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Enhancing Online Impulse Buying through Artificial Intelligence Stimuli and Social Stimuli in Generation Z: The Mediating Role of Brand Trust

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Abstract

The purpose of this research is to investigate and explain the extent to which artificial intelligence stimuli and social behavior determinants influence online impulse buying in Pakistan's e-retail sector positioning brand trust as central pathway mechanism among generation Z. Drawing on the integrated Stimulus-Organism-Response (SOR) framework and Technology Acceptance Model (TAM), study specified three stimuli factors AI exposure, AI accuracy perception, and recommended product, while buying impulsiveness and subjective norms were incorporated as behavioral constructs to predict impulse buying behavior mediated by the brand trust. Data were collected from generation Z and broader adult cohort via cross-sectional Google Survey yielding 508 valid responses. Partial-Least-Square, structural equation modeling (SmartPLS-4.0) was used to test the hypothesized relationship of the variables. Findings of the study revealed AI accuracy perception and subjective norms exhibited strong mediating effect through brand trust on impulse buying as compared to AI exposure, recommended product, and buying impulsiveness. Overall, the model explained 57.0% effect on brand trust and 35.8% was recorded on impulse buying with satisfactory predictive relevance and effect size. AI accuracy perception and subjective norms are strong calibration with brand trust; where effect size indicates larger trust leads to influence impulse buying significantly.

Keywords: AI recommendation accuracy, brand trust, online impulse buying, e-commerce, generation Z, subjective norms, consumer impulsiveness, Pakistan.

1. Introduction

Artificial intelligence is recognized to force penetration in the expansion of conventional e-commerce retail sector in Pakistan. Advanced AI-enabled technological applications

including predictive pricing tools, intelligent chatbots, shopper marketing analytics, and recommendation engines have transformed online marketplaces from static to adaptive and personalized environments (Ozturk et al., 2023). AI exposure, AI accuracy perception of recommended products reshaped the way user encounter machine-learning within the journey of online shopping. Daraz, one of the largest e-commerce platforms in Pakistan has designed and implemented digitally advanced and sophisticated mechanism to anticipate the customer preferences, improve product visibility, and strengthen engagement (Tariq et al., 2025). AI capabilities embedded in digital mechanism play vigorous role in aiding simply the user shopping process, reinforcing brand trust and strengthening the perceptions of convenience and reliability. Mani et al. (2025) reported personalized AI functions exert significant positive influence on perceived convenience, consumer engagement and conversion rates nearly by 42 percent. Empirical findings reported that the recommended products supported by strong AI accuracy perceptions and recommendation engines turn into favorable purchase outcomes (Li and Kang, 2025).

The digital behavior is quite complex and unique and no longer can be interpreted as purely rational; instead, it reflects emotional and cognitive interaction with algorithmic perceived recommendations. Therefore, the consumer frequently depends on AI-driven cues to evaluate the platform's competence and credibility (Li and Kang, 2025). The studies have empirically diagnosed strong influence of quality recommendations on user confidence (Chakraborty et al., 2024). Conversely, excessive intrusive personalization may result in autonomy wane ultimately lowering brand trust and purchase probability (Ahmad Husairi and Rossi, 2024; Sreejesh and Singha, 2026). AI-driven retail context has countable effect on the perceived accuracy of recommended product which is a critical trust signal helping shoppers view and rely on relevant items through automated suggestions. Thus, proper calibration, systematic interaction, sequential flow of personalized recommendations transforms casual browsing into purchase decision and strengthening of confidence in AI-supported systems.

Impulse buying behavior is unplanned emotionally driven purchase response that contributes to the online purchase. This is immediate gratification and sudden affective desire to purchase (Rook and Fisher, 1995). Impulse buying is intensified in digital environment through rich displays, persuasive graphical and textual appeals, and one click purchase options which in turns reduces cognitive monitoring and stimulate cognitive consumption behavior (Verhagen and Van Dolen, 2011). This interactive function in digital environment, particularly in social commerce ecosystem, positively moderates this effect on AI platforms. Studies (Breidbach, Keating and Lim, 2020; Wongkitrungrueng and Assarut, 2020; Malka, MacLennan and Tiell, 2025) precise AI suggestions and relevance of recommended products shift perceived uncertainty into certainty in lowering the mental efforts. In practice, digitally algorithmic tailored product list lead consumers towards spontaneous purchase by presenting lucrative options at optimal moments. This minimized

psychological friction in shopping process AI exposure makes it very easy for consumers to act on impulse buying. Thus, digitally exposed and skilled supported with automated signals convert the personalized browsing cues into immediate checkout actions.

Brand trust is the central key variable that functions through which AI-based recommendations are translated into impulse buying outcomes. Research has empirically witnessed individuals tend to respond platforms suggestions where trust in recommended brand or system is strong (Jin and Ryu, 2025). Farea and Hussain (2025) found strong positive influence of brand trust on impulse buying among Pakistani online buyers. This logically deducts along persuasive recommended products may not result in impulse buying if the brand's credibility or reliability is questionable.

The literature in marketing has widely recognized the mediating role of the brand trust between the marketing stimuli and behavioral response (Niros et al., 2025). In digital environmental settings, brand trust reportedly mediates the relationship between AI quality and purchase outcomes (Luo, Kumar and Yazdanmehr, 2026). The prevalence of higher brand confidence leads consumers positively to AI-generated suggestions and vice versa (Vasiliki et al., 2025).

