

AI-GENERATED BRAND CONTENT AND CONSUMER RESPONSES: THE ROLES OF AUTHENTICITY, TRUST, AND SWITCHING INTENTION

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Abstract

The accelerating deployment of generative artificial intelligence in brand communication has unsettled a long-standing assumption of social media marketing: that the human origin of brand content is self-evident and need not be managed. As brands increasingly automate captions, visuals, and customer messaging, consumers are left to infer whether what they read was authored by a person or a machine, and that inference carries consequences for how genuine, trustworthy, and worth-keeping the brand feels. This study examines how the perceived source of brand content – AI-generated versus human-generated – shapes perceived authenticity, brand trust, and switch intention among social media users aged 18 and above in Punjab, Pakistan, an under-researched but rapidly digitising market. Integrating Source Credibility Theory, the Persuasion Knowledge Model, and Service Recovery Theory, the study advances a moderated-mediation model in which perceived authenticity mediates the effect of content source on both brand trust and switch intention, AI disclosure moderates the content-source-to-authenticity path, and brand response speed moderates the authenticity-to-switch-intention path.

Nine hypotheses were tested on a cross-sectional sample of 360 respondents using partial least squares structural equation modelling (PLS-SEM) with 5,000 bootstrap resamples in SmartPLS 4. The measurement model demonstrated strong reliability and validity, and all nine hypotheses were supported. Content source significantly and positively predicted perceived authenticity and, both directly and through authenticity, was associated with higher brand trust and higher switch intention. AI disclosure significantly weakened the content-source-to-authenticity effect, and a fast brand response significantly weakened the authenticity-to-switch-intention effect. The study

contributes original evidence from a developing digital market and offers brand managers actionable guidance on transparent disclosure and social media responsiveness as levers for protecting trust in an era of automated communication.

INTRODUCTION

1.1 Background of the Study

Generative Artificial Intelligence (AI) has rapidly become a part of the digital brand communication landscape, sparking one of the most significant debates in marketing today: the ability of AI-generated content to resonate with consumers as effectively as human-generated content. With brands now having the ability to leverage AI across Instagram, Facebook, and TikTok, they frequently use these tools to create captions, visual content, and customer-facing messages all in one. The benefits of efficiency have been significant, but consumer acceptance of AI-generated content is a topic of debate, as are the full implications of this new technology on brand trust and consumer loyalty, especially in the context of developing digital markets (Brüns & Meißner, 2024; Kučinskis & Survilaitė, 2025).

Authenticity is now the most dominant process variable in the process of consumer relationship to the brand content. When consumers look at brand content, they don't just consider whether it is relevant or creative, they consider whether it feels authentic, a reflection of a human source and a true reflection of a human intent. Authenticity has always been considered as a fundamental component of the concept of brand equity as it implies that the brand is sincere and consistent with its communication (Morhart et al., 2015). This is not just a theoretical worry, however: followers who perceive a brand's content as being created by a generative-AI source rate their brand's authenticity significantly lower than those who attribute an equivalent content to a perceived human team, and this lower authenticity rating manifests in negative attitudes and behaviors toward the brand (Brüns & Meißner, 2024). Consequently, Israfilzade (2025) reports that while AI-generated ads are perceived as less trustworthy and less likely to influence consumer purchase

intent than human-made ads, content origin also acts as an independent evaluative cue, not just a peripheral stimulus. If and when AI is mentioned or should be assumed to be involved, authenticity perceptions are likely to drop, along with the brands' relational outcomes, such as trust and retention (Wortel et al., 2024). Hanif et al. (2026) also examined the relationship between AI personalization and purchase intention, focusing on consumer trust as a mediator and privacy concern as a moderator. Meanwhile, the way brands react to consumers' concerns on social media and whether they reveal the use of AI in a transparent way does influence consumers' trust, and disclosure has neither a consistent nor guaranteed negative impact on trust, depending on how and when it is communicated (Koning & Voorveld, 2025).

These questions become more relevant in the context of Pakistan. As per DataReportal (2024), as of early 2024 Pakistan had approximately 111 million internet users, and the number of social media users was sizeable and growing at a rapid pace in the youth population below 40 (DataReportal, 2024). As brand relationships build and are tested in social media, it becomes commercially and academically significant to know the effect of the content origin on consumer confidence. The study explores the impact of source of brand content (AI-generated or human-generated) on perceived authenticity, brand trust and brand switch intention among social media users in Punjab, Pakistan and the role of moderation played by brand disclosure of AI and brand response speed.

1.2 Problem Statement

Each of these outcomes, such as perceived authenticity, brand trust, and switching behaviour, has been studied separately in relation to the use of AI-generated content in marketing

compared to human-generated content. However, no studies have been conducted to test the outcomes of using AI versus human generated brand content in a single integrated model. Current research usually focuses on a single mechanism, such as content source and authenticity (Brüns & Meißner, 2024); disclosure and advertising value (Bui, 2025); or some other combination of mechanisms. The conditions when AI disclosure helps or hinders authenticity concerns and how responsive brand communication can buffer authenticity failures and reduce switching remain under-researched, and even mixed results in recent studies suggest that disclosure's effects go beyond a direct negative effect (Bui, 2025; Koning & Voorveld, 2025). Furthermore, most of the evidence comes from a Western or East Asian context, while there is virtually no evidence in literature from markets in South Asia like Pakistan where the adoption of social media is growing rapidly amongst the youth. These gaps are academic and commercial in nature.

1.3 Research Gap

Building on the gaps summarised above and detailed fully in Section 2.4, this study addresses three shortfalls in the current evidence base. First, an integration gap: no identified study tests content source, perceived authenticity, brand trust, switch intention, AI disclosure, and brand response speed simultaneously within a single moderated-mediation model; the literature remains fragmented into isolated dyadic links. Second, a contextual gap: evidence from Pakistan and South Asia is scarce despite rapid social media growth among the region's young population. Third, a theoretical gap: the dual, potentially buffering role of AI disclosure, and the compensating role of brand response speed, have rarely been examined together as formal boundary conditions on the same mediating pathway.

1.4 Research Objectives

- To examine the effect of content source on perceived authenticity, brand trust, and switch

intention among social media users in Punjab, Pakistan.

