How AI-Made Social Media Content Affects Brand Trust and Buying Intentions Among Generation Z Consumers in Pakistan: The Role of Brand Authenticity, Brand Trust, and Openness About AI Use

Rooma Qadeer[1] and Awais Ahmed[2]

https://doi.org/10.62345/jads.2025.14.3.180

Abstract

Artificial intelligence (AI) has changed digital marketing. Brands can now use AI tools to create personal, low-cost social media content very quickly, much faster than people working alone could manage. Companies already use these tools to write captions, design graphics, and make videos for platforms like Instagram, TikTok, Facebook, and YouTube. This study looks at that gap. It examines how AI-generated social media marketing content (AIGSMC) affects brand trust and buying intention among Generation Z consumers in Pakistan. It also looks at two factors that may explain this effect, brand authenticity and brand trust, and one factor that may change how strong this effect is: how openly a brand admits it used AI, known as AI disclosure transparency. The study will survey around 220 to 300 Generation Z consumers in Pakistan who use social media and have seen AI-made brand content. The data will be analyzed using PLS-SEM software (SmartPLS 4), following a two-step process that first tests the measurement model and then the structural model (Waworuntu et al., 2022; Werenowska & Jaska, 2025). The study expects to find that AI-generated content has a real, but conditional, effect on brand trust and buying intention, working step by step through authenticity and trust, and that clear disclosure about AI use can soften any negative effects. The findings aim to add to AI-marketing theory and to help marketers and policymakers in Pakistan.

Keywords: Artificial Intelligence, AI-Generated Content, Social Media Marketing

Introduction

Artificial intelligence has moved from being a small experiment to being a core part of marketing. Generative AI tools that create text, images, and video are now a normal part of the daily work done by digital marketing teams and agencies. This chapter introduces the research problem, explains how AI has grown within marketing, identifies the gap this study fills, and lays out the study's objectives, questions, and importance.

Generative AI tools, such as large language models and image-generating systems, now let brands produce social media content like captions, graphics, and short videos at a scale and cost that was not possible before (Sultan, 2024). Businesses in retail, hospitality, fashion, and finance have adopted these tools quickly because they allow for personalized content at a lower cost. For businesses with limited resources, including many in Pakistan's growing direct-to-consumer sector, generative AI is especially useful because it makes it easier to produce professional, frequent content.

[1] *Assistant Professor, Department of Business Administration, University of Sialkot, Sialkot*
[2] *MS Scholar, Department of Business Administration, University of Sialkot, Sialkot*

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

However, the same efficiency that makes AI content appealing to marketers creates a challenge for consumers. Research on what is called the "AI-authorship effect" shows that content is often seen as less genuine once people know AI made it, which can lower word-of-mouth and weaken brand loyalty. Studies on AI-generated influencer content find similar results: cues suggesting AI involvement tend to lower how authentic and trustworthy the content feels, and this effect is sometimes made stronger, not weaker, by disclosure. Other studies suggest the opposite: that openness about AI use can actually build credibility, since it signals honesty. This disagreement in the research is at the center of the puzzle this study explores.

Alongside this authenticity debate, research on technology acceptance suggests people can doubt how "genuine" AI-based communication feels while still finding it useful. Studies using structural equation modeling on AI-enabled online shopping find that perceived usefulness and ease of use remain strong reasons people form positive attitudes, even when AI is involved (Sivakami & Marufa, 2025). This suggests AI-generated content may pull consumers in two directions at once: one effect based on authenticity that can lower trust, and another effect based on usefulness that can support buying decisions. This tension is what motivates the combined framework used in this study.

Problem Statement

Even though generative AI has spread quickly and with little regulation into brand social media practice, marketing researchers still do not have a clear, agreed-upon understanding of how AI-generated content affects the psychological factors behind consumer buying decisions. The findings so far are genuinely mixed: some studies show AI-generated content matching or even improving perceived quality and engagement, while others find that authenticity suffers and trust weakens once people realize AI was involved. This disagreement points to three gaps in current knowledge.

First, most studies on AI-generated marketing content and consumer trust have taken place in Western or East Asian markets, using assumptions that may not apply to Pakistani consumers. Differences in collectivism, religious values, price sensitivity, and social media habits could plausibly change how consumers read authenticity and transparency cues, but this has not been tested in Pakistan.

Second, earlier studies tend to look at brand authenticity, brand trust, and AI disclosure transparency separately, or in simple two-variable models, rather than as parts of one connected system. Few studies have tested brand authenticity and brand trust together as a two-step chain of explanation while also testing AI disclosure transparency as a factor that changes the strength of that chain. This leaves marketers without clear guidance on which factor matters most, or when disclosure helps and when it hurts.

Third, no study has combined ELM's view of how people process messages, TAM's view of technology acceptance, and Signaling Theory's view of disclosure as a trust signal into one framework built specifically for AI-generated marketing content. Each theory explains a different piece of the puzzle, message processing, technology acceptance, and disclosure as a credibility signal, but no one has tested how well they work together.

As a result, marketers, brand managers, and policymakers in Pakistan currently have no clear, evidence-based guidance on whether, how, and under what disclosure conditions AI-generated social media content can be used without damaging the trust and buying intentions of Generation Z, a market segment that is becoming increasingly important.