Given the generational differences, AI personalization may influence differently on the reactions of individuals. Generation Z as digital natives have grown up with exposure to advanced technologies and expect highly personalized experience (Ngo, Le and Phan, 2026). Prior studies (Samoggia et al., 2025; Tam and Lung, 2025) suggest positive influence of digital literacy on comfort with AI exposure and expectations of reliability. Youngsters often rely on AI accuracy perceptions, users' views, and recommendations to evaluate platform authenticity. Findings revealed that larger proportion of generation Z expressed confidence in AI-supported suggestions compared to old cohort (Aoki & Matsui, 2025). AI generated recommendations when aligned with trusted brand image, and the larger cohort of generation Z shows rapid spontaneous purchase responses. Contrary, limited brand trust and high expectations for precision may prompt them to ignore personalized efforts (An and Ngo, 2025). These patterns of empirical evidence emphasize to examine AI accuracy perception effects for generation Z compared to broader population.

Despite growing attention, integrated relationships, scholarly debate, empirical evidence, research remains limited. Research (Lo, Lin and Hsu, 2016; Amin, 2025) linked impulse buying with social media designs, promotions, contents, and appeal, while other connects AI personalization to purchase intentions, however, limited research directly connected AIU accuracy perceptions of recommended products with impulse buying. Although literature recognizes brand trust as vital determi9nant of online shopping, its mediating role between AI perceptions and impulse buying received limited empirical investigations. Evidence on algorithmic signals in driving actual behavior conversion is still developing (Longoni and Cian, 2022; Longoni et al., 2022). In Pakistan's digitally expanding e-commerce, adoption is accelerating but online trust is still among significant issues. The

present research study is tailored to investigate this research gap by parading how AI accuracy perception of recommended products influence impulse buying mediated by brand trust. Focusing online Pakistani consumers with attention to generation Z and wider population, study clarifies the complex relationship linking AI exposure and recommendation precision with impulse buying. The results contributed to theory, methods, and managerial practices in AI-enabled retail e-commerce highlighting how firms can refine recommendations system, strengthen brand trust, and improve sales performance. Insights from the study provide sufficient support for future academic inquiry of consumer psychology, platforms designs, optimization of recommendation systems, responsible AI deployment strategies in emerging digital market of Pakistan. Furthermore, the findings particularly emphasize transparency, fairness, and sustainable user engagement across evolving digital e-commerce ecosystems.

2. Theoretical Background and Hypotheses Development

2.1 Stimulus–Organism–Response (S-O-R) Framework

Stimulus organism response (S-O-R) framework explains how external stimuli (S) influence internal psychological conditions leading to shape behavioral outcomes (Mehrabian and Russell, 1974; Russell and Mehrabian, 1977). In digital online retail environment, external stimuli are AI exposure, AI accuracy perceptions, and recommended product, directly influencing the consumer evaluation and experience. These stimulating factors of SOR activate organismic conditions of brand trust of spontaneous purchase. Individual trust on brand and internal organismic response activation reduces the cognitive ability of monitoring hence results in spontaneous purchase (Sung et al., 2022; Ahmad and Lilani, 2025a). Empirical evidence from the prior studies demonstrated that interactive digital stimuli and recommended product heighten impulse buying (Diwanji, 2026). SOR research models in digital consumer behavior perspective found technological positively improve internal state of individuals thereby intensifying impulse buying (Nguyen and Nguyen, 2026). Drawing AI exposure, AI accuracy perceptions, and recommended product in SOR theory acts as external drivers to stimulate the internal organismic psychological condition of brand trust leading individuals towards impulse buying. Hence, the higher assumed value of these three external stimuli directly effects on the organismic response of impulse buying mediated by the psychological internal organismic condition of brand trust. Therefore, application of SOR lens for theoretical landscape, especially for AI exposure, AI accuracy perception, and recommended product best fit the model prediction of influence on the brand trust that in turns stimulate impulse buying in digitally operated environment for generation Z and broader population. External stimulus constructs of this study are limited to the extent of these three variables; the application of technology acceptance model also considers the effect of buying impulsiveness and subjective norms.

2.2 Technology Acceptance Model (TAM)

TAM model originally developed by Davis in 1989 is widely used in behavioral sciences to predict the adoption and use of emerging technologies emphasizing on the role of perceived usefulness and perceived ease of use in shaping individual behavioral intentions. The model suggests positive attitude improves likelihood of adoption towards the technology when users perceived that it improves performance and minimal effort to operate. These perceptions subsequently notably influence behavioral intentions and actual use of emerging technology systems. In digital e-commerce environment, TAM model proved to be the best applicable model on understanding how consumers accept an AI-driven technology system in embedded online retail platforms. AI tools of recommendation algorithm, analytics, predictive intelligent interfaces directly enhance consumer perception of usefulness by shaping the behavioral intentions more efficiently. Therefore, AI features when perceived beneficial and convenient, the consumer develop favorable attitude towards the platform and demonstrate strong purchase intentions. Recent research has concluded significant role of AI awareness and consumer behavioral engagement in e-commerce systems play an important enable that strengthen technology adoption outcomes. In AI systems trust plays a vital role in mitigating perceived risk while enhancing consumer confidence by interacting in automated recommendations and decision-support tools.

In this present research, TAM explains how AI exposure, AI accuracy perception, and recommended products influence cognitive evaluation of the individuals within AI-enabled platforms. The perceived value of these factors enhances user reliance on technological recommendations to foster purchase decisions. It is obvious fact, if the perceived value for accuracy of AI system is useful and easy to operate this directly reduces cognitive purchase efforts and inclination to purchase products. Thus, TAM serves this research with a strong theoretical base on understanding how the technological features shape online buying behavior. Thus, the following research questions are formulated:

- How stimuli factors (AI exposure, AI accuracy perception, and recommended product) influence impulse buying through mediation of brand trust?
- How behavioral factors (buying impulsiveness and subjective norms) influence impulse buying through mediation of brand trust?