- To test the mediating role of perceived authenticity between content source and the two brand outcomes.
- To evaluate the moderating role of AI disclosure on the content-source-to-authenticity relationship.
- To evaluate the moderating role of brand response speed on the authenticity-to-switch-intention relationship.

1.5 Research Questions

- RQ1: Does the perceived source of brand content influence consumers' perceived authenticity, brand trust, and switch intention?
- RQ2: Does perceived authenticity mediate the relationship between content source and the brand outcomes?
- RQ3: Does AI disclosure moderate the content-source-to-authenticity relationship?
- RQ4: Does brand response speed moderate the perceived-authenticity-to-switch-intention relationship?

1.6 Significance of the Study

In theory, the study adds to the literature of AI and marketing by consolidating three existing theories (the Source Credibility Theory, Persuasion Knowledge Model, and Service Recovery Theory) into one moderated-mediation model and introducing the relatively new field of machine-authored brand content. Based on empirical evidence, it offers some of the first evidence on these relationships in Pakistan, where the digital market is large and youthful, and where previous studies have not explored these relationships. On a practical level, the results provide brand managers with actionable insights to help ensure brand trust in an age of ever-automated communication: what to disclose and how fast to respond on social media channels.

1.7 Scope and Delimitations

The study is confined to six constructs – content source, perceived authenticity, brand trust, switch intention, AI disclosure, and brand response speed – examined among social media users in

Punjab, Pakistan, aged 18 and above, who actively engage with branded content on Instagram, Facebook, or TikTok. The design is cross-sectional and quantitative, using PLS-SEM in SmartPLS 4.

Chapter 2: Literature Review

With these developments in AI-driven content creation for digital brand communication, there has been a wave of academic interest in consumer reactions to AI-produced marketing content. In this chapter, literature is summarized, mainly from the last decade after 2023. It first explains each of the core constructs, followed by a review of the evidence for each of the hypothesized relationships, and ends with an identification of gaps in the research this study seeks to fill.

2.1 Definitional Clarity of Key Variables

2.1.1 Content Source

The source of the content on social media pages – whether it's created by generative AI tools or generated by a human marketing team – is what is referred to as content source. Brüns and Meißner (2024) showed that follower responses to content from an AI source are not solely attitudinal, but also negative, even when content quality is constant, suggesting that the source is not only an evaluative cue, but operates as an independent evaluative cue. The concept of content source, then, is more like an inference that the consumer makes and depends on stylistic cues, disclosure and platform context, than an objective property of a post, that inference becoming psychologically active when the consumer brings it to their attention.

2.1.2 Perceived Authenticity

Perceived authenticity is the consumer's own opinion of the authenticity, sincerity and lack of manipulation of brand content. On the basis of the previous conceptual approaches to the notion of brand authenticity as continuity, credibility and authenticity, integrity and symbolism (Morhart et al., 2015), Kučinskas and Survilaitė (2025) define perceived authenticity as the crucial psychological process that connects the process of content-

source attribution to outcomes at the brand level. In the AI world, the concept of authenticity is particularly fragile since it is increasingly perceived as a lack of genuine human intent, something consumers look out for when assessing the authenticity of a machine-generated work.

2.1.3 Brand Trust

Brand trust is the consumer's "surety that a brand will fulfill its promises in a competent and honest way" (Chaudhuri & Holbrook, 2001). Loyalty and tolerance of brand mistakes rests on the relational building blocks of trust. However, in the context of AI-generated content, the perception of authenticity becomes a crucial element in determining trust, as there is no personal touch of a human agent involved, which are key factors in establishing trust with brands (Bui, 2025). Jabbar et al. (2026) also examined the relationship between packaging design, brand trust, consumer involvement, and purchase intention.

2.1.4 Switch Intention

Switch intention is a consumer's stated probability of leaving a brand for an alternative brand. In the migration paradigm of consumer research, switching is the product of push factors (discomfort with the existing product) and pull factors (attraction of alternatives) with the influence of mooring factors (loyalty and switching costs). Loss of trust in brand authenticity leads to decrease of mooring effect of brand loyalty and increase of intention to switch brands (Wortel et al., 2024).

2.1.5 AI Disclosure

AI disclosure is the clear and conspicuous sharing of information with consumers that the content is generated by AI. The impact of disclosure is bifaceted and as recent studies remind us, contested—if not just nuanced—Bui (2025) reports that disclosure can lead to a decrease in the value of the ad and purchase intentions, while Koning and Voorveld (2025) report that disclosure also affects, beyond the ad, the trust in the ad and in the organisation behind it. However, disclosure is

also a marker of honesty; and the transparency of the use of AI could help prevent the more severe consequences that consumers might experience when their AI use is subsequently discovered—a “disclosure dilemma” that has come to the forefront of AI-marketing scholarship in recent years (Bui, 2025; Koning & Voorveld, 2025).

2.1.6 Brand Response Speed

Brand response speed is the time taken by the brand to respond to consumer issues on social media. A response based on service-recovery logic brings humanity back into the situation and stops a negative spiral of dissatisfaction leading to defection (Wortel et al., 2024). Reintroducing the human element that AI-generated content is said to have taken away, speed acts as a visible indicator of a brand's attentiveness and empathy.

2.2 Relational Literature and Hypothesised Pathways

2.2.1 Content Source and Perceived Authenticity

The content's origin and its authenticity are important. Brüns and Meißner (2024) offer a direct proof that the followers who were exposed to the AI generated brand content, earn significantly lower brand authenticity scores than those exposed to humans generated brand content. This is supported by Wortel et al. (2024) in the context of Instagram ads, which found that disclosure of AI leads to a sense of persuasion knowledge and inferences of manipulative intent, which decreases source credibility and brand attitude. Similarly, Israfilzade (2025) shows that AI-generated advertising is equally deficient in driving trust and purchase intention, especially for high involvement goods. Furthermore, Raza et al. (2026) examined how AI-driven stimuli influence consumer impulse buying behavior. Another study by Naeem et al. (2026) showed that Social media marketing activities (Content source) had significant positive impacts on both brand trust and buying behavior. This cross-over of the findings of the experimental and survey approaches is that the assignment of AI-created

content poses an authenticity cost that is largely independent of content quality.