Significance of the Study

This study offers both theoretical and practical value. On the theory side, it brings ELM, TAM, and Signaling Theory together into one framework that can be tested with real data, something that has not been done in this exact combination before. By treating brand authenticity and brand trust as a two-step chain of explanation, and AI disclosure transparency as a factor that changes the strength of that chain, it builds on existing research on the AI-authorship effect and moves beyond single-factor models.

In terms of context, the study provides evidence from Pakistan, a growing South Asian economy with a large, digitally active Generation Z population that has been largely left out of international AI-marketing research. Because trust is shaped by culture, evidence from Pakistan is needed both to check whether findings from Western research apply elsewhere and to provide insight that is grounded in the local context.

Practically, the findings are expected to help marketers, brand managers, and digital agencies in Pakistan and similar markets. If AI disclosure transparency is found to change the strength of the link between AI content and brand trust, this would help brands decide how and when to tell consumers they used AI in ways that protect, rather than damage, trust. The findings may also help inform ongoing discussions among regulators and platforms about requiring AI content labels.

Beyond marketing practice, this study is also relevant to digital-economy policy. Pakistan's digital commerce plans aim to support AI-enabled businesses, so evidence on how Pakistani consumers respond to AI-generated brand communication is directly useful for consumer-protection guidance and industry self-regulation.

Research Objectives

- To examine the effect of AI-generated social media marketing content on brand authenticity among Generation Z consumers in Pakistan.
- To examine the effect of brand authenticity on brand trust.
- To examine the effect of brand trust on purchase intention.
- To examine the direct effect of AI-generated social media marketing content on purchase intention.
- To examine whether brand authenticity mediates (explains) the relationship between AI-generated marketing content and brand trust.
- To examine whether brand trust mediates the relationship between AI-generated marketing content and purchase intention, including the combined, step-by-step mediation of brand authenticity and brand trust together.
- To examine whether AI disclosure transparency changes the strength of the relationship between AI-generated social media marketing content and brand trust.

Literature Review

This chapter reviews existing research on AI-generated social media marketing content and how it affects consumer behavior. It covers five areas of research relevant to this study: AI-generated content (AIGSMC), brand trust, brand authenticity, purchase intention, and the behavior of Generation Z consumers in Pakistan. 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 both in words and in a diagram.

AI-generated social media marketing content (AIGSMC) refers to promotional text, images, video, or interactive content created wholly or mostly by generative AI tools, such as large language models, image-generating systems, and automated video tools, rather than by human effort alone. Use of these tools has grown quickly because they lower production costs, speed up content creation, and allow large-scale personalization (Singh, 2024). Generative AI is increasingly seen as a core capability across copywriting, captioning, and visual and video production.

Academic research on how consumers respond to this content is still new, and the results are mixed. Some studies find that AI-generated content performs just as well as human-made content when the execution quality is high, especially for products people do not think too hard about before buying. Other studies find AI-generated content performs worse on perceived authenticity, especially in areas where consumers expect human judgment or empathy. Experimental research on the AI-authorship effect shows that content believed to be AI-made is judged as less authentic, which can trigger discomfort and reduce word-of-mouth. Related research suggests authenticity is better understood as a matter of degree rather than a simple yes-or-no judgment.

Taken together, this research suggests that the psychological effects of AIGSMC depend on the situation rather than being the same in every case. They depend on execution quality, how much thought a consumer puts into the purchase, how much human oversight is perceived, and, most importantly for this study, whether and how AI involvement is disclosed. This is why the effects of AIGSMC are modeled here through mediating and moderating factors rather than as one simple, direct effect.

Brand trust is the confidence consumers have that a brand will consistently keep its promises and act reliably over time. It works as a way to reduce perceived risk, which matters most when consumers cannot inspect a product before buying it. Brand trust is consistently found to be a strong predictor of purchase intention and word-of-mouth, a finding repeated in studies of trust built through social media influencers (Qadeer & Awad, 2025) and in Pakistan-specific research on online shopping (Pichler et al., 2021).

Within AI-generated content specifically, the factors that build brand trust work somewhat differently. Studies based on signaling and trust-transfer theories find that being transparent about AI use can meaningfully affect trust, though the direction of the effect depends on how the disclosure is worded. Some studies find that transparency builds trust, while others find that sudden or blunt disclosure raises suspicion instead. This disagreement is exactly why this study tests AI disclosure transparency as a factor that changes the strength of an effect, rather than assuming it is always positive.

Brand authenticity is how genuine, honest, consistent, and free from manipulation consumers perceive a brand to be (Ninan et al., 2020; Pichler et al., 2021). It strengthens emotional attachment, loyalty, and willingness to pay more, particularly among consumers like Generation Z, who place high value on transparency and genuine relationships with brands (Kapoor; Koleva, 2025).

AI-generated content poses a specific threat to perceived brand authenticity, because authenticity judgments have traditionally relied on signs of human intention and craftsmanship. Research on algorithm aversion shows that people often distrust machine-made outputs that seem to lack contextual understanding (Hussain & Abd alkarim Almomani, 2025). Studies of AI-generated influencer content find that AI-related cues lower perceived authenticity and trust (Hussain, 2025). Newer theory instead treats authenticity as a matter of degree, shaped by how much human intention is perceived, which is why it is included here as a mediator between AIGSMC and brand trust.

