Center for Management Science Research
ISSN: 3006-5291 3006-5283 Volume 4, Issue 3, 2026

AI PERSONALIZATION AND PURCHASE INTENTION: THE MEDIATING ROLE OF CONSUMER TRUST AND THE MODERATING ROLE OF PRIVACY CONCERN

[1]Saadullah Hanif, [2]Hamza Naseem, [3]Dr. Yasir Aftab Farooqi, [4]Sheraz Anjum, [5]Farwa Bugvi

[1]BBA Graduate, Faculty of Management Sciences, UCP Constituent Campus, Gujrat, Pakistan.
[2]BBA Graduate, Faculty of Management Sciences, UCP Constituent Campus, Gujrat, Pakistan.
[3]Assistant Professor, Faculty of Management and Administration Sciences (FMAS) University of Gujrat, Pakistan.
[4]PhD Scholar, Faculty of Business and Management, Universiti Sultan Zainal Abidin, Terengganu, Malaysia.
[5]PhD Scholar, Superior University, Lahore, Pakistan.
[1]Saadullahhanif45@gmail.com, [2]hamza.naseem198@gmail.com, [3]yasir.aftab@uog.edu.pk, [4]sheraz153@hotmail.com, [5]farwabugvi2013@gmail.com

DOI: https://doi.org/10.5281/zenodo.22655695

Article History
Received on 19 Feb 2026
Accepted on 22 March 2026
Published on 25 March 2026

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Corresponding Author: *

Abstract

Within social media environments that use artificial intelligence (AI) to personalize advertisements, recommendations, and content, the influence of personalization on purchase decisions is uneven, shaped by consumers' trust in the platform and their concerns about privacy. This study examined the effect of AI personalization on purchase intention, the mediating role of consumer trust, and the moderating role of privacy concern on the trust–purchase intention relationship. Data were collected from 112 social media consumers in Punjab, Pakistan, and analyzed using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4 with bootstrapping (5,000 subsamples). AI personalization significantly increased consumer trust ($\beta = 0.617$, $p < .001$) and had a smaller but significant direct effect on purchase intention ($\beta = 0.264$, $p = .008$). Consumer trust significantly increased purchase intention ($\beta = 0.552$, $p < .001$), and the indirect effect of AI personalization on purchase intention through consumer trust was significant ($\beta = 0.340$, $p < .001$), indicating partial mediation. The interaction between privacy concern and consumer trust was not significant ($\beta = -0.014$, $p = .827$), and the conditional indirect effect did not differ meaningfully across levels of privacy concern; the moderation and moderated-mediation hypotheses were therefore not supported. The model explained 38.0% of the variance in consumer trust and 57.0% of the variance in purchase intention. PLSpredict indicated established predictive relevance for both endogenous constructs, with PLS-SEM producing lower prediction error than a linear-model benchmark for eight of nine indicators, and the Cross-Validated Predictive Ability Test (CVPAT) confirmed that the model significantly outperformed the indicator-average benchmark. Together, these results suggest that AI personalization is more strongly and reliably linked to purchase intention through the trust it builds than through its direct effect alone, and that digital platforms and advertisers benefit more from trustworthy, transparent personalization than from targeting accuracy alone.

Keywords: *AI personalization; consumer trust; purchase intention; privacy concern; mediation; moderation; PLS-SEM; PLSpredict*

Chapter 1: Introduction

1.1 Background of the Study

AI has changed the way consumers interact with digital marketing platforms. In the age of social media platforms and eCommerce platforms, there are now online tools that analyse browsing patterns, search histories, investments and other digital footprints to provide advertisements and product recommendations as well as content based on inferred interests, a process commonly referred to as AI personalization. AI personalization is not about targeting an audience with mass messages, but continuously tailoring its message to the individual in response to their assessment of relevance, usefulness, trustworthiness, and privacy concerns (An & Ngo, 2025; Teepapal, 2024).

Personalization can help minimize the time that consumers spend searching for what they want to buy, present products better suited to their needs and create a more compelling marketing message due to the fact that it resonates with existing interest. Research suggests that AI marketing is correlated with enhanced customer engagement, satisfaction, click intent, and purchase intent (Bilal et al., 2024; Yin et al., 2025). However the advantages of personalization don't instantly equate to buy. Kronemann, et al. (2023) note that the same attributes that deem recommendations "relevant" also make consumers aware of being tracked and profiled, creating a "personalization–privacy paradox" where personalization's benefits and its underlying data practices are counteracting consumer response. AI-enabled personalisation also has an opposite effect: it may make the recommendation more effective, and make the user more concerned about how their data is used, but a recommendation can be useful while the process that generated it is not trusted (Teepapal 2024). One explanation for how this dynamic is negotiated is consumer trust. Consumers do not know what algorithms power a recommendation system, they infer this trust from the relevance and usefulness of the recommendations that are presented to them (An & Ngo, 2025; Teepapal, 2024).

In fact, trust is a recognized solution to uncertainty that naturally exists during online transactions: When a consumer trusts an online platform, he or she will be more likely to comply with the platform's recommendation, but if he or she doubts the recommendation, he or she will be more likely to hesitate, even if the recommendation looks relevant (Morgan & Hunt, 1994). This is complicated by privacy concerns: a consumer may feel safe with a platform's capabilities and motives, but remain dissatisfied with how their information is gathered, stored and utilized, potentially diminishing the connection between trust and the purchase intent. The literature is not unanimous on this point — Teepapal (2024) finds that privacy concern does not significantly affect user engagement, whereas Yin et al. (2025) find that perceived privacy violation weakens the positive path to click intention — suggesting that the role of privacy concern may depend on which behavioural outcome and which stage of the consumer decision process is being examined.

Recent studies of AI personalization examine trust, engagement, usefulness, click intention, information disclosure, and purchase intention, but typically in different combinations of variables, at different stages of consumer decision-making, and in different national and platform contexts (An & Ngo, 2025; Bilal et al., 2024; Kronemann et al., 2023; Teepapal, 2024; Yin et al., 2025). Consequently, it cannot be assumed that relationships established for consumers in Vietnam, China, or Europe generalize to social media users in Punjab, Pakistan. Testing AI personalization, consumer trust, privacy concern, and purchase intention together in a single integrated model, in an under-studied national context, is therefore both theoretically and practically informative.

1.2 Problem Statement

While digital platforms are increasingly using AI personalisation to influence purchase behaviour, the route from personalisation to intent to purchase is not an easy or certain one. While personalized recommendations may seem helpful without being trusted, trusted platforms can also be tarnished by consumer anxieties about the use of their data. Marketers and platform operators remain without definitive cues, however, on two practical issues: the amount of impact personalisation has on purchase intent that can be attributed to consumer trust, and whether privacy concern is a boundary condition that should be proactively managed or a relatively small driver. If we don't dissect the direct, mediated, or conditional connections between AI

personalization, consumer trust, privacy concern, and purchase intent, investment in personalization technology could be misguided, such as investing in accuracy when personalization could lead to more trust and transparency and produce a greater return.