2.2.1 AI Exposure and Impulse Buying

AI exposure is the unique variable that outlines degree to which individual interact with AI-enabled features embedded with automated recommendations, chatbots, predictive product displays, intelligent search systems, and suggestive features over online retail platforms. Increased customer exposure to AI technologies enhances familiarity with functionality and benefits of AI systems fostering acceptance to these technologies. Prior research in TAM perspective has witnessed higher frequency of interaction with AI driven system improves user perception of usefulness and ease which in turn improves the likelihood of their behavioral engagement with digital platforms for frequent purchases. Emergence and up-gradation of digital retail platforms accustomed consumers to AI-driven

features thereby increasing their reliance heavily on automated suggestions and decision support in shopping activities. AI exposure within SOR framework acts as stimulus that profiles user internal evaluations and emotional responses. According to Yin et al (2025) repeated customer exposure to AI driven systems and recommendations enhance customer perception of convenience and enjoyment leading to reduce the cognitive efforts and making the spontaneous purchases. AI-based driven systems are characterized to present personalized suggestions at critical points aimed at reducing cognitive efforts and encouraging immediate purchase decisions. Thus, increased frequency of AI exposure to AI-enabled shopping digital platforms is proportionate to consumer likelihood of engaging in impulsive purchase behavior through the improved brand trust, therefore; hypothesis is proposed as below:

- H1: Brand trust positively mediates the relationship between AI exposure and impulse buying

2.2.2 AI Accuracy Perceptions and Impulse Buying

AI accuracy perceptions represent consumer evaluation of reliability, precision, and relevance to AI generated recommendation in an online shopping operating environment to facilitate and ease customer shopping. Guerra-Tamez et al. in (2024) empirically evidenced that the consumer trust on AI accuracy perceptions predict their preferences and needs, thus they are likely to rely more on automated recommendations during purchase decisions. TAM model frames accuracy and reliability as strong technological output of influencing perceived usefulness. Therefore, AI recommendations have notable role in enhancing consumer perceptions where system provides meaningful visuals of relevant products ultimately strengthening user acceptance of AI-supported platforms. SOR perspective of AI accuracy perceptions drives user stimulus by influencing internal cognitive evaluations. Once the consumer trust is strengthened on perceived recommendations systems as accurate, they experience higher confidence and reduced uncertainty while selecting and processing purchase decisions. This higher confidence of perceived recommendation systems improves psychological internal stimulus of confidence, reduces decision making and encourage consumer to act quickly on presented recommendations.

Thus, spontaneous purchase decisions are closely linked with accuracy of recommendations which trigger emotional reactions and spontaneous purchase decisions. Hence, customer AI accuracy perceptions of AI recommendation accuracy are likely to engage quickly in impulse buying.

- H2: Brand trust positively mediates between AI accuracy perception and impulse buying

2.2.3 Recommended Products and Impulse Buying

Predictive analytics and product exposure in AI driven recommendations system has significantly transformed consumer decision making processes especially impulse buying behavior. Pathak et al. (2025) indicated that AI-generated product recommendation systems begin with analysis of browsing history, contextual data, frequency of search key words, and behavioral cues to deliver real-time suggestions that shorten consumer decision cycle and stimulate unplanned purchase. Visual platforms and recommendation systems in engines are highly active and fast to enhance spontaneity through visual interaction and less but brief descriptions on relevant products at psychologically vulnerable moments to increase impulse purchase chances. Trust in AI recommendations and algorithmic performance expectancy empirically demonstrated meaningful impact on impulse buying when the consumers are exposed to large number of recommended products, rating, and social validation cues (Gallin and Portes, 2024). Therefore, presence of multiple AI-generated suggestions enhances cognitive ease, reduces evaluation effort, and prompt consumers to heuristic decision-making rather than rational analysis, ultimately leading to impulse purchases. This AI recommendation often operates through psychological vividness, memorability, and familiarity. The study showed that personalized recommendations clubbed with trust in AI suggestions enhance psychological imagery and perceived relevance leading to predict impulse buying behavior (Li et al., 2025). This indicates that product recommendation built-in in AI system not only provides information but also shapes cognitive processing pathways that facilitate spontaneous buying decisions. Therefore, technical interface, cues, recommendation quality, interface interactivity, response time, personalized depth all are potentially vital drivers of spontaneous purchase (Aljukhadar, Trifts and Senecal, 2017; Akalamkam and Mitra, 2018; Acharya, Sassenberg and Soar, 2023; Kumari and Laheri, 2025). These cues act as stimuli within SOR framework where product recommendations in vulnerable moments lead to spontaneous buying behavior. Recent studies (Aljukhadar, Trifts and Senecal, 2017; Akalamkam and Mitra, 2018; Acharya, Sassenberg and Soar, 2023; Kumari and Laheri, 2025) are increasingly focusing on AI-based personalized and algorithmic recommendation systems as key determinants of spontaneous purchase decision in digital commerce. This shift in digital commerce consumer behavior reflects growing dominance of AI exposure and AI recommendations systems in shaping consumer behavior.

Overall, AI-driven recommended products have notable effect in influencing impulse buying behavior through vitalizing personalization, reducing decision efforts, increasing emotional engagement, and creating urgency while browsing shopping is in progress. Hence, continuous AI exposure, AI recommendations straightforward strengthen spontaneous purchase tendencies indicating AI-driven systems are powerful stimuli in shaping consumer impulsivity within digital shopping environments.