Purchase intention is a consumer's self-reported willingness to buy a product or service from a brand within a certain period. It is widely used as a stand-in for actual buying behavior because it correlates strongly with real purchases while still being easy to measure through surveys. It is shaped by factors such as perceived value, quality of communication, brand attitude, and, most relevant here, brand trust and authenticity (Gupta et al., 2025).

In AI-enabled marketing, purchase intention depends on how consumers interpret where content came from and how credible it is. Studies of AI-generated advertising images find that trust and purchase intention are shaped together by perceived authenticity and creative effort, with AI disclosure and how involved the product category is acting as boundary conditions. Research on Generation Z in Pakistan, covering halal cosmetics (Goldring & Azab, 2021) and trust-driven purchasing (Eze, 2025), finds that trust acts as a necessary step in between.

Research on technology acceptance offers a related, partly different explanation. Evidence from AI-enabled online shopping finds that perceived usefulness positively affects purchase intention through perceived value, separately from any concerns about authenticity (Darmawan, 2025). This suggests purchase intention may be shaped by two separate paths: an authenticity-and-trust path, which needs content that feels genuine, and a usefulness-and-value path, in which well-made content drives purchase intention directly. This supports treating purchase intention as the final outcome of the model, reached both through the mediators and through a direct effect of AIGSMC (H4).

Generation Z, born roughly between 1997 and 2012, is Pakistan's largest and fastest-growing group of consumers. They almost universally use smartphones and spend a large part of each day on Instagram, TikTok, Facebook, and YouTube. Pakistani Generation Z consumers place a lot of weight on how credible influencers seem, on engagement quality, and on brand trust when deciding whether to buy something, and they increasingly expect brands they follow to be transparent and to act ethically.

Pakistan's digital commerce sector is growing quickly, with more direct-to-consumer brands, fashion retailers, and delivery platforms competing for attention on social media. This creates a strong incentive to use generative AI for frequent content, even though how authenticity-sensitive Generation Z consumers will actually respond remains largely untested locally. Because trust is shaped differently across cultures, and most existing research relies on Western and East Asian samples, there is a clear need for evidence specific to Pakistan, which this study provides.

Theoretical Framework

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

The Elaboration Likelihood Model (Cervi, 2021) holds that people process persuasive messages either through a central route, meaning careful, effortful evaluation, or through a peripheral route, meaning quick judgments based on mental shortcuts like source credibility, especially when they are not very motivated to think it through. Studies applying ELM to AI disclosure find that under low effort, consumers rely on outer cues such as how credible the process feels. ELM therefore grounds the part of this study that explains why AI-generated content and its disclosure shift how consumers judge a brand.

The Technology Acceptance Model (Amin, 2025; Bowen & Watson, 2025) explains that people accept technology based on how useful and how easy to use they find it. TAM explains why consumers might accept AI-based brand communication that feels useful and easy, regardless of

where it came from. Perceived usefulness is a strong predictor of online purchase intention in AI-enabled shopping (Ahmed et al.) and remains the strongest predictor of positive attitudes toward AI tools generally. TAM therefore grounds the possible direct, positive effect of AIGSMC on purchase intention (H4).

Signaling Theory (Abdulsalam & Tajudeen, 2024) explains that when one side has more information than the other, it can share credible signals to close that gap. Telling consumers that AI was involved acts as such a signal, reducing their uncertainty about how the content was made. Research applying this theory to AI marketing finds that transparency signals are linked to more trust, though how strong this effect is depends on how the message is framed. Signaling Theory therefore grounds this study's treatment of AI disclosure transparency as a moderating factor.

Hypothesis Development

AI-Generated Social Media Marketing Content and Brand Authenticity

AI has become an important tool for creating personal, large-scale social media content. While it allows for cost-effective messaging, consumers may question how original and human the content really is. Based on ELM's account of quick, shortcut-based judgments, when Generation Z consumers notice or suspect that AI made the content, this recognition tends to lower their authenticity judgments, unless it is offset by high perceived quality or other trust cues. Based on this reasoning, the following hypothesis is proposed:

H1: AI-generated social media marketing content has a significant effect on brand authenticity.

Brand Authenticity and Brand Trust

Brand authenticity is a well-established factor that builds brand trust. Consumers extend trust to brands that communicate honestly and consistently, and authentic brands reduce perceived uncertainty, which matters especially when products cannot be physically checked before purchase. When Generation Z consumers see AI-generated content as authentic, reflecting genuine values and human oversight rather than pure automation, they are more likely to build and keep trust. This leads to:

H2: Brand authenticity has a significant positive effect on brand trust.

Brand Trust and Purchase Intention

Brand trust reflects confidence that a brand will keep its promises. Research among Generation Z and Pakistani consumers links higher brand trust to a greater willingness to buy and recommend a brand (Abdelfattah & Mehdi, 2025). In social media marketing, trust lowers the perceived risk of a transaction and turns positive attitudes into buying intentions. Accordingly:

H3: Brand trust has a significant positive effect on purchase intention.