1.3 Research Gap

This study is motivated by three gaps, which are presented in full after the literature is reviewed in Section 2.7. The empirical gap is that while some studies examine the direct impact of AI personalization on subsequent customer behaviors—such as purchase intention, trust, relevance, usefulness, engagement, information disclosure, or click intention—few studies focus on both the direct and indirect effects of personalization on purchase intention, mediated by trust, and moderated by privacy concern together within one model (Bilal et al., 2024; Teepapal, 2024; Yin et al., 2025; An & Ngo, 2025). Second, a contextual gap: The body of evidence is limited to Vietnam, China, and Europe, and there is no study of social media use in Pakistan that might inform those same relationships in a different way due to the platform's context-specific conditions, including cultural, institutional, and platform dynamics. Thirdly there is a methodological gap: previous research generally estimates direct, mediating and moderating effects independently of each other rather than simultaneously, making it more difficult to determine if and how privacy concern moderates the indirect (not direct) effect of personalization on purchase intent.

1.4 Research Objectives

- To examine the relationship between AI personalization and consumer trust among social media users in Punjab, Pakistan.
- To examine the relationship between consumer trust and purchase intention.
- To examine the direct relationship between AI personalization and purchase intention.
- To test whether consumer trust mediates the relationship between AI personalization and purchase intention.
- To test whether privacy concern moderates the relationship between consumer trust and purchase intention.
- To test whether privacy concern moderates the indirect relationship between AI personalization and purchase intention via consumer trust (moderated mediation).

1.5 Research Questions

- RQ1: How is AI personalization related to consumer trust among social media users in Punjab, Pakistan?
- RQ2: How is consumer trust related to purchase intention?
- RQ3: What is the direct relationship between AI personalization and purchase intention?
- RQ4: Does consumer trust mediate the relationship between AI personalization and purchase intention?
- RQ5: Does privacy concern moderate the relationship between consumer trust and purchase intention, and does it condition the indirect effect of AI personalization on purchase intention through trust?

1.6 Significance of the Study

Theoretically, the study extends the Commitment-Trust Theory of relationship marketing (Morgan & Hunt, 1994) and Privacy Calculus Theory (Dinev & Hart, 2006) to the field of algorithmic, AI-mediated marketing and examines the direct, mediated, and direct mediated and moderated indirect relationships in a single PLS-SEM model, which is not attempted in most previous single-mechanism studies. In practice, the results provide digital marketers, social platforms, and policy-makers with some guidance on where to invest: either in accuracy in targeting or in trust-building and transparency or privacy protection. The study, from a largely overlooked context of Pakistan's province of Punjab, which is a large and rapidly digitalising consumer market, offers evidence for this context.

1.7 Scope and Delimitations

The study focuses on four constructs that were studied in social media users aged 18–40 from Punjab, Pakistan, who are exposed to AI personalization (in advertising or product recommendations) and who have some experience in online shopping. The design is cross sectional and quantitative with PLS-SEM in SmartPLS 4. The study focuses on purchase intention instead of actual purchases, does not consider platform differentiation (with regard to social media) or product differentiation (with regard to product type) and does not model other antecedents, such as perceived usefulness and platform reputation, directly. These limitations and the restrictions placed on this analysis due to the sample size of this modest

non-probability sample (n = 112) are discussed again in Section 4.10 and in Chapter 6.

Chapter 2: Literature Review

AI has revolutionised digital communication, allowing ads, recommendations, and content to be delivered to users based on individual preferences and actions, instead of a one-size-fits-all approach. The previous studies have demonstrated this ability as relevance, usefulness, engagement, and convenience, as well as dissatisfaction with data collection, lack of transparency, and loss of personal control (An & Ngo, 2025; Kronemann et al., 2023; Teepapal, 2024; Yin et al., 2025). Consumer trust and privacy concern are accordingly central to explaining why AI personalization produces stronger effects in some contexts than others (An & Ngo, 2025; Teepapal, 2024; Zimmermann et al., 2023).

2.1 AI Personalization in Digital Marketing

AI personalization relies on algorithms, machine learning, and consumer data analysis to create advertisements, product suggestions, and content that matches the individual user, adjusting to consumer browsing trends, purchasing behaviour, and search patterns and preferences (An & Ngo, 2025; Yin et al., 2025). The literature is unanimous about the principle benefits of personalization: relevance and ease of use – when recommendations match consumers' needs, they do save time and efforts for the shopper in locating appropriate products. An and Ngo (2025) demonstrate that it is the perceived value and relevance of personalization, not the actual personalization itself, that is responsible for consumer response to AI-driven ads. Likewise, Bilal et al. (2024) establish a connection between AI-driven consumer experiences and engagement and purchase behaviour, thereby underscoring the importance of how relevant, useful, and appropriate the content is perceived as by consumers.

The benefits are not guaranteed as in the same way that timely recommendations can empower consumers to know that they are being tracked and profiled, this technology can increase their awareness of the tracking and profiling. This can be formalized as the personalization-privacy paradox by Kronemann et al. (2023) who claim that personalization can increase both attitudes and disclosure intentions, whereas privacy concern can decrease them. Canhoto et al. (2024) provide empirical evidence that consumers actively reject personalisation based on AI technologies that they view as 'invasive', 'autonomy-reducing' or 'disruptive' to their shopping context. Therefore, the level of sophistication of personalization needs to be assessed based on consumers' perception of the process of data collection; welcomed when relevant and reasonable, resisted when opaque (Canhoto et al., 2024; Kronemann et al., 2023; Teepapal, 2024).

2.2 Consumer Trust in AI-Mediated Marketing

Consumer trust in an AI mediated environment is a willingness to engage and accept the recommendations of a platform, based on trust in the competence, reliability, and ethical behaviour of that platform. Since consumers cannot see exactly how the algorithm works, they are learning trustworthiness indirectly from the algorithm's suggested relevance, prior platform experiences, information credibility, and how they think the platform processes their data (An & Ngo, 2025; Teepapal, 2024). Findings by An and Ngo (2025) indicate that trust is a predictor of purchase intention in personalized advertising, and that this trust is a result of perceived relevance and usefulness, not directly personalized advertising.

This definition of trust is aligned with the general role of trust in relationship marketing, which is to cope with the uncertainty associated with exchange, especially in cyberspace because the buyer cannot inspect the seller directly and assess his or her credibility (Morgan & Hunt, 1994). In the context of AI in marketing, trust replaces transparency consumers lack when it comes to how recommendations are being made and that they are being made in line with their needs, while their transactions are considered secure (An & Ngo, 2025; Morgan & Hunt, 1994).

2.3 Privacy Concern in Personalized Environments

Consumers are rightfully concerned about the capture, retention, processing, and sharing of personal information by firms, and their concerns grow sharper with the increasing use of behavioural data in personalisation by AI (Dinev & Hart, 2006; Kronemann et al., 2023; Teepapal, 2024). The personalisation-privacy paradox is to the point: people could be okay with the personalised recommendation, but not with how it's done. Kronemann et al. (2023) propose a conceptual model of this paradox whereby attitude towards

personalization positively influences disclosure intention, but privacy concern has a negative influence on the same.

It sounds like privacy concern is a bigger issue when there is perceived intrusion into personalisation. Yin et al. (2025) report that perceived IV undermines the positive impact of immersive tech experiences on click intention; and Canhoto et al. (2024) reveal that consumers limit information access and resist AI-generated offers when personalization is perceived as violating their autonomy or going beyond their privacy norms. The influence of privacy concern is not consistent across outcomes, however; it has been reported in studies on relationship formation (engagement), disclosure of personal information, attitudes, and click intention, and the types of platforms, information, and decision stage examined vary significantly across studies (Canhoto et al., 2024; Kronemann et al., 2023; Teepapal, 2024; Yin et al., 2025). There is a unifying theory: Privacy Calculus Theory (PCT), which suggests that consumers compare perceived benefits and risks of engaging in disclosure or privacy and decide to do so when perceived benefits are greater than perceived risks (Dinev & Hart, 2006).