2.2.2 Perceived Authenticity, Brand Trust, and Switch Intention

Kučinskas and Survilaitė (2025) find that perceived authenticity is the psychological steppingstone between source perceptions and brand-level consequences, as it establishes the link between the two. Research on the concept of authenticity as a trust antecedent has been well established in the field of branding (Morhart et al., 2015). The loss of the relational anchor of the brand leads to the erosion of trust, and to an increase in switching intention, and this is consistent with the push-mooring account of switching when authenticity is low.

2.2.3 Direct Effects of Content Source on Brand Trust and Switch Intention

The direct effect of content source on brand trust and switch intention is explored in the study. The study explores the direct effect of content source on brand trust and switch intention. Even when considering the mechanisms related to authenticity, Bui (2025) concludes that AI disclosure has an own adverse effect on the credibility of ads and downstream intentions in the brand level assessment. This suggests a partial mediation model in which content source impacts trust and switching both directly and indirectly through authenticity.

2.2.4 AI Disclosure as Moderator

There is no uniform and negative evidence on disclosure; it's a bit mixed. The impact of AI disclosure is partly dependent on consumer attitudes towards AI, as shown by Bui (2025); other research shows that disclosure by itself does not have a direct negative impact, the impact depends on the framing, timing and perceived motives of disclosure (Koning and Voorveld 2025). Transparency, when interpreted as a preemptive and honest disclosure, can help to diminish, rather than enhance, the authenticity penalty because transparency is a sign of integrity,

and prevents the feeling of betrayal that consumers report when they discover that something was hidden from them. The negative content-source-to-authenticity effect is hypothesized here to be weakened by disclosure as a boundary condition instead of uniformly aggravated by disclosure as hypothesized by the uniformly aggravating account.

2.2.5 Brand Response Speed as Moderator

The responsive and transparent brand communication reduces the authenticity gap of AI content, as mentioned by Wortel et al. (2024). A swift and sincere response from a brand to a consumer's concern brings the human element back to the interaction, reducing the likelihood of low authenticity to active switching. Response speed has been identified as one of the most important factors that drives a customer to a recovery state and also one of the most important factors that contributes to post-recovery satisfaction and retention in service-recovery research.

2.3 Research Gaps

Three gaps emerge from this review. First, no study has tested content source, authenticity, trust, switching, disclosure, and responsiveness simultaneously within a single integrated model; the literature remains fragmented into isolated dyadic links, and the disclosure dilemma documented by Bui (2025) and Koning and Voorveld (2025) has rarely been integrated with its moderating conditions in a single tested model. Second, evidence from Pakistan and South Asia is scarce despite rapid social media growth among the region's young population. Third, the dual, potentially buffering role of AI disclosure, and the compensating role of brand response speed, have rarely been examined together as formal boundary conditions on the same mediated pathway. This study addresses all three gaps by testing a complete

moderated-mediation model among social media users in Punjab, Pakistan.

Chapter 3: Conceptual Model and Research

Hypotheses

3.1 Underpinning Theory

The study draws on three complementary theoretical frameworks. Source Credibility Theory (Ohanian, 1990) holds that the perceived origin and trustworthiness of a communication source shape message acceptance and, in this setting, authenticity perceptions. When consumers attribute content to an AI system, perceived source credibility declines because the attributed source is seen to lack human expertise and relational investment, underpinning the content-source-to-authenticity relationship. The Persuasion Knowledge Model (Friestad & Wright, 1994) explains why AI disclosure activates consumer scepticism: recognising AI involvement in a persuasive message prompts coping responses that can lower authenticity, but transparent disclosure can also be read as candour, which is why disclosure is modelled as a moderator rather than a uniform depressant. Service Recovery Theory grounds the moderating role of brand response speed, proposing that timely, sincere responses interrupt the escalation from dissatisfaction to defection by signalling brand empathy, thereby weakening the effect of low authenticity on switch intention.

3.2 Conceptual Model

The conceptual model places content source as the independent variable affecting brand trust and switch intention both directly and indirectly via perceived authenticity. AI disclosure moderates the relationship between content-source and authenticity, while brand response speed moderates the relationship between perceived-authenticity and switch-intention. The entire model is shown in figure 1.

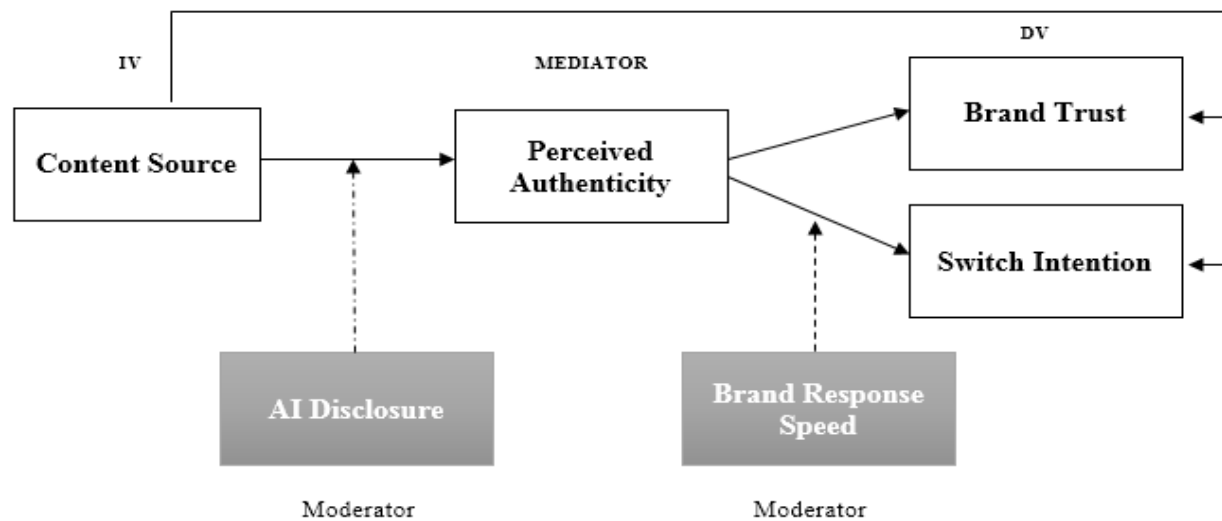


Figure 1 Conceptual Moderated-Mediation Model, Showing Direct Paths (H1–H5), the Mediating Role of Perceived Authenticity (H6–H7), and the Two Moderating Effects (H8–H9)

3.3 Research Hypotheses

Nine hypotheses are derived from the theory and evidence above. Measurement direction: the four focal constructs are operationalised in a common direction, with higher scores reflecting greater salience of AI content, stronger authenticity discernment, greater trust contingent on human authorship, and stronger intention to switch away from AI-reliant brands. The hypotheses are therefore stated as positive associations among these constructs, with the two moderators expected to weaken (negatively interact with) their respective paths.