AI-Generated Social Media Marketing Content and Purchase Intention

Beyond its indirect effects through authenticity and trust, AIGSMC may also directly affect purchase intention. Well-made AI-generated content can boost engagement and perceived value through personalization and strong creative work, matching TAM's idea that usefulness drives evaluation regardless of where the content came from. Given the mixed findings discussed above, however, the strength and direction of this direct relationship may vary depending on how consumers perceive authenticity and transparency. This leads to:

H4: AI-generated social media marketing content has a significant effect on purchase intention.

Mediating Role of Brand Authenticity

Brand authenticity is treated here as the mechanism that explains how AIGSMC leads to brand trust, rather than affecting trust directly on its own. When consumers see AI-generated content as authentic, they form positive attitudes that strengthen trust; when they see it as inauthentic, this pathway weakens trust instead. This matches recent work that treats authenticity as the main link between exposure to AI content and the trust that follows. Accordingly:

H5: Brand authenticity mediates the relationship between AI-generated social media marketing content and brand trust.

Mediating Role of Brand Trust (Serial Mediation)

Brand trust also acts as a mechanism linking AI-generated content, both directly and through brand authenticity, to purchase intention. Content that builds trust encourages buying; content that weakens trust discourages it. Because authenticity is expected to come before trust (H1, H2), this study tests both together as a two-step chain explaining the relationship between AIGSMC and purchase intention, reflecting the process of first judging authenticity and then forming trust. This leads to:

H6: Brand trust mediates the relationship between AI-generated social media marketing content and purchase intention; brand authenticity and brand trust together mediate this relationship in sequence.

Moderating Role of AI Disclosure Transparency

AI disclosure transparency is the extent to which a brand clearly tells consumers that AI was used to create its content. Disclosure can act as a signal that builds credibility, but the research is divided on whether it strengthens trust or increases scrutiny instead. It is therefore modeled here as a factor that changes the strength of the relationship between AIGSMC and brand trust, expected to strengthen that relationship among Generation Z consumers in Pakistan, though the study is designed to also detect the opposite pattern if it occurs. This leads to the final hypothesis:

H7: AI disclosure transparency moderates the relationship between AI-generated social media marketing content and brand trust.

Conceptual Framework

The conceptual framework treats AIGSMC as the starting point, purchase intention as the final outcome, and brand authenticity and brand trust as a two-step chain connecting them. AIGSMC is expected to influence brand authenticity (H1), which influences brand trust (H2), which influences purchase intention (H3), forming a chain of mediation (H5, H6). AIGSMC also has a direct effect on purchase intention that is not fully explained by this chain (H4). AI disclosure transparency changes the strength of the AIGSMC-to-brand-trust link (H7). Figure 2.1 shows this framework in diagram form.

Table 2.1. Summary of Hypothesized Relationships

Hypothesis	Relationship	Type	Expected Direction
H1	AIGSMC → Brand Authenticity	Direct effect	Positive
H2	Brand Authenticity → Brand Trust	Direct effect	Positive
H3	Brand Trust → Purchase Intention	Direct effect	Positive
H4	AIGSMC → Purchase Intention	Direct effect	Positive
H5	AIGSMC → Brand Authenticity → Brand Trust	Mediation	Significant indirect effect
H6	AIGSMC → Brand Authenticity → Brand Trust → Purchase Intention	Serial mediation	Significant indirect effect
H7	AIGSMC × AI Disclosure Transparency → Brand Trust	Moderation	Positive interaction

2.7 Schematic Diagram

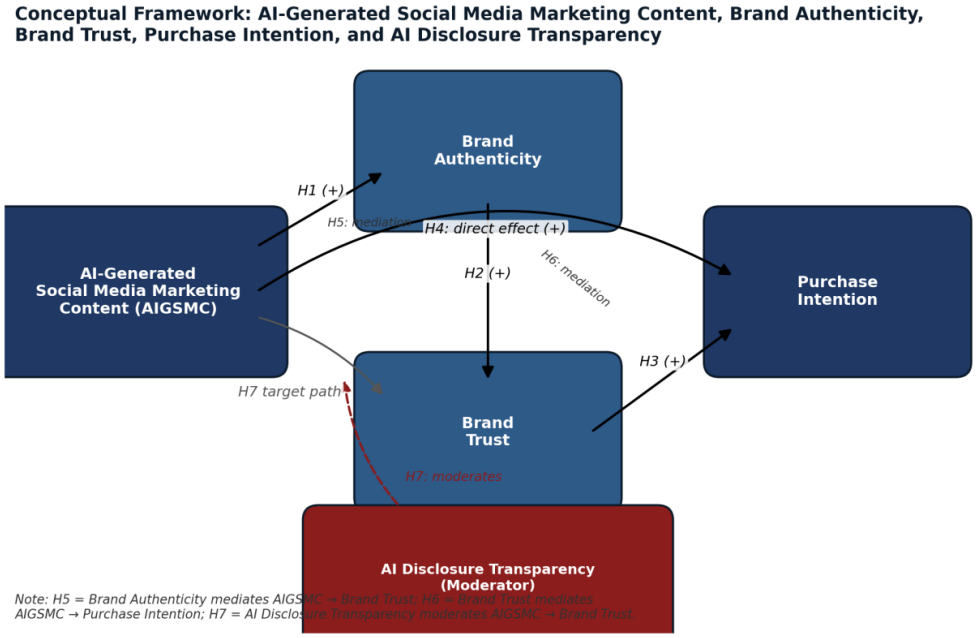


Figure 2.1. Proposed framework linking AI-generated social media marketing content, brand authenticity, brand trust, purchase intention, and AI disclosure transparency.