2.4 Purchase Intention in AI-Personalized Marketing

Purchase intention is the consumer's declaration of his/her willingness or readiness to acquire a product or service, as opposed to an actual purchase. As for AI-driven marketing, recommendation relevance, consumer experience, and trust and convenience in the search process are are associated with purchase intention (An & Ngo, 2025; Bilal et al., 2024; Zimmermann et al., 2023). Bilal et al., (2024) find that personalized experiences have a positive impact on the purchase and engagement outcomes of consumers, and An and Ngo (2025) see relevance, usefulness, and trust as the three mechanisms through which personalized ads affect purchase intentions.

Not all evidence is this optimistic e.g. Zimmermann et al. (2023) demonstrate that while personalized recommendations are more likely to produce superior experiential results, this does not necessarily lead to greater purchase intention as consumers can find a recommendation satisfactory without intending to purchase. Therefore, two direct paths are suggested from AI personalization to purchase intention: the direct path – personalization decreases search efforts and makes relevant alternatives clear, and the indirect path – perceived relevance and usefulness of the provided content, which leads to trust, and further to purchase intention (An & Ngo, 2025; Bilal et al., 2024).

2.5 Relationships Among AI Personalization, Consumer Trust, and Purchase Intention

The connection between AI personalization, consumer trust, and purchase intent is found across many digital marketing and e-commerce studies, but is presented in various ways: some studies present it as the direct path from AI personalization to purchase intent, while others present it as the direct path from AI personalization through a mediating variable such as consumer trust, satisfaction, engagement, or relevance (An & Ngo, 2025; Bilal et al., 2024; Teepapal, 2024). There is weight of evidence supporting a positive relationship between the appropriate level of personalization and consumer trust: recommendations built on the platform's understanding of the consumer's needs suggest competence. However, An and Ngo (2025) demonstrate that this is indirect, not direct — that is, consumers judge its relevance and usefulness first, and then their level of trust follows.

Trust, in turn, is consistently linked to purchase intention: consumers who believe a platform is reliable are correspondingly more willing to act on its recommendations. Taken together, the literature broadly supports a mediation model in which personalization builds perceived relevance and usefulness, which cultivates trust, which then drives purchase intention — while also indicating that trust is not the sole explanatory mechanism, since personalization can independently deliver value through convenience and reduced search effort (An & Ngo, 2025; Bilal et al., 2024).

2.6 Privacy Concern as a Boundary Condition

Trust may promote purchase intention, yet privacy concern could constrain how fully that trust converts into behaviour: a consumer can trust a platform's competence while remaining uneasy about its data practices. Privacy Calculus Theory and research on perceived privacy violation together motivate treating privacy concern as a boundary condition on the trust–purchase intention relationship (Dinev & Hart, 2006; Yin et al., 2025).

The evidence for this boundary condition is mixed. Yin et al. (2025) show that perceived privacy violation weakens the positive path to click intention; Kronemann et al. (2023) argue conceptually that privacy concern negatively affects attitudes and disclosure intention; and Canhoto et al. (2024) show that privacy and autonomy concerns explain consumer resistance to AI-enabled personalized offers. Critically, none of these studies examines the specific relationship central to this research — the moderating role of privacy concern on the link between consumer trust and purchase intention — focusing instead on information disclosure, click intention, engagement, or attitudes toward in-store personalized offers (Canhoto et al., 2024; Kronemann et al., 2023; Teepapal, 2024; Yin et al., 2025). It remains plausible that privacy concern also conditions the indirect relationship between AI personalization and purchase intention through trust, consistent with privacy calculus logic and corroborating research on AI-personalization outcomes (Dinev & Hart, 2006; Yin et al., 2025).

2.7 Research Gaps

2.7.1 Empirical Gap

The literature reviewed above examines AI personalization alongside trust, relevance, usefulness, engagement, information sharing, and click or purchase intention, but rarely tests these variables jointly, or at comparable stages of the consumer response process, in a single study. No reviewed study examines the direct relationship between AI personalization and purchase intention, the mediating role of trust, and the moderating role of privacy concern on the trust–purchase-intention relationship together (An & Ngo, 2025; Bilal et al., 2024; Teepapal, 2024; Yin et al., 2025; Zimmermann et al., 2023). Consequently, the conditional indirect relationship proposed in this study — whereby privacy concern moderates the indirect effect of AI personalization on purchase intention via trust — remains largely untested, even though privacy concern has been examined as a moderator of engagement, information sharing, acceptance, and click intention elsewhere (Canhoto et al., 2024; Kronemann et al., 2023; Teepapal, 2024; Yin et al., 2025).

2.7.2 Contextual Gap

Much of the reviewed evidence derives from studies conducted in Vietnam, China, and Europe (An & Ngo, 2025; Bilal et al., 2024; Yin et al., 2025; Zimmermann et al., 2023). Because consumer response to personalized marketing is shaped by cultural, institutional, and platform-specific factors, these findings cannot be assumed to generalize to social media users in Pakistan. This review finds virtually no comparable evidence on social media users in Punjab specifically, making contextualized evidence from this setting independently valuable.

2.7.3 Methodological Gap

Most reviewed studies examine direct effects and mediation or moderation processes separately rather than estimating direct, mediated, moderated, and conditional indirect effects within one integrated model. This separation obscures whether, and how far, AI personalization's effect on purchase intention operates through consumer trust, and whether that trust-based pathway varies systematically with privacy concern (An & Ngo, 2025; Bilal et al., 2024; Teepapal, 2024; Yin et al., 2025). The present study addresses this gap by applying PLS-SEM to estimate the measurement model and the full set of direct, mediated, moderated, and conditional indirect relationships simultaneously.

Chapter 3: Conceptual Model and Research Hypotheses

3.1 Underpinning Theories

This study draws on two complementary theoretical frameworks: the Commitment-Trust Theory of relationship marketing and Privacy Calculus Theory. Together, they explain the significance of trust in consumer purchase decisions and the effect of privacy concern on AI-enabled advertising.

Commitment-Trust Theory holds that trust is among the most important elements in building durable exchange relationships (Morgan & Hunt, 1994). In AI-enabled marketing, consumers cannot observe how algorithms generate advertisements, suggestions, and personalized content, so their judgement of the platform rests on perceived competence, reliability, and responsibility. When a platform consistently delivers relevant, trustworthy recommendations, consumer trust in that platform increases, which is theorised to shape subsequent purchase intention.