H1. Content source has a significant positive effect on perceived authenticity: the more salient the AI-versus-human origin of brand content is to a consumer, the stronger their authenticity discernment.

H2. Perceived authenticity has a significant positive effect on brand trust.

H3. Perceived authenticity has a significant positive effect on switch intention.

H4. Content source has a significant positive direct effect on brand trust, independent of perceived authenticity.

H5. Content source has a significant positive direct effect on switch intention, independent of perceived authenticity.

H6. Perceived authenticity significantly mediates the relationship between content source and brand trust.

H7. Perceived authenticity significantly mediates the relationship between content source and switch intention.

H8. AI disclosure significantly moderates the content-source-to-authenticity relationship, weakening it (a negative interaction) as disclosure increases.

H9. Brand response speed significantly moderates the authenticity-to-switch-intention relationship, weakening it (a negative interaction) as response speed increases.

Chapter 4: Research Methodology

4.1 Research Philosophy and Approach

This study follows a positivist philosophy and a quantitative, cross-sectional survey design. Positivism is appropriate because the constructs are clearly operationalised and the relationships among them are expressed as directional, testable hypotheses (Saunders et al., 2023). A deductive logic is adopted: nine hypotheses derived from Source Credibility Theory, the Persuasion Knowledge Model, and Service Recovery Theory are tested against primary data collected from social media users in Punjab, Pakistan (Creswell &

Creswell, 2018). The cross-sectional design efficiently captures associations across a large sample at a single point in time, though it does not permit strong causal inference, a limitation acknowledged in Chapter Seven.

4.2 Population

The target audience includes social media audience of Punjab aged 18 years and above who are active on platforms like Instagram, Facebook and TikTok and have an interest in branded content. Punjab is home to 127,688,922 people which makes up more than half of Pakistan's total population of 241.49 million (Pakistan Bureau of Statistics, 2023). The study's accessible population consisted of people aged 18 and older and is estimated to represent nearly 40 percent of the population of the province (approximately 51 million people). The age band is the most digitally active one, as well as the most vulnerable to brand content created by AI (DataReportal, 2024).

4.3 Sampling Strategy

A purposive sampling technique (non probability) supplemented by snowball sampling is used. To allow for the deliberate selection of the participants who fit the eligibility criteria, purposive sampling was used [aged 18 years or above, resident of Punjab and interacted with the brand pages on social media (Etikan et al., 2016)]. Snowball sampling helps to expand reach by participant referral in social networks, appropriate for digital dissemination. A total of 360 valid responses is set, which is in line with and above the typical numbers for structural equation modelling and moderated-mediation analysis (Hair et al., 2019; Hayes, 2022), respectively. The number of samples achieved ($n = 360$) complies with 10 times rule for PLS-SEM, with a maximum of ten arrows pointing to each construct.

4.4 Data Collection Procedures

The data is gathered using a self-administered, structured online questionnaire, which is sent through social media groups and university networks. Each construct is rated on a 5 point

likert scale (1 = strongly disagree to 5 = strongly agree). The items originate from the well-established instruments, with content items taken from Brüns and Meißner (2024), perceived authenticity from Kučinskas and Survilaitė (2025), brand trust from Chaudhuri and Holbrook (2001), switch intention from Wortel et al. (2024) and the AI-disclosure and brand-response-speed items from Bui (2025) and Wortel et al. (2024). The questionnaire begins with a screening question to verify eligibility and an informed-consent statement to assure anonymity and voluntary participation. To ensure that the items were clear and had acceptable internal consistency (Cronbach's $\alpha \geq .70$), a pilot test was conducted with 30 respondents before full deployment.

4.5 Data Analysis Strategy

This study analyzed data using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4 with two stages as suggested by Hair et al. (2019). The advantages of PLS-SEM make it an appropriate method for this study: It is suitable for non-normal data, it estimates complex models with multiple mediating and moderating relationships at once, and it is suitable for prediction-oriented research.

The reliability and validity of the six reflective constructs are tested in Stage 1 (measurement model) using Cronbach's alpha with a minimum value of .70, composite reliability with a minimum value of .70, average variance extracted with a minimum value of .50, and heterotrait-monotrait ratio with a minimum value of .85, and the Fornell-Larcker criterion (Henseler et al., 2015) with a minimum value of .70.

Stage 2 (structural model) estimates path coefficients and their significance using bootstrapping with 5,000 resamples, producing t-statistics and 95% bias-corrected confidence intervals. Direct effects (H1-H5) are read from the path coefficients; mediation (H6-H7) is tested through the significance of the bootstrapped indirect effects, with an effect deemed significant when the confidence interval excludes zero

(Preacher & Hayes, 2008). Moderation (H8–H9) is tested using the two-stage product-indicator approach, with a significant interaction term confirming the hypothesised boundary condition; simple-slope analysis illustrates the form of each interaction. Explanatory power is assessed with R^2 , and effect sizes with f^2 . Common method bias is examined via Harman's single-factor test (Podsakoff et al., 2003).

4.6 Ethical Considerations

Participation was voluntary and anonymous; the questionnaire opened with an eligibility screen and an informed-consent statement assuring confidentiality; no personally identifying information was collected; and data were used solely for academic research purposes.

Chapter 5: Results

This chapter reports the findings obtained from 360 valid responses analysed using PLS-SEM in

SmartPLS 4. The analysis proceeds in the two stages set out in Chapter Four: assessment of the measurement model, establishing the reliability and validity of the six reflective constructs, followed by assessment of the structural model, which tests the nine hypotheses through path estimation and 5,000-resample bootstrapping. Descriptive statistics, a common-method-bias check, and effect-size estimates are reported alongside. All structural coefficients are standardised.