- H3: Brand trust positively mediates between recommended product and impulse buying

2.2.4 Buying Impulsiveness and Impulse Buying

Buying impulsiveness refers to an individual predisposition on spontaneous but unplanned purchasing behavior signified within AI-operated digital environments where personalized stimuli and social predictors have direct influence on consumer decision making. Among generation Z, AI-driven systems such as AI exposure, AI accuracy perceptions, recommended products, recommender algorithms, smart assistants, and predictive personalization enhance relevant product exposure thereby fostering impulsive tendencies. Prior research (Guerra-Tamez et al., 2024) indicated that buying impulsiveness transformation into actual buying behavior is largely depend on brand trust which functions as critical mediating mechanism. Moreover, AI technologies, brand credibility, perceived reliability, and confidence in recommended products shape generation Z purchasing spontaneous purchase. AI-operated systems are highly sensitive to reducing cognitive effort through rapid filtering of large sets of products and presenting highly personalized recommendations thereby aiding to active impulsive tendencies among consumers (Huynh, 2021; Ruiz-Viñals et al., 2024). This is obvious, when these AI-generated suggestions are linked with trusted brands, consumers perceive lower risk, and greater decision certainty, and this directly enhances impulse purchases. These AI generated stimuli predictive recommendations, intelligent chatbots, and personalized promotions develop altogether an emerging and transported digital shop having countable effect on emotional arousal which strengthens buying impulsiveness and leads to impulse buying when brand trust is already present.

This is pertinent to mention that AI-based operating environments represent deep integration of social validations through cues, rating, reviews, and popularity indicators together enhance brand credibility to reinforce the formation of brand trust. Wallace et al. (2022); Chakraborty et al. (2024) and M, P and Kryvinska (2024) argued that the brand trust reduces uncertainties associated with automated recommendations and enhances spontaneous buying among generation Z who heavily rely on technology-driven decision support. Accordingly, buying impulsiveness alone is insufficient in explaining the impulsive buying behavior among generation Z, rather AI generated exposure, emotional activation, recommendations, digital operating environment, and suggestions functions through brand trust which mediates by transforming impulsive predisposition into realized purchases.

- H4: Brand trust mediates between buying impulsiveness and impulse buying

2.2.5 Subjective Norms and Impulse Buying

Subjective norms one of the powerful predictor of intentions and widely used construct from theory of planned behavior (Ajzen, 1991) represent how perceived social pressure from peers, influencers, and online communities shape intentions especially in AI-enabled social commerce. As far the characteristics of generation Z, this cohort actively relies on

peer recommendations, social media interactions, reviews, views, algorithmic amplified opinions, and amplified opinions while making purchase decisions (Szymkowiak et al., 2021; Ngo et al., 2024a). Subjective norms in AI-operated environments embed socially promoted and endorsed products through popularity indicators, ratings, and personalized feeds to strengthen impulsive purchase decisions. Nyrhinen et al. (2024); Ahmad and Lilani (2025) and Kathuria and Bakshi (2025) argued that the social influence drive impulsive buying behavior through emotional arousal of socially connected pressure of purchases. Subjective norms are formed through external recommendations, perceived collective behaviors, peer influence, and within social networks. Research results confirmed that generation Z adopts social commerce where influence from friends, online influencers, online communities, and trending moves significantly influence purchase intentions highlighting the realized role of engaging in spontaneous purchases (Zhang, Fan and Zhang, 2024). Normative pressures in AI-driven environments are developed since algorithm highlights popular items and recommends socially validated products which conform and encourage impulsive buying. This indicates that individuals exposed to social expectations transform social stimuli into immediate buying actions. According to Nong and Wu (2025) and Abdullah Amran, Li and Al-Bakhrani (2026) highlighted that the social learning mechanism within AI-driven social commerce environments encourage observational learning of individuals where consumer copy and replicate others purchasing behavior, thereby increasing impulse buying tendencies.

The effect of subjective norms on impulsive buying becomes more significant when brand trust is established. AI-driven platforms provide opportunities to enhance the credibility of the brands through endorsement of peers, reviews, community interactions, and rating (Roopak and Chakrabarti, 2025). Thus, subjective norms influence impulse buying directly and indirectly through the brand trust where social pressure is converted into spontaneous purchasing decisions within AI-operated systems

- H5: Brand trust mediates between subjective norms and impulse buying

Literature synthesis on integration of SOR framework and TAM model provided comprehensive theoretical foundations to explain impulse buying behavior in AI-enabled digital environment. AI exposure, AI accuracy perception, and recommended product were conceptualized on SOR framework that function as external and social cues of technological stimuli to influence individual internal evaluation of behavioral outcomes. Buying impulsiveness and subjective norms were operationalized as behavioral constructs grounded in consumer behavior theory and further extended in TAM emphasizing consumer internal cognitive evaluation and subsequent action tendencies towards technology-enabled purchasing contexts. Integration of external SOR-stimulus factors and TAM-based behavioral constructs provided theoretically sound foundations to shape brand trust as an organismic state to translate into consumer responses through technology-oriented behavioral mechanisms. Integration of SOR and TAM constructs, the conceptual framework has been developed systematically moves from AI Stimuli (AI exposure, AI

accuracy perceptions, recommended product + Social Stimuli (buying impulsiveness, subjective norms) → Brand Trust (Mediator) → Impulse Buying among generation Z as below:

