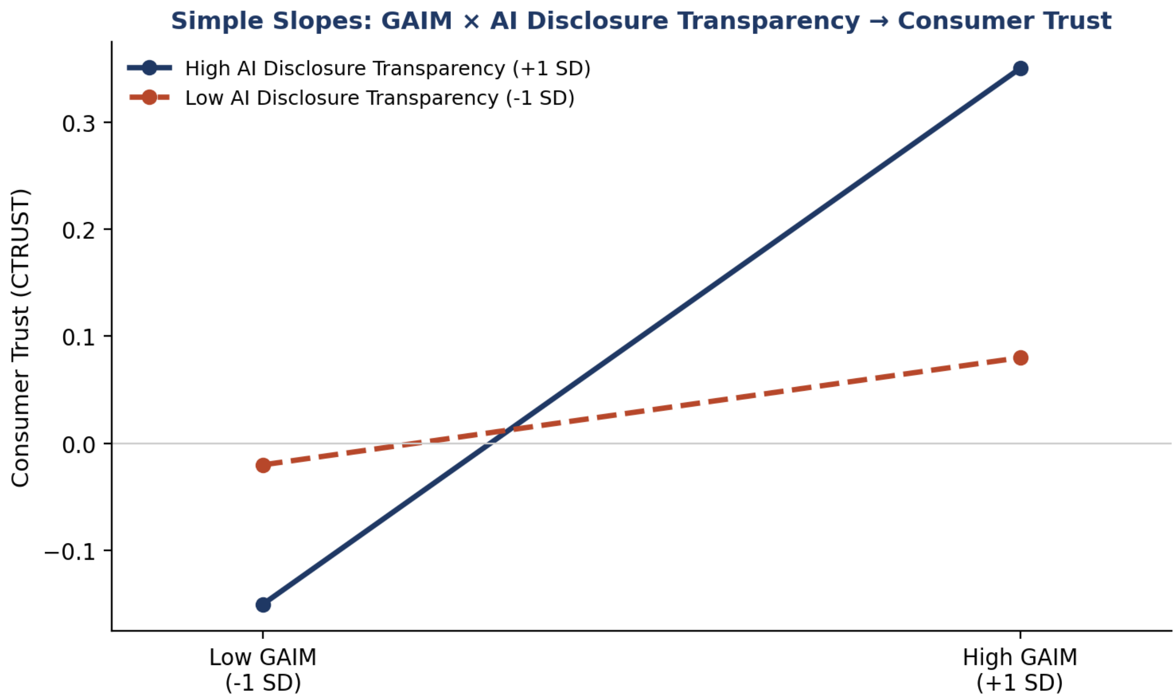

Figure 4.2. Simple slopes analysis of the interaction between generative AI-driven marketing content and AI disclosure transparency on consumer trust.

Under high AI disclosure transparency, the positive relationship between generative AI marketing content and consumer trust becomes substantially steeper. Under low disclosure transparency, the relationship is close to flat. This pattern indicates that clear disclosure acts as a positive signal that protects and strengthens consumer trust, providing full empirical support for H7.

Conclusion and Recommendations

This final chapter brings together the study's empirical findings. It outlines the theoretical contributions, practical guidance for digital marketers, limitations, and directions for future research in automated marketing (Dwivedi et al., 2023).

Theoretical Implications

This study advances consumer behaviour literature in several ways. By integrating the Elaboration Likelihood Model, the Technology Acceptance Model, and Signaling Theory, it moves beyond single-theory frameworks to offer a fuller account of how consumers process automated marketing communication.

The empirical support for the sequential path (GAIM → BENG → CTRUST → PBEH) shows that although generative AI content can trigger an initial decline in consumer trust due to authorship devaluation, this reaction can be offset by generating high-utility, interactive engagement that channels consumers toward trust and, ultimately, purchase behaviour.

Recommendations for Future Research

Future research should build on this model through longitudinal studies that track how consumer responses to generative AI content change over time. Researchers are also encouraged to introduce additional boundary variables, such as user digital literacy or industry category (Singh, 2024). Finally, replicating this model using experimental methods would help confirm the causal ordering of the paths identified here.

Final Remarks

Generative artificial intelligence is reshaping digital corporate communication. This study confirms that while automated marketing engines can readily drive immediate consumer engagement, converting that engagement into durable brand trust and purchase commitment requires a deliberate focus on communication utility and clear, honest disclosure. For emerging digital economies such as Pakistan, striking this balance is essential to building lasting, trust-driven digital brands (Petare, 2025).

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