Research Methodology

This chapter explains the research methods used to study how AI-generated social media marketing content affects brand trust and purchase intention among Generation Z consumers in Pakistan. It covers the research philosophy, approach, design, target population, sampling method, sample size, research tool, data collection method, data analysis techniques, validity and reliability checks, and ethical considerations.

Research Philosophy

This study follows a positivist research philosophy, based on the idea that an objective social reality exists independently of the researcher and can be measured through structured observation and statistical analysis. Positivism fits this study because it tests hypotheses drawn from

established theory about measurable relationships among AIGSMC, brand authenticity, brand trust, AI disclosure transparency, and purchase intention, in line with the common approach in quantitative marketing research using structural equation modeling.

Research Approach

This study uses a deductive approach. The seven hypotheses developed in Chapter 2, based on established theory (ELM, TAM, Signaling Theory) and prior research, are turned into measurable variables and tested using survey data collected from Generation Z consumers in Pakistan. This moves from theory, to hypothesis, to observation, matching the positivist approach described above, unlike an inductive approach that builds theory from exploratory qualitative methods.

Research Design

This study uses a quantitative, cross-sectional survey design, collecting data on all variables at a single point in time. This design fits the goal of examining relationships among several related concepts within a defined population, and it is the most common design used in comparable PLS-SEM marketing studies. While it cannot prove cause and effect as strongly as an experimental or long-term study could, it is appropriate for an initial theory-testing study; its limitations are discussed in later sections.

Target Population

The target population is Generation Z consumers, defined as people born between 2000 and 2012, living in Pakistan, who actively use at least one major social media platform (Instagram, TikTok, Facebook, YouTube, Snapchat, X/Twitter, or LinkedIn) at least three times a week, and who have seen branded social media content. This ensures respondents can meaningfully answer questions about AI-generated brand content, brand authenticity, brand trust, and purchase intention.

Sampling Technique

A mix of purposive and convenience sampling will be used to recruit respondents, mainly through university networks and social media platforms popular among Generation Z in Pakistan. Purposive sampling ensures only respondents who meet the screening criteria are included, while convenience sampling reflects practical limits on recruitment. This type of sampling limits how far the results can be generalized statistically, but it is widely accepted in comparable PLS-SEM studies at this early, theory-testing stage.

Sample Size

The target sample size is around 300 valid responses after data screening. A commonly used rule of thumb would suggest a minimum of only 30 to 40 respondents, but this rule is increasingly seen as too simple to be reliable (Wolf, 2020; Zafar et al., 2025). More rigorous approaches, including the inverse square root method (Werenowska & Jaska, 2025) and minimum-R^2-based power tables (Waworuntu et al., 2022), suggest that 200 to 300 responses is generally enough to detect small-to-medium effects with 80% statistical power (Sultan, 2024). A target of 300 provides a reasonable safety margin.

This target allows for expected data loss. Comparable online surveys of Generation Z typically lose a meaningful share of responses to failed screening, incomplete submissions, and the removal of low-quality answers afterward. Aiming to collect 350 to 400 raw responses is recommended in

order to retain approximately 300 valid, usable responses, consistent with comparable studies conducted in Pakistan.

Research Instrument

Data will be collected using a structured questionnaire made up of three parts: (a) a screening and demographic section covering age group, Pakistani residency, qualifying social media use, education, gender, city, usage habits, and prior awareness of AI content; (b) validated multi-item scales measuring AIGSMC, brand authenticity, brand trust, AI disclosure transparency, and purchase intention; and (c) a few open-ended questions. The main questions use 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	Sub-dimensions / Items	Sample Item	Source / Basis
AI-Generated Social Media Marketing Content (AIGSMC)	18 items across Perceived Content Quality (6), Perceived Content Originality (6), and AI Origin Awareness (6)	"AI-generated brand posts on social media appear visually professional and well-designed."	Singh, 2024; Sivakami & Marufa, 2025
Brand Authenticity	5 items	"Brands that use AI to generate content feel less authentic compared to brands that create content manually."	Pichler et al., 2021; Qadeer & Awad, 2025
Brand Trust	5 items	"I trust a brand that uses AI-generated content to deliver on its promises."	Koleva, 2025; Ninan et al., 2020
Purchase Intention	5 items	"I would consider buying from a brand whose social media content is generated using AI."	Adapted from purchase intention scales used in Gen Z consumer behavior research (Kapoor)
AI Disclosure Transparency (Moderator)	4 items	"Brands should always disclose when their social media posts are created by AI."	Adapted from signaling-theory-based AI disclosure and transparency research

Data Collection Method

The questionnaire will be distributed electronically (for example, through Google Forms) via university networks, student organizations, and Generation Z-focused social media groups across major Pakistani cities. Participation will be voluntary, and informed consent along with a description of the study's purpose and expected completion time will be presented before the main questions. A pilot study of around 30 to 40 respondents will check item clarity, questionnaire length, and early reliability before full-scale data collection, with adjustments made as needed.