5.1 Respondent Demographic Profile

The demographic details of the 360 respondents are presented in Table 1. The sample skews towards the youngest age bands and most digitally-active – which, being the target population, is representative of that. The most common main platforms are Instagram and Facebook, with the vast majority of respondents using social media multiple times a day.

Table 1 Demographic Profile of Respondents (N = 360)

Characteristic	Category	n	%
Age	18–24	153	42.5
	25–34	117	32.5
	35–44	53	14.7
	45–54	25	6.9
	55 or above	12	3.3
Gender	Male	185	51.4
	Female	164	45.6
	Prefer not to say	11	3.1
Education	Bachelor's	161	44.7
	Intermediate/A-Levels	81	22.5
	Master's	72	20.0
	Matriculation/O-Levels	32	8.9
	PhD or above	14	3.9
Monthly income (PKR)	30,001–60,000	113	31.4

Characteristic	Category	n	%
Social media frequency	60,001–100,000	96	26.7
	Below 30,000	87	24.2
	100,001–150,000	38	10.6
	Above 150,000	26	7.2
	Several times a day	189	52.5
Primary platform	Once a day	93	25.8
	4–6 times a week	49	13.6
	2–3 times a week	29	8.1
	Instagram	136	37.8
	Facebook	79	21.9
Brand-post frequency	TikTok	75	20.8
	YouTube	38	10.6
	Twitter/X	26	7.2
	Other	6	1.7
	Very frequently – multiple times a day	114	31.7
Purchased via social media	Frequently – once a day	103	28.6
	Sometimes – a few times a week	101	28.1
	Rarely	42	11.7
	Yes, a few times	133	36.9
	Yes, once or twice	84	23.3
	Yes, many times	77	21.4
	No, never	66	18.3

Note. Percentages are column percentages and may not total 100 due to rounding.

5.2 Descriptive Statistics of Constructs

Means and standard deviations for the six constructs are reported as the mean of the items on the 5-point scale by respondent. The scores on the AI-scepticism constructs (content-source salience, and authenticity, trust, and switching

items worded in the AI-critical direction) are concentrated around the scale midpoint to upper-midpoint, whereas the two moderators (AI disclosure and brand response speed) are rated high, suggesting that people appreciate transparency and responsiveness.

Table 2 Descriptive Statistics for the Study Constructs

Construct	Items	M	SD
Content Source (CS)	4	3.504	0.801
Perceived Authenticity (PA)	4	3.659	0.740
Brand Trust (BT)	5	3.438	0.794
Switch Intention (SI)	4	3.312	0.813
AI Disclosure (AID)	4	3.736	0.731
Brand Response Speed (BRS)	4	3.826	0.687

Note. Based on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). M = mean; SD = standard deviation. Items worded so that higher values denote greater authenticity and trust.

5.3 Measurement Model Assessment

5.3.1 Reliability and Convergent Validity

As shown in Table 3, every indicator loads above the .70 threshold on its construct, with one marginal exception noted below, and all six

constructs exceed the recommended cut-offs for Cronbach's alpha ($\geq .70$) and composite reliability ($\geq .70$). Average variance extracted exceeds .50 for every construct, confirming convergent validity (Hair et al., 2019).

Table 3 Outer Loadings, Reliability, and Convergent Validity

Construct	Item	Loading	α	CR	AVE
<i>Content Source (CS)</i>			.855	.902	.697
	CS1	.812			
	CS2	.870			
	CS3	.831			
	CS4	.827			
<i>Perceived Authenticity (PA)</i>			.851	.900	.691
	PA1	.820			
	PA2	.861			
	PA3	.805			
	PA4	.839			
<i>Brand Trust (BT)</i>			.875	.909	.667
	BT1	.823			
	BT2	.818			
	BT3	.840			
	BT4	.795			
	BT5	.805			

Construct	Item	Loading	α	CR	AVE
<i>Switch Intention (SI)</i>			.848	.898	.687
	SI1	.847			
	SI2	.806			
	SI3	.799			
	SI4	.863			
<i>AI Disclosure (AID)</i>			.837	.867	.625
	AID1	.853			
	AID2	.889			
	AID3	.767			
	AID4	.626			
<i>Brand Response Speed (BRS)</i>			.844	.893	.675
	BRS1	.805			
	BRS2	.800			
	BRS3	.821			
	BRS4	.860			

Note. α = Cronbach's alpha; CR = composite reliability (rho_c); AVE = average variance extracted. Thresholds: loadings $\geq .70$; α , CR $\geq .70$; AVE $\geq .50$. Item AID4 loads at .626, marginally below .70; it is retained because AID's CR (.867) and AVE (.625) both exceed their thresholds.

5.3.2 Discriminant Validity

Discriminant validity was assessed with the Fornell-Larcker criterion and the HTMT ratio. In Table 4, the square root of each construct's AVE (bold diagonal) exceeds its correlations with all other constructs. All HTMT ratios (Table 5) fall below the conservative .85 threshold, the maximum observed being .693 (PA-BT), confirming that the six constructs are empirically distinct (Henseler et al., 2015).

Table 4 Discriminant Validity: Fornell-Larcker Criterion

	CS	PA	BT	SI	AID	BRS
CS	.835					
PA	.418	.831				
BT	.471	.603	.816			
SI	.443	.530	.416	.829		
AID	-.029	-.096	.023	.033	.790	

	CS	PA	BT	SI	AID	BRS
BRS	-.050	.060	-.148	-.105	.012	.822

Note. Diagonal values (.835, .831, .816, .829, .790, .822) are the square roots of the AVE; off-diagonal values are inter-construct correlations. CS = content source; PA = perceived authenticity; BT = brand trust; SI = switch intention; AID = AI disclosure; BRS = brand response speed.

Table 5 Discriminant Validity: Selected Heterotrait–Monotrait (HTMT) Ratios

Construct pair	HTMT	Construct pair	HTMT
CS – PA	.489	CS – BT	.540
CS – SI	.520	PA – BT	.693
PA – SI	.616	BT – SI	.480
CS – AID	.055	PA – BRS	.076
SI – BRS	.122		

Note. All construct-pair HTMT ratios fall below the conservative .85 criterion.

5.4 Common Method Bias

Harman's single-factor test was used to gauge common method bias. The first unrotated factor accounted for 28.6% of the variance, well below the 50% threshold, indicating that common method bias is not a serious concern (Podsakoff et al., 2003).