Privacy Calculus Theory suggests that when using a digital technology, consumers consider the benefits they anticipate from the technology with the potential costs (Dinev & Hart, 2006). Consumers can also appreciate some helpful suggestions and

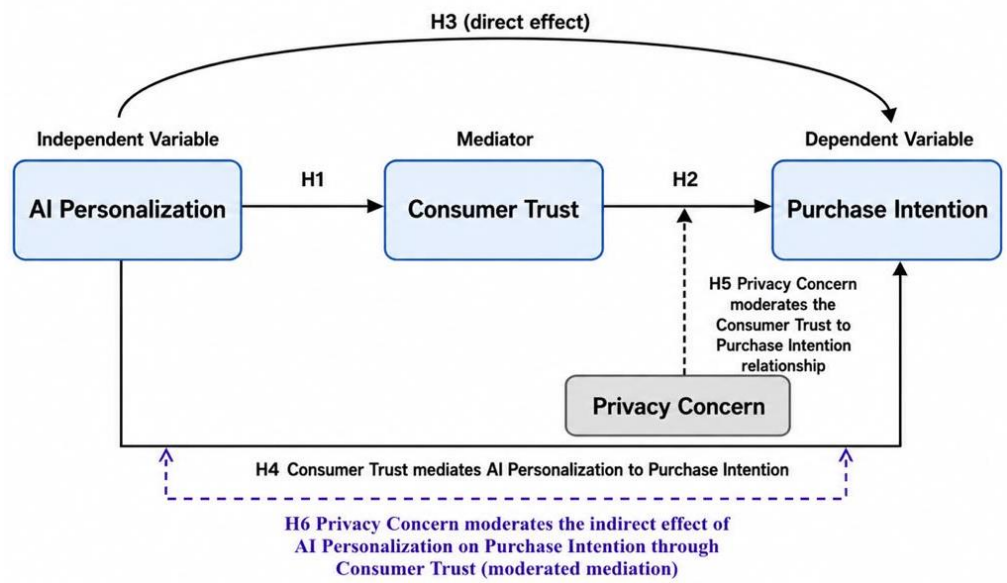
convenience while wondering about their data. This study utilizes Privacy Calculus Theory to address the question of whether the level of privacy concern moderates the relationship between consumer trust and purchase intention and whether it conditions the indirect relationship between AI personalization and purchase intention through consumer trust.

The two theories contribute to the model's theoretical foundation: Commitment-Trust Theory's motivation is the put in place of consumer trust, and Privacy Calculus Theory's motivation is the moderating effect of consumer privacy concern on the trust–purchase-intention relationship and on the indirect path from personalization to purchase intention.

3.2 Conceptual Model

Based on this, the independent variable is AI personalization, while the dependent variable is purchase intention, with consumer trust as the mediator and privacy concern as the moderator in the proposed model. The two ways AI personalization impacts purchase intention are direct (relevance, convenience, search efficiency) and indirect (consumer trust, which is built through personalization). Consumers' concern over how information is collected, stored, and used is modelled as a boundary condition on the trust–purchase-intention link, even when consumers trust the platform. The full conceptual model is shown in figure 1, with the moderated-mediation pathway (H6) included.

Figure 1: Conceptual model of study



3.3 Research Hypotheses

3.3.1 AI Personalization and Consumer Trust

AI personalization can help platforms create ads, recommendations, and content that are tailored to individual consumers. If this custom content is useful and informative to the user, they can reasonably expect that the platform is attuned to their needs, which reduces uncertainty of product selection and, consequently, increased user confidence in the platform and product recommendation (An & Ngo, 2025; Teepapal, 2024).

H1. AI personalization is positively related to consumer trust.

3.3.2 Consumer Trust and Purchase Intention

The uncertainty of online buying is inherent, as consumers cannot always be sure that the recommendations are genuine, sellers are reliable, or that transactions are safe. Consumer trust decreases this uncertainty, increasing consumers' confidence in the platform and the information it provides; and consumers who feel that a platform is trustworthy and responsible are more likely to take action based on its recommendations (An & Ngo, 2025; Morgan & Hunt, 1994). Jabbar et al. (2026) found that packaging design influences purchase intention through brand trust.

H2. Consumer trust positively affects purchase intention.

3.3.3 AI Personalization and Purchase Intention

AI personalization can also directly impact purchase intent. Appropriate recommendations lessen the effort required to search, simplify product comparison, and assist the consumer in finding appropriate products more quickly and easily; in this way, appropriate recommendations can encourage consumers to purchase. Additionally, the platform itself has direct effects on consumers, as they will consider whether or not the platform is trustworthy, so the model tests the direct relationship as well as the indirect pathway via the platform's trustworthiness (An & Ngo, 2025; Bilal et al., 2024; Zimmermann et al., 2023). Raza et al. (2026) found that AI-driven stimuli significantly predicted impulse buying in Pakistani consumer market.

H3. AI personalization positively influences purchase intention.

3.3.4 Mediating Role of Consumer Trust

The influence of AI personalisation on purchase intent could work in part through the trust that is cultivated: The more consumers feel that the content is relevant and credible, the more they will trust the platform, which could lead to increased willingness to take action on the platform's recommendations. Personalization can also affect purchase intention directly as it can be relevant and convenient, thus a partial (not full) mediation is theoretically possible.

H4. Consumer trust mediates the relationship between AI personalization and purchase intention.

3.3.5 Moderating Role of Privacy Concern

Consumer trust may be linked with purchase intention in a non-stronger relationship due to privacy concern. The consumer may have trust in a platform's competence but may not feel comfortable about a platform's collection and processing of his or her personal data, and therefore trust does not translate into purchase intent as effectively as it otherwise would. Consumers who have lower-level privacy concern will be more willing to comply with the recommendations from a trusted platform, while those who have higher privacy concern will be hesitant to do so even if they trust the platform, as privacy calculus logic suggests and evidence indicates that the perceived privacy violation can negatively affect otherwise positive behavioural intentions (Dinev & Hart, 2006; Yin et al., 2025).

H5. Privacy concern negatively moderates the effect of consumer trust on purchase intention.

3.3.6 Conditional Indirect Effect of Privacy Concern (Moderated Mediation)

The weaker the trust–purchase-intention relationship, the weaker the indirect relationship between AI personalization and purchase intention that goes through trust, meaning that as privacy concern increases, so may the indirect pathway between AI personalization and purchase intention. This represents a moderated-mediation pattern, similar to what has been found in previous research on the moderating role of privacy concern in AI-driven communication (Dinev & Hart, 2006; Yin et al., 2025).

H6. Privacy concern moderates the indirect effect of AI personalization on purchase intention through consumer trust.

Chapter 4: Research Methodology

4.1 Research Philosophy and Approach

This study has a positivist research philosophy, which suggests that the relationships between the hypothesized variables (AI personalization, consumer trust, privacy concern, and purchase intention) can be measured through structured numerical measures (Bryman, 2016). The problem is that positivism is appropriate for an investigation in which the theory is already established and relationships between variables are already stated in advance, and the data being collected are quantitative in nature.

Based on the findings from the literature review in Chapter 2, the six hypotheses (H1–H6) were developed before the data collection process, using a quantitative approach to measure the relationships between the constructs in the study, and a deductive strategy was employed. The cross-sectional survey approach captured participants' perceptions at a single time, suitable for examining current attitudes and perceptions of consumers towards AI-driven advertising, but not for examining changes over time; since data were collected at one time, it is appropriate to draw a statistical association, but not causal inferences.

4.2 Target Population

The target population comprised social media users in Punjab, Pakistan, who had encountered AI-personalized advertisements, product recommendations, or marketing content on platforms such as Facebook, Instagram, or TikTok. Eligible participants were aged 18–40 and had

experience with online shopping and exposure to digital marketing content.