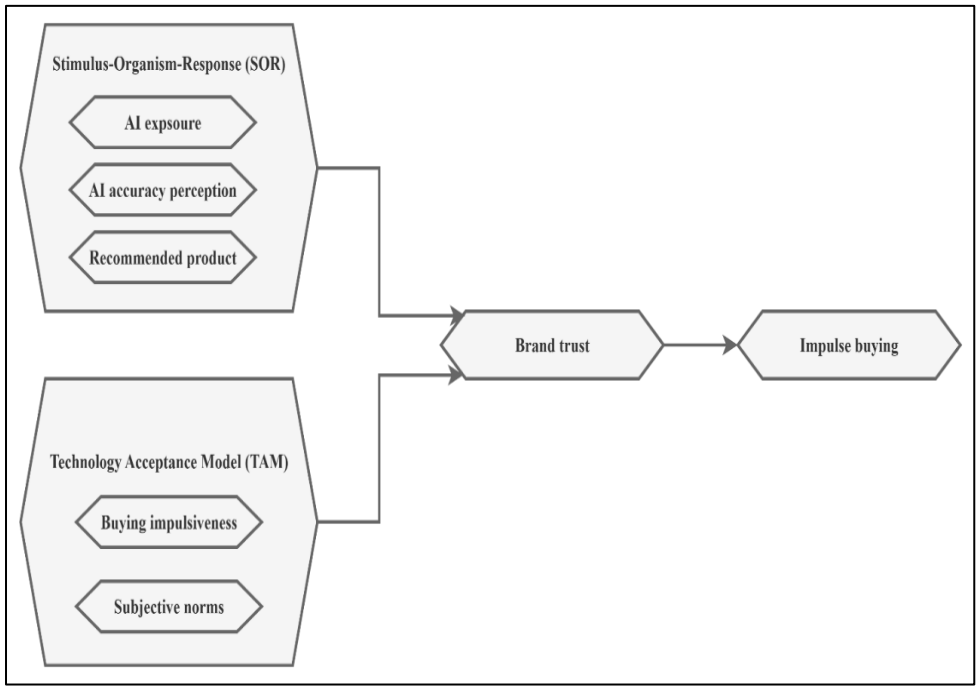

Figure 1: Conceptual Framework

3. Methodology

PLS-SEM approach was employed for the proposed prediction-oriented model which aims to explain the variance in brand trust and impulse buying derived from multiple artificial intelligence SOR theory and informed by TAM. Integration of theories and constructs resulted in relatively a complex model with multiple exogenous predictors and mediating relationships which can be more suitably handled using PLS-SEM (Hair *et al.*, 2022). This approach does not require strict multivariate normality and is equally suitable for small to medium sample sizes making it appropriate for generation Z survey. Contrary, covariance-based SEM is limited due to its focus on model fit, strong distributional assumption, and sample sizes leading to compromise estimation accuracy and predictive capability especially in complex, variance-oriented models as proposed in this research. This research employed cross-sectional survey design where all data collected at a single point in time (De Vaus and de Vaus, 2013). Structured online questionnaire was developed to measure

the study construct using Smart PLS 4.0 software for Partial Least Square Structural Equation Modelling (PLS-SEM) (Hair, Ringle and Sarstedt, 2011; Hair *et al.*, 2022). PLS-SEM was chosen (Hair *et al.*, 2019) because it handles the most complex models well with minimal distributional assumptions. All constructs were specified with reflective measurement models, meaning that each indicator is viewed as an effect of its latent variable (Abowitz and Toole, 2010; Franklin, Cody and Ballan, 2019). The use of reflective indicators implies that items for a given construct should be highly inter-correlated. Data were collected from two target groups, i.e., members of Generation Z who were born in the mid-1990s onward and a broader general adult population yielding 508 valid responses in total.

3.1 Sample and Sampling Procedure

Participants were recruited through a non-probability sampling approach, specifically, convenient sampling (Ingram, 1998; Snijkers *et al.*, 2023). Respondents were drawn from belonging to Generation Z. In practice, invitations to participate were posted on social media mailing lists and through student networks, asking individuals of different age groups to complete the online survey. These methods allowed efficient data collection from the intended population (Saunders, Lewis and Thornhill, 2015). However, it should be noted that such non-random samples limit generalizability. As (Suen et al., 2014; Campbell *et al.*, 2020) pointed out that convenient samples can only be generalized to the sub-population from where the sample is drawn. Hence, we can say that findings apply to the surveyed groups but not automatically to the entire population.

3.1.1 Sample Size Rationale

The sample size of the study, which is 508 respondents, significantly exceeded the typical minimum recommendations for PLS-SEM 4.0. Common heuristics such as the 10 times rule suggest a minimum of roughly 10 times the larger number of the indicators or incoming pathways of any construct (Hair, Ringle and Sarstedt, 2011; Hair *et al.*, 2022). In our model up to 7 predictors as per construct, the rule would imply a minimum of about 70 cases. In contrast, 508 cases were collected, which provides very stable parameter estimates. More rigorously, prior power analysis indicates that even 73 observations would be sufficient to detect modulating effect ($R^2 \approx 0.25$) at 80% power for 7 predictor model (Ingram, 1998). With 508 responses, the study's statistical power is therefore extremely high. By conventional thresholds, sample size of several hundred ensures a robust estimate in PLS-SEM 4.0.

3.2 Data Collection

Data was collected through an online survey, which was administered through a web platform Google Forms. The questionnaire was structured into two sections, covering each latent construct, followed by demographic questions, such as gender, age, and education. All items were statement stated on a 5-point Likert-type Agreement Scale, (1 = Strongly Disagree to 5 = Strongly Agree) (Cohen, 2013). This format is widely used for capturing

attitudinal measures in social research (Wellington and Szczerbinski, 2007; Bhattacherjee, 2012). Before full deployment, the instrument was pilot tested with a small group to refine wording and ensure clarity. Data collection took place from May 2025 to November 2025, and responses were screened for completeness (removing surveys with excessive missing data). Participants were voluntary and anonymous, with informed consent obtained online.