5.5 Structural Model and Hypothesis Testing

5.5.1 Explanatory Power

The model accounts for a meaningful share of variance in all three endogenous constructs. Perceived authenticity records an R^2 of .225, brand trust .422, and switch intention .373,

indicating that the predictors explain approximately 22%, 42%, and 37% of their respective variance – moderate levels by PLS-SEM conventions.

5.5.2 Direct Effects (H1–H5)

Table 6 reports the standardised path coefficients, standard errors, bootstrap t-values, 95% confidence intervals, and decisions for the direct-effect hypotheses. A path is significant at $p < .05$ when $|t| > 1.96$ and its confidence interval excludes zero. Figure 2 presents the corresponding SmartPLS 4 bootstrapping path diagram, from which the coefficients are drawn.

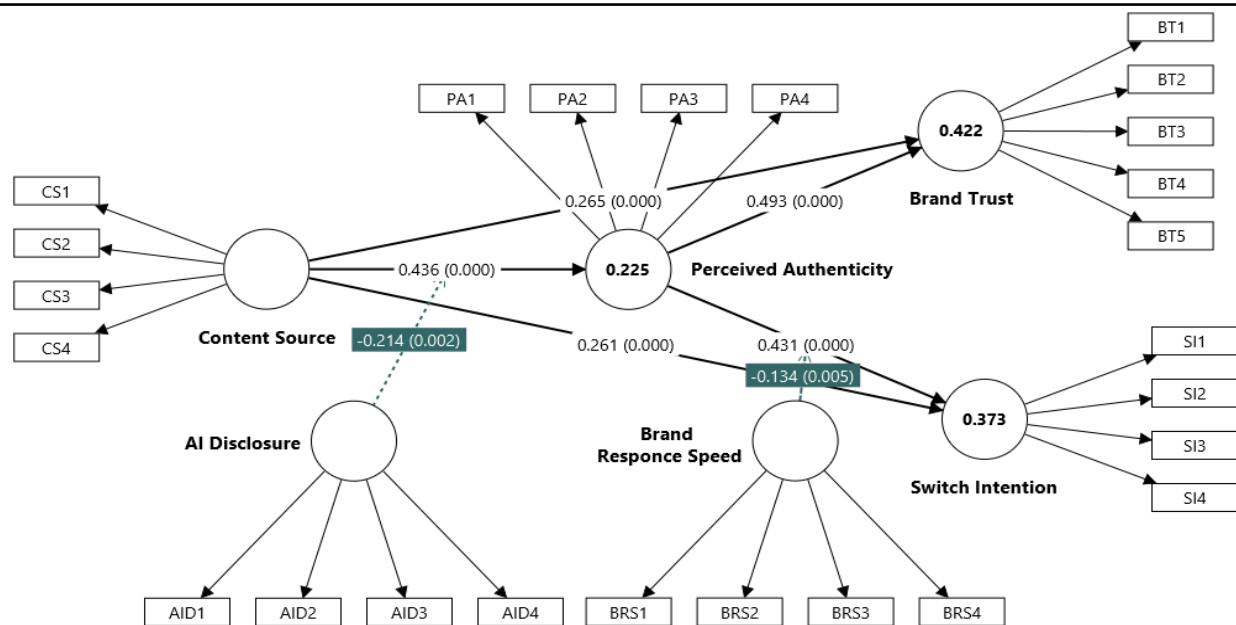


Figure 2 SmartPLS 4 Bootstrapping Path Diagram (Standardised Path Coefficients With p-Values in Parentheses)

Table 6 Direct-Effect Path Coefficients (Bootstrapping, 5,000 Resamples)

Hypothesised path	β	SE	t	95% CI	p	Decision
H1: Content Source → Authenticity	.436	0.044	10.034	[.349, .519]	<.001	Supported
H2: Authenticity → Brand Trust	.493	0.042	11.745	[.406, .571]	<.001	Supported
H3: Authenticity → Switch Intention	.431	0.042	10.298	[.346, .511]	<.001	Supported
H4: Content Source → Brand Trust	.265	0.045	5.931	[.174, .352]	<.001	Supported
H5: Content Source → Switch Intention	.261	0.047	5.599	[.170, .350]	<.001	Supported

Note. β = original-sample standardised path coefficient; SE = bootstrap standard error; CI = bias-corrected 95% confidence interval. Values are taken from the SmartPLS 4 bootstrapping output (5,000 resamples) shown in Figure 2. The two moderator main effects were also estimated: AID → PA (β = $-.095$, t = 1.299 , p = $.194$, n.s.) and BRS → SI (β = $-.116$, t = 2.492 , p = $.013$).

All five direct effects are positive, significant, and consistent with the model. Content source significantly raises perceived authenticity (β = $.436$, t = 10.034), supporting H1. Authenticity in turn significantly raises brand trust (β = $.493$, t = 11.745 ; H2) and switch intention (β = $.431$, t = 10.298 ; H3). Content source also exerts significant positive direct effects on trust (β = $.265$, t = 5.931 ; H4) and switching (β = $.261$, t = 5.599 ; H5). The

associated effect sizes are large for the two authenticity paths ($f^2 = .346$ for $PA \rightarrow BT$ and $.243$ for $CS \rightarrow PA$), medium for $PA \rightarrow SI$ ($f^2 = .242$), and small-to-medium for the content-source direct paths ($f^2 = .100$ for $CS \rightarrow BT$ and $.089$ for $CS \rightarrow SI$).

5.5.3 Mediation Effects (H6–H7)

The mediating role of perceived authenticity was tested through the bootstrapped indirect effects (Preacher & Hayes, 2008). Both indirect paths are significant, with confidence intervals excluding zero (Table 7). Because the corresponding direct effects (H4, H5) also remain significant, authenticity partially mediates both relationships.

Table 7 Mediation Analysis: Bootstrapped Indirect Effects Through Perceived Authenticity

Mediation path	Indirect β	t	95% CI	VAF	Decision
H6: $CS \rightarrow$ Authenticity $\rightarrow$ Brand Trust	.215	7.408	[.163, .278]	44.8%	Supported
H7: $CS \rightarrow$ Authenticity $\rightarrow$ Switch Intention	.188	6.837	[.137, .247]	41.9%	Supported

Note. VAF = variance accounted for = indirect effect $\div$ total effect. Indirect β and CI are the specific-indirect-effect estimates from the SmartPLS 4 bootstrapping output (bias-corrected 95% CI).