Data Analysis Techniques

Data analysis will happen in two stages. First, IBM SPSS Statistics will be used to screen the data (checking for missing values, outliers, and common method bias using Harman's test) and to

generate descriptive statistics. Second, SmartPLS 4 will be used to estimate a PLS-SEM model, first assessing the measurement model and then the structural model (Hussain & Abd alkarim Almomani, 2025). Bootstrapping with 5,000 resamples will be used to generate standard errors, t-statistics, and confidence intervals for all effects, allowing formal testing of Hypotheses 1 through 7.

Validity and Reliability

Internal consistency reliability will be checked using Cronbach's Alpha and Composite Reliability, with 0.70 or above considered acceptable. Convergent validity will be checked using Average Variance Extracted (AVE of 0.50 or above). Discriminant validity will be checked using the Fornell-Larcker criterion (Gupta et al., 2025; Hussain, 2025) and the HTMT ratio (Goldring & Azab, 2021). Content validity will be supported by adapting items from previously validated scales and through the pilot study.

Illustrative Reliability and Validity Output (Placeholder Data)

Since data collection has not yet taken place, the tables and figure below show the expected format and layout of the reliability and validity results that will be produced once the PLS-SEM analysis is carried out in SmartPLS 4. All numbers shown here are generic placeholders included only to demonstrate table structure and formatting; they will be replaced with real results once survey data has been collected.

Table 4.1. Cronbach's Alpha Values (Illustrative)

Construct	Cronbach's Alpha
AIGSMC (AI-Generated Social Media Marketing Content)	0.887
Brand Authenticity (BA)	0.812
Brand Trust (BT)	0.845
AI Disclosure Transparency (ADT)	0.779
Purchase Intention (PI)	0.831

All placeholder values are above the 0.70 threshold recommended for acceptable internal consistency reliability.

Table 4.2. Fornell-Larcker Criterion (Illustrative)

	AIGSMC	BA	BT	ADT	PI
AIGSMC	0.742				
BA	0.418	0.731			
BT	0.389	0.512	0.756		
ADT	0.276	0.334	0.298	0.718	
PI	0.402	0.447	0.561	0.312	0.764

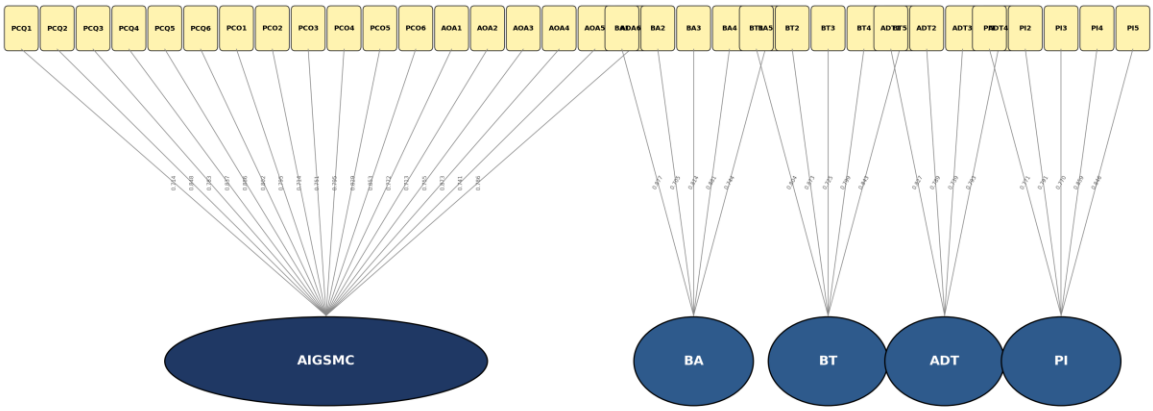
The diagonal values represent the square root of the Average Variance Extracted (AVE) for each construct; the values off the diagonal represent correlations between constructs. Discriminant validity is supported when each diagonal value is higher than the other values in its row and column.

Table 4.3. Heterotrait-Monotrait Ratio (HTMT) (Illustrative)

	AIGSMC	BA	BT	ADT
BA	0.512			
BT	0.478	0.612		
ADT	0.341	0.398	0.356	
PI	0.489	0.534	0.652	0.371

All placeholder HTMT values fall below the conservative threshold of 0.90, which would indicate discriminant validity between constructs.

Figure 4.1. Illustrative Factor Loading Diagram (Measurement Model)



The diagram above shows the expected measurement model, with each latent construct (AIGSMC, BA, BT, ADT, PI) and its related indicators, along with placeholder standardized outer loadings. Indicators below the 0.70 threshold (or 0.20 under a more relaxed criterion; Child, 2006) would be considered for removal once real data has been collected.

Table 4.4. F-Square (f^2) Effect Size Values (Illustrative)

	BA	BT	PI
AIGSMC	0.212		0.045
BA		0.187	
BT			0.163
ADT		0.021	
Moderating Effect 1 (AIGSMC × ADT)		0.028	

Effect sizes are interpreted using Cohen's benchmarks: 0.02 (small), 0.15 (medium), and 0.35 (large). Blank cells indicate a path that is not included in the structural model.