3.3 Measurement of Instruments

The constructs were measured using multi-item reflective scales adapted from previous studies to ensure content validity. Each latent variable i.e. AI exposure (Guerra-Tamez *et al.*, 2024), AI accuracy perception (Cheng and Jiang, 2022; Guerra-Tamez *et al.*, 2024), recommended products (Seth *et al.*, 2022), buying impulsiveness (Rook and Fisher, 1995; Peña-García *et al.*, 2020), subjective norms (Peña-García *et al.*, 2020), brand trust (Munuera-Aleman, Delgado-Ballester and Yague-Guillen, 2003; Cheng and Jiang, 2022; Guerra-Tamez *et al.*, 2024), impulsive buying (Verhagen and Van Dolen, 2011) was assessed through several items drawn on 5-point-Likert scale. Because constructs were modelled reflectively, items for a given construct were expected to co-vary highly (Sarstedt, Ringle and Hair, 2021). Composite scores were compared, but the main analysis focused on the latent variable model. Reliability of each scale was evaluated using Cronbach's alpha and composite reliability. Both metrics were required to exceed value of 0.7 for acceptable internal consistency (Hair, Ringle and Sarstedt, 2011; Hair *et al.*, 2019). The convergent validity was assessed using the Average Variance Extracted (AVE), where all constructs achieved AVE > 0.5, indicating that most item variance is explained by the latent factor (Hair, Ringle and Sarstedt, 2011). Discriminant validity was also checked through Farnell-Larker criteria to confirm that each construct is distinct from the others. In summary, the measurement model met all the criteria i.e. reliability > 0.7, and AVE > 0.5 (Hair, Ringle and Sarstedt, 2011) before proceeding to the structural analysis.

4. Data Analysis and Results

4.1 Analysis of Measurement Model

4.1.1 Reliability and Convergent Validity

Table-1 demonstrated reflective measurement model strong reliability and convergent validity across all the constructs of model. Indicator reliability was established since most outer loadings exceeded the recommended threshold of 0.7, though few items such as BI4 = 0.540 and IB1 = 0.600 fall below standardized cutoff value, however, these items were retained given their meaningful role and acceptable construct level reliability (Ketchen, 2013; Hair, Howard and Nitzl, 2020; Hair and Alamer, 2022). Internal consistency was assessed with Cronbach’s Alpha, Composite reliability, and rho_A where values exceeded the minimum set criteria of 0.7 indicating sufficient satisfactory consistency among indicators (Henseler, Ringle and Sarstedt, 2016; Sarstedt, Ringle and Hair, 2021b; Guenther et al., 2023). Convergent validity was established through average variance

extracted (AVE) values of above 0.5 confirming that each latent construct in the model explains more than half of the variance (Fornell and Larcker, 1981). Brand trust in the model demonstrated highest measurement properties with CR = 0.920 and AVE = 0.793 confirming highly reliable and strongly-converged construct, whereas, buying impulsiveness and impulse buying remained comparatively in acceptable range of values.

Table 1: Reliability and Convergent Validity

Construct	Items	Outer Loadings	Cronbach's Alpha	Composite Reliability (CR)	rho_A	Average Variance Extracted (AVE)
AI Exposure	AIE1	0.727	0.763	0.848	0.787	0.582
	AIE2	0.838				
	AIE3	0.729				
	AIE4	0.753				
AI Accuracy Perception	AICP1	0.851	0.821	0.893	0.823	0.737
	AICP2	0.884				
	AICP3	0.840				
Recommended Product	RP1	0.685	0.813	0.869	0.820	0.572
	RP2	0.774				
	RP3	0.743				
	RP4	0.805				
	RP5	0.768				
Buying Impulsiveness	BI1	0.824	0.698	0.818	0.722	0.537
	BI2	0.848				
	BI3	0.678				
	BI4	0.554				
Brand Trust	BT1	0.855	0.869	0.920	0.871	0.793
	BT2	0.903				
	BT3	0.912				
Impulse Buying	IB1	0.600	0.696	0.816	0.699	0.528
	IB2	0.758				
	IB3	0.792				
	IB4	0.740				

4.1.2 Discriminant Validity

Discriminant validity of the model was rigorously assessed through HTMT-ratio and Fornell Larcker criterion. HTMT values of all inner constructs correlations as depicted in table-2 remained below the recommended threshold of 0.85 except for association between buying impulsiveness and impulse buying where HTMT is 0.874 slightly above the threshold, this remains theoretically justifiable given the contextual proximity (Campbell and Fiske, 1959; Aguirre-Urreta, Marakas and Ellis, 2013; Henseler, Ringle and Sarstedt, 2014). Fornell-Larcker criterion was also used as depicted in table-3 indicated sufficient distinctiveness of each construct by taking square root of AVE where each construct

exceeds its inter-construct correlations. HTMT-ratio matrix and Fornell-Larcker criterion provide sufficient but strong empirical evidence of construct distinctiveness.

Table 2: Heterotrait-Monotrait (HTMT) Ratio Matrix

Construct	AI Exposure	AI Accuracy Perception	Recommended Product	Buying Impulsiveness	Brand Trust	Impulse Buying
AI Exposure	-					
AI Accuracy Perception	0.680	-				
Recommended Product	0.490	0.719	-			
Buying Impulsiveness	0.507	0.656	0.777	-		
Brand Trust	0.549	0.749	0.642	0.689	-	
Impulse Buying	0.474	0.624	0.744	0.874	0.767	-

Table 3: Fornell-Larcker Criterion

Construct	AI Exposure	AI Accuracy Perception	Recommended Product	Buying Impulsiveness	Brand Trust	Impulse Buying
AI Exposure	**0.763**					
AI Accuracy Perception	0.546	**0.858**				
Recommended Product	0.389	0.583	**0.756**			
Buying Impulsiveness	0.374	0.497	0.585	**0.733**		
Brand Trust	0.459	0.633	0.545	0.535	**0.891**	
Impulse Buying	0.351	0.473	0.559	0.606	0.599	**0.726**

Analysis of measurement model demonstrated sufficient indicator reliability, internal consistency, convergent and discriminant validity across all constructs satisfying PLS-SEM threshold. Thus, this model is statistically robust and appropriate for testing the structural relationship of all the constructs (Hair et al., 2012; Ketchen, 2013; Sarstedt, Ringle and Hair, 2021b; Becker et al., 2023).