Punjab was selected because it is Pakistan's most populous province: the 2023 Seventh Population and Housing Census recorded Punjab's population at over 127 million, more than half of Pakistan's total population (Pakistan Bureau of Statistics, 2023). This scale and its correspondingly large base of digitally engaged consumers make Punjab a substantively relevant setting for studying consumer response to AI-personalized marketing.

4.3 Sampling Strategy and Sample

Purposive sampling was used with a few individuals who were sampled in a snowball (chain-referral) sampling approach. The information obtained from respondents could be reflective of the constructs under study, given that they met the criteria for the respondents in the study and had past experience with personalized advertisements or personalized product recommendations. The respondent had to be aged between 18 and 40, living in Punjab, Pakistan and engage with social media, and had experienced personalized ads or product recommendation while on social media or shopping online. Based on the fact that there is no complete sampling frame of AI-personalized-marketing-exposed social media users from Punjab, the snowball sampling method was used where the respondents were requested to share the survey with other potential eligible respondents (Etikan et al., 2016).

Following data cleaning, 112 usable responses were kept for analysis. The selection of PLS-SEM was not only based on the sample size, but also due to its ability to examine direct, mediational, moderational, and conditional indirect relationships at the same time, within a single analytical model, and its explanatory and predictive nature (Hair et al., 2022). While the results from this type of sampling will lack statistical generalizability, purposive and snowball sampling do ensure that participants are selected from overlapping social, educational, or professional networks, meaning that they may share characteristics and views that do not represent the larger population.

4.4 Data Collection Procedure

A survey was used to gather data, taking a structured Google Forms and circulating it through social media, personal contact networks and education facilities to reflect the population of interest, which is highly active in social media and used online advertising and shopping. The survey consisted of two sets of questions: Demographics and Background (age, gender, city of residence, social media usage) and the items for AI personalization, consumer trust, privacy concern, and purchase intention. All construct items used a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). It was decided to have one response format for all constructs because this made the survey easier to complete; however, this does not ensure measurement quality and was overcome by the procedure controls outlined in Section 4.5.

4.5 Common Method Bias and Procedural Controls

Common method bias was considered since all constructs (independent, mediating, moderating, and dependent) were measured using the same questionnaire and responded by the same individuals (Podsakoff et al., 2003). Several procedural controls were put in place to reduce this risk: demographic data was gathered separately from construct data, different items were used to measure each construct, wording on the items was kept simple and concise, and data were collected online. The relationships proposed in the conceptual model were not directly asked of the respondents instead, AI personalization, trust, privacy, and purchase intention were presented as separate topics, making it difficult for respondents to make inferences regarding the study hypotheses. The use of such controls does not fully remove the risk involved with single source self-reported data (Podsakoff et al., 2003).

4.6 Measurement of Constructs

Four latent constructs (AI personalisation, consumer trust, privacy concern and purchase intention) were modelled reflectively, meaning the questionnaire items were interpreted as expressions of the underlying construct rather than as elements that define the construct. The number of indicators in the complete measurement model was 19.

To measure AI personalization, five items (AIP1–AIP5) were selected based on previous studies in the area of perceived personalization in digital marketing and social media (An & Ngo, 2025; Teepapal, 2024). To assess consumer trust, the researchers used five items (CT1- CT5) that reflect the reliability,

expertise, and ethical practices of AI-powered content platforms as in past studies of consumer trust in AI in marketing (An & Ngo, 2025; Teepapal, 2024). The privacy concern was assessed using five items that assess the discomfort with personalised recommendations based on the collection, storage, processing, and use of the personal and behavioural data of the respondents (Dinev & Hart, 2006; Teepapal, 2024). The purchase intention was measured by four items (PI1-PI4) the same as previous AI-advertising literature (An & Ngo, 2025; Bilal et al., 2024) as respondents' intention to buy a product they have been exposed to through personalized advertising, but haven't actually purchased.

4.7 Data Analysis Technique and Model Evaluation Criteria

Partial least squares structural equation modelling (PLS-SEM) was performed in SmartPLS 4. PLS-SEM was appropriate because the study sought to explain and predict variance in consumer trust and purchase intention while simultaneously estimating direct, indirect, interaction, and conditional indirect relationships; because it accommodates mediation and moderation within a single analytical framework; because it performs well in predictive research on endogenous constructs; and because it is less constrained by multivariate normality assumptions than covariance-based SEM (Hair et al., 2022). The analysis proceeded in three stages: measurement model assessment, structural model assessment, and assessment of the model's out-of-sample predictive performance.

Measurement model assessment examined indicator reliability (outer loadings), internal consistency (Cronbach's alpha, Dijkstra–Henseler's ρA, and composite reliability ρC, each expected to exceed .70, with values above .95 flagged for possible redundancy), convergent validity (average variance extracted, AVE ≥ .50), discriminant validity (heterotrait–monotrait ratio, HTMT, with values below .85 indicating discriminant validity and values up to .90 considered acceptable), and collinearity (variance inflation factor, VIF < 3.0). Approximate model fit was assessed via the standardized root mean square residual (SRMR), with values below .08 indicating acceptable fit, interpreted alongside reliability, validity, explanatory power, and effect sizes rather than in isolation (Hair et al., 2022).

Structural model assessment examined path coefficients, indirect and interaction effects, 95% bias-corrected confidence intervals, R^2 and adjusted R^2, effect sizes (f^2, with .02, .15, and .35 denoting small, medium, and large effects), t-values, and p-values for the hypothesised relationships. Mediation (H4) was evaluated via the indirect effect of AI personalization on purchase intention through consumer trust, with partial mediation indicated when both the indirect and the direct effect were statistically significant. Moderation (H5) was evaluated via the interaction between consumer trust and privacy concern in predicting purchase intention, and the conditional effect of trust on purchase intention was examined at low (−1 SD), mean, and high (+1 SD) levels of privacy concern. Moderated mediation (H6) was evaluated via the conditional indirect effect of AI personalization on purchase intention through trust at these same three levels of privacy concern.

Bootstrapping used 5,000 subsamples, a two-tailed test at $\alpha = .05$, and 95% bias-corrected confidence intervals, with the path-weighting scheme, a maximum of 3,000 iterations, and a stopping criterion of 10^{-7}; an effect was considered statistically significant when $p < .05$ and the corresponding confidence interval excluded zero (Hair et al., 2022). Out-of-sample predictive performance was assessed using PLSpredict, run with ten folds repeated ten times, examining Q^2predict at the indicator and construct level (positive values indicating that PLS-SEM outperforms a naive benchmark) and comparing PLS-SEM root mean square error (RMSE) against a linear-model benchmark (Shmueli et al., 2019), and using the Cross-Validated Predictive Ability Test (CVPAT) to test whether PLS-SEM's prediction error was significantly lower than that of an indicator-average benchmark, with a negative average loss difference and $p < .05$ indicating superior PLS-SEM performance (Liengaard et al., 2021; Sharma et al., 2023).

4.8 Ethical Considerations

Participation was voluntary and anonymous; informed consent was obtained electronically before survey commencement; no personally identifying information was collected; and data were stored securely and used solely for academic research purposes.

4.9 Methodological Limitations

The methodology carries several limitations. The cross-sectional design precludes establishing temporal order or definitive causal relationships. Reliance on self-reported data raises the possibility of response bias and common method bias notwithstanding the procedural controls in Section 4.5. Purposive and snowball sampling reduce the statistical generalizability of the results. The achieved sample of 112 valid responses, while sufficient to estimate direct, mediating, moderating, and conditional indirect relationships, is too small to support reliable multi-group comparisons, which were accordingly not attempted. Finally, the study measured purchase intention rather than completed purchases; stated intention does not guarantee subsequent behaviour. Future research could address these limitations using behavioural data, experimental designs, or transaction records, as discussed further in Section 6.4.