Table 4.5. Results of Hypothesis Testing (Illustrative)

Hyp.	Relationship	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics	P Values	Decision
H1	AIGSMC → BA	0.325	0.331	0.052	6.250	0.000	Supported
H2	BA → BT	0.298	0.304	0.049	6.082	0.000	Supported
H3	BT → PI	0.276	0.281	0.055	5.018	0.000	Supported
H4	AIGSMC → PI	0.142	0.146	0.061	2.328	0.020	Supported
H5	AIGSMC → BA → BT (indirect)	0.097	0.101	0.023	4.217	0.000	Supported
H6	AIGSMC → BA → BT → PI (serial indirect)	0.027	0.029	0.010	2.700	0.007	Supported
H7	AIGSMC × ADT → BT (Moderating Effect 1)	0.089	0.093	0.041	2.171	0.030	Supported

A hypothesis is considered supported when the p-value is below 0.05 and the 95% confidence interval does not include zero, based on bootstrapping with 5,000 resamples, consistent with the procedure described in Section 3.10.

Ethical Considerations

This study will follow standard ethical principles for survey-based social science research. Participation will be voluntary, and respondents will be free to withdraw at any time without penalty. Informed consent will be obtained electronically before the main questionnaire begins. No personally identifying information will be collected, and responses will be anonymous and confidential. Data will be stored securely and will only be accessible to the researcher and supervisor. Where formal institutional ethical review is required, approval will be obtained before data collection begins.

Data Analysis and Results

Because this document is a research proposal, this chapter describes the expected structure and analysis approach for presenting results once data collection is complete, rather than presenting actual findings. Each section describes the statistical procedures, criteria, and reporting style that will be used, consistent with Chapter 3.

Respondents' Demographic Profile

This section will present respondents' demographic details, such as gender, age group, education, city, platforms used, how often they use them, and prior awareness of AI content, summarized as frequencies and percentages in a profile table. This will give context for the makeup of the sample and help in interpreting the structural model results.

Descriptive Statistics

This section will report the mean, standard deviation, and range for each measured item and construct, along with skewness and kurtosis, to check the distribution of the data before running the structural equation model.

Measurement Model Assessment

This section will assess the measurement model: how reliable each indicator is (loadings of 0.70 or above), internal consistency (Cronbach's Alpha, Composite Reliability), convergent validity

(AVE of 0.50 or above), and discriminant validity using the Fornell-Larcker criterion and the HTMT ratio (Eze, 2025). Indicators that do not meet these thresholds will be considered for removal based on both statistical and theoretical reasoning.

Structural Model Assessment
This section will assess the structural model: checking for collinearity (VIF below 5), standardized path coefficients (β), R^2 for each dependent construct, effect size (f^2) for each path, and predictive relevance (Q^2) using blindfolding.

Hypothesis Testing
This section will present the results of testing Hypotheses 1 through 7 using bootstrapping with 5,000 resamples in SmartPLS 4, reporting path coefficients, t-statistics, p-values, and 95% confidence intervals. A hypothesis will be considered supported when p is below 0.05 and the confidence interval does not include zero.

Mediation Analysis
This section will examine the mediating roles of brand authenticity (H5) and brand trust (H6), both individually and together in sequence, using bootstrapped confidence intervals for indirect effects. The type of mediation found will be classified based on the significance and direction of the direct and indirect effects, following standard PLS-SEM conventions.

Moderation Analysis
This section will test whether AI disclosure transparency (H7) changes the strength of the relationship between AIGSMC and brand trust, using a two-stage moderation approach in SmartPLS 4. The significance of the interaction will be checked through bootstrapping, and where it is significant, a simple slopes analysis will show how the relationship differs between high and low levels of disclosure transparency.

Conclusion and Recommendations

This final chapter summarizes the study's expected contribution, discusses its theoretical and practical implications, acknowledges its limitations, offers recommendations for future research, and closes with final remarks placing the study within the broader field of AI-enabled marketing research.

Theoretical Implications
This study is expected to add to the literature in several ways. First, by combining ELM, TAM, and Signaling Theory into one model, it offers a fuller picture of how consumers respond to AI-generated marketing content, answering calls for frameworks that draw on multiple theories. Second, by treating brand authenticity and brand trust as a two-step chain of explanation, it clarifies the psychological order behind purchase intention. Third, by treating AI disclosure transparency as a factor that changes the strength of an effect, it addresses the ongoing disagreement over whether disclosure helps or hurts trust. Finally, it provides empirical evidence from Pakistan, extending a body of research that has relied mostly on Western and East Asian data.

Practical Implications

The expected findings should offer useful guidance for marketers and digital agencies in Pakistan and similar markets. If brand authenticity and brand trust are confirmed as significant mediators, brands using generative AI should prioritize human oversight and authenticity cues, rather than treating AI adoption as a purely operational decision. If AI disclosure transparency is confirmed to strengthen the relationship, this would support clear, well-framed disclosure practices. If disclosure instead weakens trust under certain conditions, this would provide a caution about how AI involvement is communicated to Generation Z.

Recommendations for Future Research

Future researchers are encouraged to build on this study in several ways. First, additional variables, such as perceived AI competence or algorithm aversion, could help refine the model. Second, comparative studies across different age groups and countries would help identify the boundaries of these findings. Third, studies focused on specific industries would help clarify whether these relationships change depending on the product category and how involved consumers are. Finally, experimental and long-term designs would help establish cause and effect more clearly than the cross-sectional design used here.