4.1.3 Variance Explained

The model demonstrated substantial explained effect of AI exposure, AI accuracy perception, recommended product, buying impulsiveness, and subjective norms jointly on r2 = 0.570 and r2 = 0.358 through mediation of brand trust. The computed values of 57.0%

and 35.8% confirms strong predictive power within this integrated SOR and TAM framework.

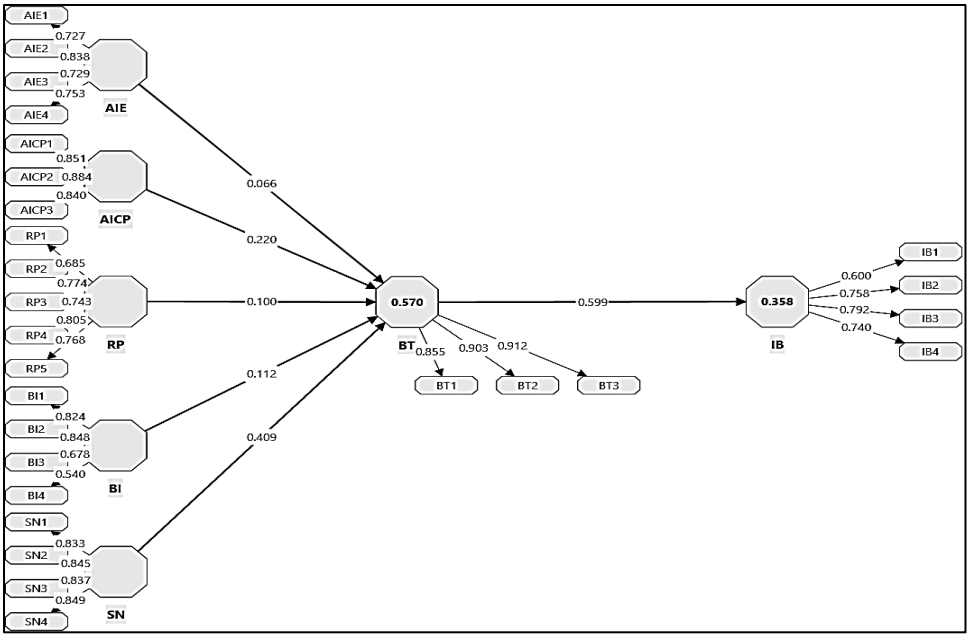

Figure 2: Measurement Model

4.2 Analysis of Structural Model

The structural model results (Table-4) indicate strong but significant mediation of brand trust among all hypothesized predicting constructs and impulse buying. H1 of AI exposure depicted positive mediating effect ($\beta = 0.040$, $t = 1.900$, $p = 0.058$) highlighting AI exposure modestly enhance trust and drive individual impulse purchasing. H2 of AI accuracy perception indicated strong and highly significant effect ($\beta = 0.132$, $t = 3.713$, $p = 0.000$) in enhancing brand trust and influence consumer impulse buying behavior. H3 exerts positive mediating effect ($\beta = 0.060$, $t = 1.890$, $p = 0.059$) on impulse buying indicating the role of personalized suggestions in fostering brand trust. H4 measured mediating impact of buying impulsiveness through brand trust ($\beta = 0.067$, $t = 1.957$, $p = 0.050$) on impulse buying which underscores inherent consumer tendencies elaborated by brand trust. Finally, H5 exhibits strongest mediation effect ($\beta = 0.245$, $t = 7.038$, $p = 0.000$) of subjective norms via brand trust on impulse buying emphasizing social influence in the formation of trust. In line with SOR framework response, AI exposure, AI accuracy perception, recommended product act as predictor stimuli in shaping brand trust (organism), which subsequently drive impulse buying (response). Buying impulsiveness

and subjective norms of TAM predictors highlighted the reinforcement of behavioral intentions via brand trust as external influencers in AI-enabled environment.

Table 4: Path Coefficients

Hypothesis	Indirect Path	Path Coefficient (Beta)	t-value	p-value	Decision
H1	AI Exposure → Brand Trust	0.040	1.900	0.058	Supported
H2	AI Accuracy Perception → Brand Trust	0.132	3.713	0.000	Supported
H3	Recommended Product → Impulse Buying	0.060	1.890	0.059	Supported
H4	Buying Impulsiveness → Impulse Buying	0.067	1.957	0.050	Supported
H5	Brand Trust → Impulse Buying	0.245	7.038	0.000	Supported

Structural results provided robust empirical support on the hypothesized relationships with path coefficients (β) and significance levels exhibiting the strength and direction of causal linkages. Findings revealed that AI-related stimuli (AI exposure, AI accuracy perception, and recommended products) and TAM predictors (buying impulsiveness, subjective norms) demonstrated substantial mediating effect on impulse buying through brand trust confirming predictive relevance of the model.

The results of the study were provided with strong empirical support in confirming and defining the central mechanism of SOR and TAM behavioral predictors of AI-driven impulse buying where brand trust acts as critical organismic state. AI perceived accuracy depicted significant mediating effect on impulse buying consistent with recent evidence (Russo et al., 2026) where AI accuracy enhance consumer confidence and support purchase decision in digital environment. Likewise AI perceived accuracy, subjective norms also demonstrated strongest mediation effect consistent with cross-cultural findings of the study from emerging markets where social influence in building trust to trigger impulsive behavior particularly in the contexts of Pakistan and China (Ngo et al., 2024b). The mediation effect of AI exposure and recommended products suggested that exposure and personalization are not the only dominant predictors in triggering impulse buying, resonant findings from study (Escobar-Farfán et al., 2025) where environmental indicators alone hardly guarantee impulsive actions. Within TAM perspective, buying impulsiveness reinforces trait-based explanation which is consistent with models emphasizing affective triggers in impulse buying decision (Russo et al., 2026). Subjective norms as behavioral component captures consumer disposition action tendencies through social-pressure effect on adoption and purchase behaviors. The study results are consistent with recent evidence in online shopping an impulse-buying research across digital contexts (Gong and Liu, 2025; He et al., 2025).