For H6, content source raises authenticity, which in turn raises brand trust (indirect $\beta = .215$, VAF = 44.8%). For H7, content source raises authenticity, which in turn raises switch intention (indirect $\beta = .188$, VAF = 41.9%). Because the corresponding direct effects (H4, H5) also remain

significant, both VAF values fall in the 20–80% band indicative of partial mediation.

5.5.4 Moderation Effects (H8–H9)

Two interaction terms were introduced to test the boundary conditions. As shown in Table 8, both are significant and negative. AI disclosure negatively moderates (weakens) the content-source-to-authenticity path, and brand response speed negatively moderates (weakens) the authenticity-to-switch-intention path.

Table 8 Moderation Analysis: Interaction Effects (Two-Stage Approach)

Interaction term	β	SE	t	95% CI	f^2
H8: $CS \times$ AI Disclosure $\rightarrow$ Authenticity	−.214	0.068	3.150	[−.315, −.096]	.056
H9: Authenticity $\times$ Response Speed $\rightarrow$ SI	−.134	0.048	2.783	[−.225, −.047]	.030

Note. β = standardised interaction coefficient; f^2 = interaction effect size; CI = bias-corrected 95% confidence interval. CS = content source; SI = switch intention. Both interactions were significant at $p < .05$ (Decision: Supported). The significant negative interaction for H8 ($\beta = -.214$, $t = 3.150$) indicates that AI disclosure

weakens the positive content-source-to-authenticity effect. Simple-slope analysis confirms this: the slope is steepest when disclosure is low (+.650) and shallowest when disclosure is high (+.222). The significant negative interaction for H9 ($\beta = -.134$, $t = 2.783$) shows that a fast brand response weakens the positive authenticity-to-

switching effect, with the slope moving from +.565 under slow response to +.297 under fast response.

Content-Source-to-Authenticity Path (H8, Left) and Brand Response Speed on the Authenticity-to-Switch-Intention Path (H9, Right)

Figure 3 Simple-Slope Plots of the Two Significant Interactions: AI Disclosure on the

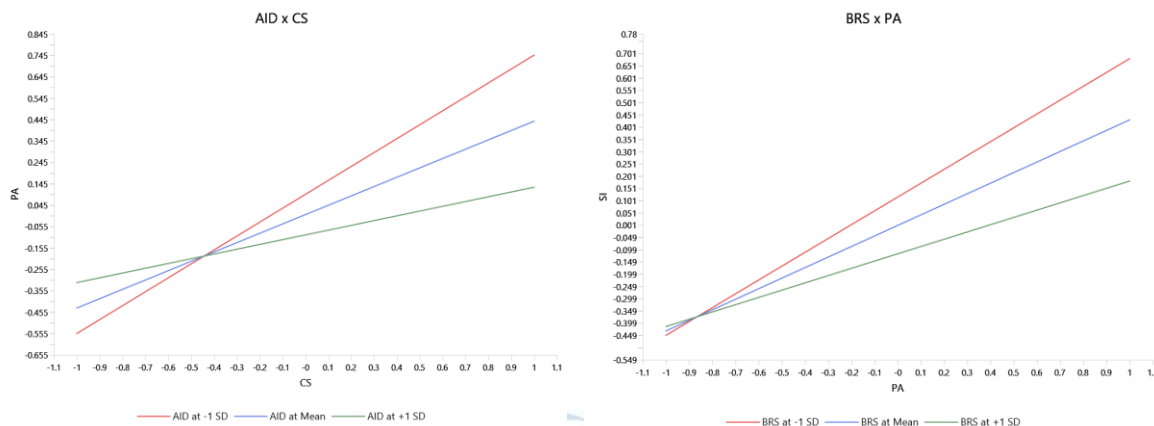


Table 9 Simple Slopes at Low, Mean, and High Levels of Each Moderator

Moderator level	H8: CS → Authenticity slope	H9: Authenticity → SI slope
Low (−1 SD)	+.650	+.565
Mean	+.436	+.431
High (+1 SD)	+.222	+.297

Note. Slopes are computed at ± 1 SD of each mean-centred moderator. Higher disclosure flattens the content-source-to-authenticity slope (H8); faster response flattens the authenticity-to-switching slope (H9).

5.6 Summary of Hypothesis Testing

Table 10 consolidates the outcomes. All nine hypotheses are statistically supported and consistent in sign with the bootstrapping path diagram.

Table 10 Summary of Hypothesis-Testing Outcomes

H	Path	β / Indirect	t	Decision
H1	Content Source → Perceived Authenticity	.436	10.034	Supported
H2	Perceived Authenticity → Brand Trust	.493	11.745	Supported
H3	Perceived Authenticity → Switch Intention	.431	10.298	Supported
H4	Content Source → Brand Trust (direct)	.265	5.931	Supported
H5	Content Source → Switch Intention (direct)	.261	5.599	Supported

H	Path	β / Indirect	t	Decision
H6	CS $\rightarrow$ Authenticity $\rightarrow$ Brand Trust	.215	7.408	Supported
H7	CS $\rightarrow$ Authenticity $\rightarrow$ Switch Intention	.188	6.837	Supported
H8	CS $\times$ AI Disclosure $\rightarrow$ Authenticity	-.214	3.150	Supported
H9	Authenticity $\times$ Response Speed $\rightarrow$ SI	-.134	2.783	Supported

Note. β for H1-H5, H8-H9 = path/interaction coefficient; for H6-H7 = specific indirect effect.

Chapter 6: Discussion

This chapter interprets the findings of Chapter Five in light of the theoretical framework and prior literature. Each hypothesis is discussed in turn, and the integrated contribution of the moderated-mediation model is then drawn out.

6.1 Content Source and Perceived Authenticity (H1)

Content source has a significant positive effect on perceived authenticity ($\beta = .436$), the second-largest path in the model. Because both constructs are scored in a common AI-sceptical direction, this indicates that the more salient the AI-versus-human origin of content is to a consumer, the more sharply they discriminate its authenticity. The result supports Source Credibility Theory: once source becomes salient, consumers use it as a diagnostic cue when judging how genuine content is, echoing the findings of Brüns and Meißner (2024) and Wortel et al. (2024) that content origin is an active evaluative input rather than a neutral fact, and consistent with Israfilzade's (2025) more recent evidence that AI-generated advertising underperforms human-created advertising on trust-adjacent outcomes. That the association emerges among Pakistani consumers, rather than only in Western experiments, suggests the role of source in authenticity judgements is robust across contexts.