Chapter 5: Results

Partial least squares (PLS) structural equation modelling (SEM) was conducted using SmartPLS 4. The measurement and structural models were evaluated using 5000 bootstrapped samples, two-tailed tests, 95% bias-corrected confidence intervals, and assessing the models for predictive performance, explanatory capacity, effect size, and approximate fit.

5.1 Measurement Model Assessment

The loadings of the indicators varied from .753 to .840 for AI personalization, .723 to .815 for consumer trust, .701 to .826 for privacy concern, and .775 to .832 for purchase intention. All 19 indicators were included in the final measurement model (Table 1) as few were slightly lower than the accepted .708 threshold, but were close to this value and were highly reliable and had acceptable AVE for their respective parent constructs.

All the Cronbach's α, ρA and composite reliability (ρC) values were above .70, and the average variance extracted (AVE) values were above .50, confirming the internal consistency reliability and convergent validity of each construct (Table 1). HTMT was used as the measure of discriminant validity for all construct comparisons and ranged between .308 and .883, with the highest value being for the construct pair of consumer trust–purchase intention. This is a higher than the more strict threshold of .85, but lower than the more lenient threshold of .90, suggesting that consumer trust and purchase intention are related, but empirically distinct; all other HTMT values were below both thresholds. Collinearity is not a problem in the structural model as inner-model variance inflation factors (VIF) lie below 3.0 with a range between 1.000 and 1.857.

Table 1: ***Measurement Model: Loadings, Reliability, and Convergent Validity***

Construct	Items	Loading Range	Cronbach's α	ρA	ρC	AVE
AI Personalization	5	0.753–0.840	0.843	0.843	0.889	0.616
Consumer Trust	5	0.723–0.815	0.814	0.816	0.870	0.574
Privacy Concern	5	0.701–0.826	0.819	0.882	0.867	0.567
Purchase Intention	4	0.775–0.832	0.820	0.822	0.881	0.649

Note. ρA = Dijkstra–Henseler's rho_A; ρC = composite reliability; AVE = average variance extracted. HTMT values ranged from .308 to .883 (all below the .90 threshold); inner-model VIF values ranged from 1.000 to 1.857 (all below 3.0).

5.2 Structural Model and Hypothesis Testing

Consumer perception of personalization in ads/recommendations/content was significantly correlated with consumer trust in the platform, in support of H1: Consumer trust in the platform was significantly greater when they perceived ads, recommendations, and content as more personalized (β = .617, t = 8.210, p < .001, 95% CI [0.418, 0.727]). H2 was supported by consumer trust which had a strong and significant positive impact on purchase intention (β = .552, t = 6.270, p < .001, 95% CI [0.370, 0.713]). AI personalization also had a significant, though smaller, direct effect on purchase intention (β = .264, t = 2.670, p = .008, 95% CI [0.082, 0.472]), supporting H3. The direct effect of trust on purchase intention (β = .552) was greater than the direct effect of personalization on purchase intention (β = .264) in this sample.

The indirect effect of AI personalization on purchase intention through consumer trust was significant (β = .340, t = 4.744, p < .001, 95% CI [0.203, 0.486]).

The direct effect of personalization on purchase intention (H3) was also significant; thus, purchase intention is a complementary partial mediator of consumer trust, a result of personalization (H4: personalization increases consumer trust and consequently purchase intention). The total effect of AI personalization on purchase intention was β = .605 (t = 5.946, p < .001, 95% CI [0.389, 0.769]).

The interaction between consumer trust and privacy concern in predicting purchase intention was small, negative, and not statistically significant (β = −.014, t = 0.218, p = .827, 95% CI [−0.137, 0.108]), so H5 was not supported. The conditional effect of trust on purchase intention was .566 at low privacy concern (−1 SD), .552 at mean privacy concern, and .539 at high privacy concern (+1 SD): although the point estimate declines slightly as privacy concern increases, this decline is not statistically significant and does not constitute evidence of moderation. Correspondingly, the conditional indirect effect of AI personalization on purchase intention through trust was .349 at low privacy concern, .340 at mean privacy concern, and .332 at high privacy concern; all three conditional indirect effects were individually significant, but the differences among them were negligible, so the moderated-mediation pattern proposed in H6 was not confirmed.

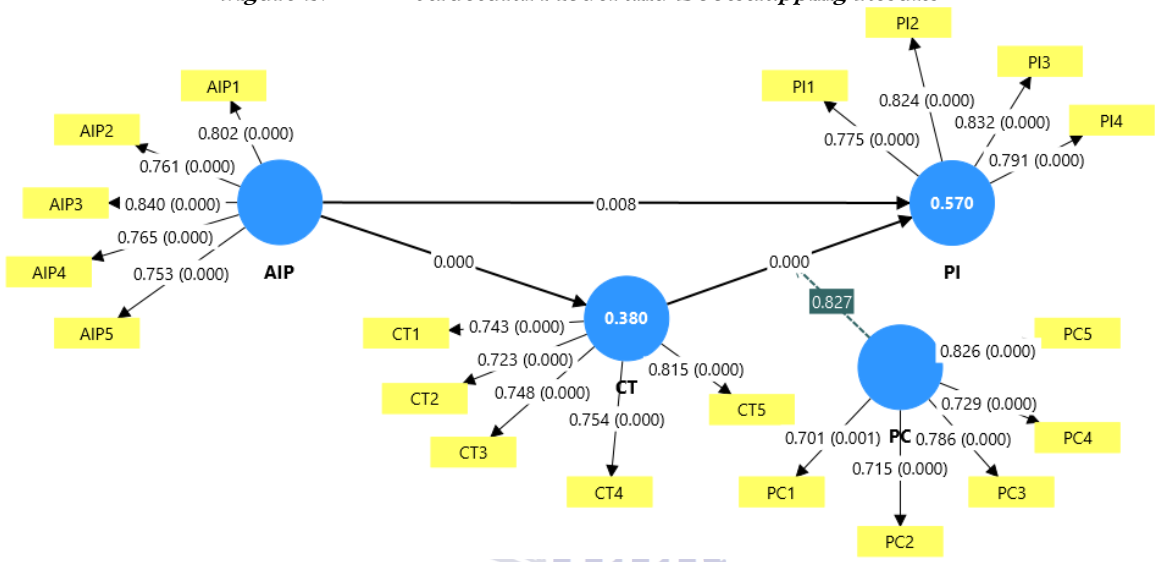
Table 2: ***Structural Model: Hypothesis Testing Results***

H	Relationship	β	t	p	95% CI	Decision
Direct effects						
H1	AI Personalization → Consumer Trust	.617	8.210	<.001	[0.418, 0.727]	Supported
H2	Consumer Trust → Purchase Intention	.552	6.270	<.001	[0.370, 0.713]	Supported
H3	AI Personalization → Purchase Intention	.264	2.670	.008	[0.082, 0.472]	Supported
Mediating effect						
H4	AI Personalization → Consumer Trust → Purchase Intention	.340	4.744	<.001	[0.203, 0.486]	Supported
—	Total effect: AI Personalization → Purchase Intention	.605	5.946	<.001	[0.389, 0.769]	—
Moderating effect						
H5	Privacy Concern × Consumer Trust → Purchase Intention	−.014	0.218	.827	[−0.137, 0.108]	Not supported
Conditional indirect effect (moderated mediation)						
H6	AIP → CT → PI at low privacy concern (−1 SD)	.349	4.720	<.001	[0.199, 0.489]	Not supported (overall H6)
	AIP → CT → PI at mean privacy concern	.340	4.744	<.001	[0.203, 0.486]	Not supported (overall H6)
	AIP → CT → PI at high privacy concern (+1 SD)	.332	3.777	<.001	[0.155, 0.502]	Not supported (overall H6)

Note. Coefficients are standardised path estimates from a two-tailed, bias-corrected bootstrap with 5,000 resamples. Although each conditional indirect effect in H6 is individually significant, the differences among the low, mean, and high privacy-concern estimates are minimal, so the proposed moderated-mediation pattern is not confirmed.