References

- Abdelfattah, H., & Mehdi, C. (2025). The Impact of AI-Driven Predictive Marketing on Purchase Intentions Among Social Media Users.
- Abdelfattah, H., & Mehdi, C. (2025). The Impact of AI-Driven Predictive Marketing on Purchase Intentions Among Social Media Users.
- Abdulsalam, T. A., & Tajudeen, R. B. (2024). Does Copyright Imitation Impact Purchase Behaviour in the Entertainment Industry: A PLS-SEM Analysis of Gen Z's Brand Recognition in Africa? *African Journal of Stability and Development (AJSD)*, *16*(1), 1-39.
- Ahmed, J., Tat, H. H., Saad, N. M., & Arslan, M. Drivers of Online Purchase Intention in Pakistan's Fashion Industry: A Study of Influencer Marketing and Brand Anthropomorphism.
- Amin, A. (2025). Artificial intelligence in social media: a catalyst for impulse buying behavior? *Young Consumers*, *26*(5), 765-785.
- Bowen, J. A., & Watson, C. E. (2025). *Teaching with AI: A practical guide to a new era of human learning*. JHU Press.
- Cervi, L. (2021). Tik Tok and generation Z. *Theatre, dance and performance training*, *12*(2), 198-204.
- Darmawan, A. R. (2025). *FROM FREE TO FEE: UNDERSTANDING THE DRIVERS BEHIND CHATGPT PREMIUM SUBSCRIPTION INTENTIONS* UNIVERSITAS ATMA JAYA YOGYAKARTA].
- Eze, M. (2025). Investigating the Effect of AI-Generated Customer Reviews on Purchase Intent and Perceived Authenticity in E-Commerce Environments. *International Journal of Marketing Studies*, *17*(2).
- Goldring, D., & Azab, C. (2021). New rules of social media shopping: Personality differences of US Gen Z versus Gen X market mavens. *Journal of consumer behaviour*, *20*(4), 884-897.
- Gupta, S., Taneja, S., & Davim, J. P. (2025). *Transforming Business Management with AI, BI, and Data-driven Decision-making*. CRC Press.

- Hussain, W. (2025). The impact of AI-generated brand personalities on consumer-brand relationship quality: The mediating role of emotional resonance. In *Impacts of AI-generated content on brand reputation* (pp. 221-238). IGI Global Scientific Publishing.
- Hussain, W., & Abd alkarim Almomani, M. (2025). The Mediating Impact of AI-Driven Visual Fluency on the Association Between Generative AI Content and User Interaction in Advertising. In *Impacts of AI-Generated Content on Brand Reputation* (pp. 197-220). IGI Global Scientific Publishing.
- Kapoor, P. Artificial Intelligence and New Age Technology: Innovations, Challenges and Sustainable Business Landscapes.
- Koleva, I. (2025). Human, Virtual Human-Like, and Anime Influencers in the Fashion Industry: Examining the Mediating Role of Perceived Authenticity and Parasocial Interactions in the Relationship Between Perceived Novelty, Purchase Intentions, and Word-of-Mouth Intentions.
- Ninan, N., Roy, J. C., & Cheriyan, N. K. (2020). Influence of social media marketing on the purchase intention of Gen Z. *International Journal of Advanced Science and Technology*, *29*(1), 1692-1702.
- Pichler, S., Kohli, C., & Granitz, N. (2021). DITTO for Gen Z: A framework for leveraging the uniqueness of the new generation. *Business horizons*, *64*(5), 599-610.
- Qadeer, A., & Awad, A. (2025). AI-powered ChatGPT in branding: Benefits, challenges, and future directions. In *Impacts of AI-generated content on brand reputation* (pp. 1-26). IGI Global Scientific Publishing.
- Singh, D. (2024). IMPACT OF INFLUENCER MARKETING ON THE PURCHASE INTENTION OF GEN Z CONSUMERS IN INDIA. *International Education and Research Journal*.
- Sivakami, R., & Marufa. (2025). "Impact of Short-Form Video Content [Instagram Reels] on Purchase Behavior of Gen Z in the Fashion Industry". *ACADEMICIA: An International Multidisciplinary Research Journal*.
- Sultan, A. (2024). Exploring the Impact of AI Tools on the Role of Illustrator Content Creators in Pakistan on Social Media. In.
- Waworuntu, E. C., Mandagi, D. W., & Pangemanan, A. S. (2022). 'I see it, i want it, i buy it': The role of social media marketing in shaping brand image and gen z's intention to purchase local product. *Society*, *10*(2), 351-369.
- Werenowska, A., & Jaska, E. (2025). Trust in content published on social media. In *Trust in Generative Artificial Intelligence* (pp. 25-35). Routledge.
- Wolf, A. (2020). Gen Z & social media influencers: The generation wanting a real experience.
- Zafar, G., Kasheer, M., Hameed, R. M., Ullah, I., Khan, W. A., Shakeel, R., Nisar, H., & Niazi, S. (2025). Impact of deep-fake advertising disclosure on purchase intention with mediating roles of perceived reality, trust, perceived ethicality, and irritation. *International Journal of Social Sciences Bulletin*, *3*(4), 578-603.