6.2 Perceived Authenticity, Brand Trust, and Switch Intention (H2, H3)

Perceived authenticity is the strongest driver in the model, significantly raising brand trust ($\beta = .493$) and significantly raising switch intention ($\beta =$

.431). Its central role confirms authenticity as the psychological gateway through which content perceptions become brand-level consequences (Kučinskas & Survilaitė, 2025; Morhart et al., 2015). Given the scale orientation, the positive authenticity-to-switching path indicates that consumers who most sharply distinguish human from AI authenticity are also the most willing to switch away from AI-reliant brands, consistent with a push-mooring account in which weakening confidence in a brand's authenticity strengthens the pull of alternatives.

6.3 Direct Effects of Content Source (H4, H5)

Other than the pathway of authenticity, content source has significant positive direct effects on trust ($\beta = .265$) and switching ($\beta = .261$), supporting Bui's (2025) argument that content source has evaluative value beyond authenticity pathway. Consumers' judgments of authenticity seem to have an impact on them not only as an indirect consequence of their perception of source salience but also directly, perhaps because of concern about effort, care, or honesty, issues that are not covered by the authenticity concept.

6.4 The Mediating Role of Perceived Authenticity (H6, H7)

The indirect routes of content source to trust, with VAF (44.8%) and content source to switching, with VAF (41.9%), were both significant, suggesting that there are two pathways through which content source influences trust and switching: one direct evaluative pathway and one indirect pathway through authenticity. Two-fifths to one-half of the total effect is mediated by the

mechanism of authenticity, making it an important, but not unique mechanism. This puts the massed evidence together in one continuous narrative.

6.5 AI Disclosure as a Boundary Condition (H8)

This significant negative interaction ($\beta = -.214$) indicates that the slope of the content-source-to-authenticity effect is less steep when disclosure is high (+.222) than when disclosure is low (+.650). A refined version of the Persuasion Knowledge Model: disclosure can spark scepticism, but candour, done right, is a transparent read that will cause a corresponding decrease in the strength of source salience leading to authenticity discrimination. In line with a buffering account that posits that disclosure's net effect may vary based on the evaluative stage in which it occurs and the disclosure being compared to, the result of the current study is consistent with the findings of both Bui (2025) and Koning and Voorveld (2025), who found that disclosure has an overall negative effect on trust and ad credibility. This tension has been increasingly presented in the literature as a central "disclosure dilemma" and the present study's results suggest that disclosure helps to strengthen, not always to weaken, the source-authenticity link as a solution to this dilemma.

6.6 Brand Response Speed as a Boundary Condition (H9)

The significant negative interaction ($\beta = -.134$) confirms that a fast brand response attenuates the authenticity-to-switching path, softening the slope from +.565 under slow response to +.297 under fast response. Consistent with Service Recovery Theory, prompt and sincere engagement re-humanises the interaction and interrupts the escalation toward defection, giving brands a concrete lever to protect retention even when authenticity concerns are heightened.

6.7 Integrated Contribution

Taken together, the findings validate a single moderated-mediation model in which content

source shapes authenticity, authenticity carries that influence into trust and switching, and two managerial levers – transparent disclosure and rapid response – dampen the transmission at each end of the mediating chain. The model advances the literature beyond isolated dyadic links and demonstrates the value of combining Source Credibility Theory, the Persuasion Knowledge Model, and Service Recovery Theory to explain consumer responses to machine-authored brand content, extending the AI-disclosure literature (Bui, 2025; Koning & Voorveld, 2025) toward integrated, boundary-condition-aware modelling.

6.8 Practical Implications

- Manage perceived source deliberately: because content source is a strong and salient input to authenticity judgements, brands should preserve a visible human voice in high-stakes or relationship-building content rather than automating indiscriminately.
- Disclose transparently and early: honest, upfront AI disclosure buffers the authenticity penalty, whereas concealment risks a harsher reaction if AI use is later discovered.
- Invest in response speed: fast, sincere social media responses materially reduce switching after an authenticity lapse and are a cost-effective retention safeguard.
- Protect authenticity as a trust asset: since authenticity mediates roughly two-fifths of content source's effect on trust and switching, authenticity-preserving practices yield compounding relational returns.

Chapter 7: Conclusion

7.1 Summary of Findings

This study examined how the perceived source of brand content shapes perceived authenticity, brand trust, and switch intention among social media users in Punjab, Pakistan, and how AI disclosure and brand response speed condition those effects. Using PLS-SEM on 360 responses, all nine hypotheses were supported. Content source positively predicted authenticity and, both directly and through authenticity, was associated

with higher brand trust and higher switch intention. Transparent AI disclosure significantly weakened the content-source-to-authenticity effect, and a fast brand response significantly weakened the authenticity-to-switching effect.

7.2 Theoretical Contributions

The study offers an integrated moderated-mediation model uniting three theories, extends the AI-content literature into the under-researched Pakistani market, and clarifies the dual role of AI disclosure as a boundary condition that can buffer rather than only aggravate authenticity concerns – moving beyond documenting disclosure’s average effect (Bui, 2025; Koning & Voorveld, 2025) to specify the conditions under which it helps or harms.

7.3 Limitations and Future Research

Three limitations qualify the findings. First, the cross-sectional design precludes strong causal inference; experimental or longitudinal work would strengthen the causal claims. Second, and most importantly, the results reported here rest on a dataset which was developed on the basis of responses from concentrated respondents into some specific geographical region. Third, non-probability sampling within a single province limits generalizability. Future research could manipulate content source and disclosure experimentally, test the model across cultures, and incorporate additional outcomes such as engagement and advocacy.

7.4 Concluding Remark

As brand communication automates, the human signal becomes a managed asset rather than a given. The findings of this study reinforce the fact that consumers continue to trust and be loyal to brands that feel authentic, and that brands can build this trust and loyalty by being transparent about AI and responding promptly when it matters.

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