Figure 2 presents the bootstrapped structural model. The path from AI personalization to consumer trust was the strongest in the model, followed by the path from consumer trust to purchase intention; the direct path from AI personalization to purchase intention was positive but comparatively weak, and the interaction involving privacy concern was negative but negligible and non-significant, consistent with the hypothesis-testing results in Table 2.

Figure 2: Structural Model and Bootstrapping Results



Note. Values on the structural paths are standardised path coefficients; values in parentheses are p-values. SmartPLS displays p-values below .001 as .000; these are reported in the text as $p < .001$.

5.3 Explanatory Power, Effect Sizes, and Model Fit

AI personalization explained 38.0% of the variance in consumer trust ($R^2 = .380$, adjusted $R^2 = .374$). AI personalization and consumer trust jointly explained 57.0% of the variance in purchase intention ($R^2 = .570$, adjusted $R^2 = .554$), indicating that more than half of the variation in purchase intention in this sample is accounted for by the two predictors. Effect-size analysis (f^2) showed a large effect of AI personalization on consumer trust ($f^2 = .613$) and a large effect of consumer trust on purchase intention ($f^2 = .439$), a small direct effect of AI personalization on purchase intention ($f^2 = .087$), and a negligible effect for the privacy concern × consumer trust interaction ($f^2 = .001$), consistent with the non-significant moderation result reported in Section 5.2. The standardized root mean square residual (SRMR) was .077 for both the saturated and estimated models, below the .08 threshold conventionally used to indicate acceptable approximate fit; SRMR is nonetheless interpreted jointly with the reliability, validity, explanatory power, and effect-size results above, rather than as a stand-alone indicator of model adequacy (Table 3).

Table 3: ***Explanatory Power, Effect Sizes, and Model Fit***

Assessment	Construct or Relationship	Value	Interpretation
R^2	Consumer Trust	.380	38.0% variance explained
Adjusted R^2	Consumer Trust	.374	Adjusted explanatory power
R^2	Purchase Intention	.570	57.0% variance explained
Adjusted	Purchase Intention	.554	Adjusted explanatory

Assessment	Construct or Relationship	Value	Interpretation
R^2			power
f^2	AI Personalization → Consumer Trust	.613	Large
f^2	AI Personalization → Purchase Intention	.087	Small
f^2	Consumer Trust → Purchase Intention	.439	Large
f^2	Privacy Concern × Consumer Trust → Purchase Intention	.001	Negligible
SRMR	Saturated model	.077	Acceptable approximate fit
SRMR	Estimated model	.077	Acceptable approximate fit

5.4 Predictive Relevance and Out-of-Sample Predictive Performance

PLSpredict produced positive Q^2predict values for every indicator: values ranged from .166 to .267 for the consumer trust indicators and from .148 to .292 for the purchase intention indicators, and at the construct level, Q^2predict was .362 for consumer trust and .351 for purchase intention, jointly establishing predictive relevance for both endogenous constructs (Shmueli et al., 2019). Comparing PLS-SEM prediction error against a linear-model (LM) benchmark, PLS-SEM produced lower root mean square error (RMSE) for eight of the nine indicators; the exception, PI3, showed a negligible difference (PLS-SEM RMSE = .764 versus LM RMSE = .762). This pattern indicates medium out-of-sample predictive power rather than uniformly superior prediction across every indicator.

The Cross-Validated Predictive Ability Test (CVPAT) provided further evidence of predictive performance. For consumer trust, the PLS-SEM loss (0.801) was significantly lower than the indicator-average loss (1.001), an average loss difference of −0.200 ($t = 2.450$, $p = .016$). For purchase intention, the PLS-SEM loss (0.711) was significantly lower than the indicator-average loss (0.912), an average loss difference of −0.201 ($t = 2.319$, $p = .022$). At the overall model level, the PLS-SEM loss (0.761) was significantly lower than the indicator-average loss (0.961), an average loss difference of −0.201 ($t = 2.479$, $p = .015$). Across all three comparisons, PLS-SEM produced significantly smaller prediction error than the indicator-average benchmark (Liengaard et al., 2021; Sharma et al., 2023).

Table 4: ***PLSpredict and CVPAT Results***

Assessment	Construct or Result	Value	Interpretation
Q^2predict	Consumer Trust	.362	Predictive relevance established
Q^2predict	Purchase Intention	.351	Predictive relevance established
RMSE comparison	PLS-SEM lower than LM	8 of 9 indicators	Medium predictive power
CVPAT	Consumer Trust	$p = .016$	PLS-SEM significantly outperformed IA benchmark
CVPAT	Purchase Intention	$p = .022$	PLS-SEM significantly outperformed IA benchmark
CVPAT	Overall model	$p = .015$	Overall predictive performance supported

Note. IA = indicator-average benchmark; LM = linear-model benchmark.

5.5 Summary of Results

The measurement model achieved satisfactory reliability, convergent validity, discriminant validity, and collinearity diagnostics, and all 19 indicators were retained. The structural model supported H1 through H4: AI personalization strongly increased consumer trust and had a smaller but significant direct effect on purchase intention; consumer trust strongly increased purchase intention and partially mediated the effect of AI personalization on purchase intention. H5 and H6 were not supported: privacy concern did not significantly moderate the trust–purchase-intention relationship, and the conditional indirect effect of AI personalization on purchase intention via trust did not vary meaningfully across levels of privacy concern. The model explained 38.0% of the variance in consumer trust and 57.0% of the variance in purchase intention, with large effect sizes for AI personalization's effect on trust and for trust's effect on purchase intention, and a negligible effect size for the privacy-concern interaction. Model fit was acceptable (SRMR = .077), and PLSpredict and CVPAT jointly confirmed the model's out-of-sample predictive relevance for both consumer trust and purchase intention.

Chapter 6: Discussion

6.1 Discussion of the Main Findings

This study examined how AI personalization affects purchase intention through consumer trust, and whether privacy concern conditions that relationship. Four of the six hypotheses were supported, indicating that AI personalization is related to purchase intention both directly and indirectly through consumer trust, while privacy concern did not significantly alter the trust–purchase-intention relationship in this sample.