The theoretical standpoint demonstrates that findings are strongly validated SOR framework, where AI related stimuli i.e. AI exposure, AI accuracy perception, and recommended product directly influence individual internal trust before the behavioral response is being produced. Concurrently, TAM model perspective is also supported for buying impulsiveness and subjective norms which directly enhance cognitive trust and system acceptance. Comparative study (Shamim and Misra, 2025) confirmed that trust mediation pathways significantly motivate in structured marketplaces with presence of heuristic cues. Cumulative results of the study are consistent with research high-impact empirical evidence, establishing the robustness and generalizability of AI-driven trust mechanism across diverse digital retail contexts.

4.2.2 Structural Model Predictive Relevance

Table-5 provides empirical evidence on predictive relevance of the model demonstrated strong predictive value for brand trust at 0.555, lower RMSE and MAE values establishing higher predictive precision. Moderate predictive values were observed for impulse buying at 0.331. Model overall exhibits satisfactory predictive performance within this integrated SOR and TAM framework.

Table 5: Predictive Relevance

DVs	Q^2 predict	RMSE	MAE
Brand Trust	0.555	0.670	0.489
Impulse Buying	0.331	0.822	0.630

4.2.3 Effect Size (f^2)

Table-6 demonstrates that AI accuracy perception and subjective norms have substantial and strong influence on brand trust reinforcing critical role in the model. AI exposure, recommended products, and buying impulsiveness have comparatively smaller contribution of effect on the model.

Table 6: Effect Size (f^2)

Predictor → Dependent Variable	f^2 *Value*	Effect Size Interpretation
AI exposure → Brand Trust	0.008	Small effect
AI accuracy perception → Brand Trust	3.937	Very large effect
Recommended product → Brand Trust	0.014	Small effect
Buying impulsiveness → Brand Trust	0.030	Small–moderate effect
Subjective norms → Brand Trust	0.207	Large effect
Brand Trust → Impulse Buying	0.637	Large effect

5. Implications

5.1 Managerial Implications

The managers in the light of findings, prioritizing leverage AI accuracy perception and enhancing subjective norms since these constructs within conceptual framework exhibited strong meaningful mediating influence via brand trust in driving impulse buying. Optimizing recommended product strategies and strengthening AI exposure can reinforce trust formation aiding brand trust can be effectively translate technological stimuli and behavioral responses to foster impulse buying outcomes within AI-driven systems.

5.2 Theoretical Implications

This research redefined extending SOR frameworks by integrating novel variables i.e. AI exposure, AI accuracy perception, recommended product as stimuli to influence brand trust that leads to drive impulse buying. It expanded TAM framework to establish behavioral components i.e. buying impulsiveness as critical antecedents in the formation of brand trust to trigger impulse buying. Integration of SOR and TAM formed a comprehensive theoretical lens to advance systematic academic understanding of linking AI exposure, AI accuracy perception, recommended product, buying impulsiveness, and subjective norms as central mechanism to foster impulse buying through brand trust.

6. Conclusion

This research study offered a very rich contextually grounded and systematically integrated theoretical explanation of impulse buying behavior among generation Z in Pakistani's AI-driven retailing environment combining SOR framework and TAM. It advanced prior literature to clearly link AI exposure, AI accuracy perception, recommended product, buying impulsiveness, and subjective norms while positioning brand trust as central mediator within developing digital market often characterized by the trust deficit and rapid technological reliance and its adoption. Empirical statistical findings highlighted strong influential and mediating role of brand trust in critical pathway of technological driven stimuli and behavioral factors translate generation Z impulse buying behavior. The results further indicated that AI accuracy perception and subjective norms in AI-driven systems emerged strong predictors highlighting substantial reliance on system reliability and social validity for this cohort of sample in forming trust and triggering impulse buying. In contrast at 5% level of significance AI exposure and recommended product exerted comparatively weaker effects, revealing that AI exposure and personalization should be battered with precision and peer endorsement. Additionally, behavioral component of buying impulsiveness reflected inherent tendencies commanding brand trust to actualize predisposition into actual purchasing behavior.

The findings confirm and reinforce SOR mechanism that AI related technological stimuli are internal psychological states, while TAM behavioral constructs emphasize cognitive evaluation and social pressure in the technology acceptance. In sum, the study contributed

to enhancement in the academic knowledge clarifying how AI-enabled systems intermingle in the formation of trust in generational characteristics of generation Z consumer behavior in Pakistan's evolving digital commerce landscape.

6.1 Limitations

This research employed cross-sectional research design and self-reported survey data which may restrict the generalizability in establishing causal relationships of the variables in the framework. Non-probability convenience sampling targeted specific cohort of generation Z in Pakistan limiting generalizability across different demographic groups and cultural contexts.

6.2 Future Research

Future research in this domain can employ longitudinal and experimental designs to rigorously to unite causal pathways involving AI-driven stimuli, AI behavioral constructs on impulse buying obtaining larger data from generalized cohort of population for real-time data from digital platforms to strengthen ecological and external validity. In addition, cross-cultural and multi-generational investigation integrating critical moderating dimensions would offer more refined and generalizable contextual variability for AI-enabled consumer behavior framework.

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Availability of Data

The dataset is available from the corresponding author upon reasonable request.

Declaration of AI Use

In this research paper no AI tool is used in either generating or rephrasing the text. No AI tool is used for generating data or analysis. The methodology, results, and interpretations were entirely developed by the authors.

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