H1 proposed that AI personalization would positively affect consumer trust; this was confirmed, indicating that consumers extend greater trust to a platform when its advertisements, recommendations, and content feel relevant to them. This result is consistent with Teepapal (2024), who found that AI-powered personalization positively affects trust, privacy concern, and perceived usefulness, and broadly consistent with An and Ngo (2025), although that study identified the personalization–trust link as indirect — operating through perceived relevance and usefulness — rather than direct. The contrast suggests that the personalization–trust relationship may be direct in some contexts and channelled through intervening perceptions in others, depending on how explicitly relevance and usefulness are measured and modelled.

H2 proposed that consumer trust would positively affect purchase intention; this was also confirmed, consistent with An and Ngo (2025), who identify trust as a key predictor of purchase intention in AI-based personalized advertising, and with Commitment-Trust Theory's broader claim that trust reduces uncertainty and supports commitment (Morgan & Hunt, 1994). Because consumers typically cannot observe how a recommendation system works, trust functions as the mechanism that allows them to rely on the platform's suggestions despite that opacity.

H3 proposed a positive direct effect of AI personalization on purchase intention; this was confirmed, consistent with the reasoning that personalization reduces search effort and helps consumers identify suitable products more efficiently. This finding aligns with Bilal et al. (2024), who link AI-driven personalization to consumer utility and purchase satisfaction, and is broadly compatible with Zimmermann et al. (2023), although that study found that an improved, personalized shopping experience does not automatically raise purchase intention — underscoring that consumers can evaluate personalization favourably without a corresponding increase in buying intent. Notably, trust exerted a stronger direct effect on purchase intention (β = .552) than personalization did (β = .264), suggesting that relevance and convenience alone are unlikely to generate strong purchase intention unless accompanied by confidence in the platform providing them.

H4 proposed that consumer trust would mediate the relationship between AI personalization and purchase intention; the data showed significant partial mediation, with AI personalization affecting purchase intention both directly, through relevance and convenience, and indirectly, through the trust that personalization builds. This result reinforces An and Ngo's (2025) identification of trust formation as a key explanatory mechanism for purchase intention in AI-based personalized advertising, and is consistent with Commitment-Trust Theory's

emphasis on trust as the mechanism converting favourable platform perceptions into behavioural intention (Morgan & Hunt, 1994). That mediation was partial rather than full also matters substantively: trust is an important but not exclusive mechanism, and other factors — perceived relevance, recommendation quality, and search convenience among them — likely also contribute to the personalization–purchase-intention relationship.

H5 proposed that privacy concern would weaken the positive relationship between consumer trust and purchase intention; this was not supported. The interaction coefficient was negative but negligible and statistically insignificant, and trust remained a significant positive predictor of purchase intention at low, mean, and high levels of privacy concern alike. This result diverges from privacy-impact findings in other contexts: Kronemann et al. (2023) argue conceptually that privacy concern negatively affects attitudes and disclosure intention in AI interactions, and Yin et al. (2025) find empirically that perceived privacy violation weakens the positive effect of immersive experience and technology acceptance on click intention. These studies, however, examine different outcomes — attitudes, disclosure intention, and click intention — rather than the trust–purchase-intention relationship examined here, so the divergence may reflect genuine differences across outcomes and decision stages rather than a contradiction. It remains possible that privacy concern shapes behaviour earlier in the consumer response process — for instance, in whether trust forms at all — rather than at the point where existing trust is converted into purchase intention; the sample's composition, drawn from social media users with substantial prior exposure to personalized advertising, may also mean that repeated exposure has habituated respondents to personalization in ways that a less experienced population would not share. These explanations are offered as plausible interpretations rather than confirmed conclusions.

H6 proposed that privacy concern would weaken the indirect effect of AI personalization on purchase intention through trust (moderated mediation); this was also not supported. The indirect effect remained significant and positive at low, mean, and high privacy concern, and the differences among these conditional estimates were too small to constitute evidence of moderated mediation. This contrasts with Yin et al. (2025), who found that perceived privacy violation weakened a positive path to click intention, though again in a different outcome variable and decision context. Taken together, the absence of both the moderation (H5) and moderated-mediation (H6) effects suggests that, at least for the trust-to-purchase-intention stage examined here, privacy concern may exert more influence earlier in the personalization process — for example, on whether personalization builds trust in the first place — than at the point where trust is converted into purchase intention, a possibility future research could test directly.

Overall, the results indicate that consumer trust is the central mechanism in this model: AI personalization's relationship with purchase intention operates substantially, though not exclusively, through the trust it builds, while privacy concern, at least as measured here, does not alter either the direct trust–purchase-intention relationship or the indirect personalization–trust–purchase-intention pathway.

6.2 Theoretical Contributions

This study offers five contributions. First, it extends the logic of the Technology Acceptance Model (Davis, 1989) into AI-mediated marketing: the positive relationship between AI personalization and purchase intention is consistent with personalization improving the relevance and efficiency of the consumer's search process, though perceived usefulness and perceived ease of use were not measured directly, so the findings should be read as broadly consistent with, rather than a direct test of, the model's constructs. Second, the study extends Commitment-Trust Theory (Morgan & Hunt, 1994) into algorithmic recommendation contexts, showing that consumer trust functions as a positive predictor of purchase intention and partially mediates the effect of AI personalization on purchase intention — evidence that the platform's perceived credibility remains consequential even where the underlying interaction is technological and opaque to the consumer.

Third, the study demonstrates that Privacy Calculus Theory's (Dinev & Hart, 2006) predicted trade-off between personalization's benefits and its privacy costs is context-dependent rather than universal: privacy concern did not weaken the trust–purchase-intention relationship in this sample, which does not

invalidate the theory but suggests that its predicted effect may depend on the specific platform, consumer population, behavioural outcome, and decision stage under study (Kronemann et al., 2023; Yin et al., 2025). Fourth, by jointly estimating direct, mediated, moderated, and conditional indirect effects in a single PLS-SEM model, the study integrates strands of the AI-personalization literature that are typically examined separately — trust, privacy concern, usefulness, engagement, information disclosure, click intention, and purchase intention (An & Ngo, 2025; Kronemann et al., 2023; Teepapal, 2024; Yin et al., 2025) — offering a more complete account of how these mechanisms jointly shape purchase intention. Fifth, the study provides contextual evidence from social media users in Punjab, Pakistan, a setting largely absent from the existing AI-personalization literature, and demonstrates that relationships established in Vietnam, China, and Europe (An & Ngo, 2025; Bilal et al., 2024; Yin et al., 2025; Zimmermann et al., 2023) do not automatically generalize — most notably, the moderating role of privacy concern found in some of that literature was not reproduced here.

6.3 Practical Implications

6.3.1 Implications for Digital Marketers and Online Retailers

One of the most important points for marketers to focus on is the relevance and correctness of the personalised recommendations, as irrelevant and repetitive suggestions will only affect the credibility of the personalisation approach. Personalization alone will not be enough, as trust proved to be more influential than personalization when it comes to purchase intention, so businesses should back it up with a reliable payment system, timely delivery, and responsive customer service, which will all help to reinforce the platform trust and drive purchase intention.

6.3.2 Implications for Social Media and E-Commerce Platforms

This study did not directly test the impact of a platform's ability to communicate how personalized recommendations are created, but it makes sense that better communication of this process would build more trust. Enhancing consumers' ability to control personalization and data settings – such as changing the type of recommendations they receive, viewing their history of recommendations saved, or restricting the use of certain data – could also help build trust. A lack of significance of the moderating effect of privacy concern in this study does not imply that privacy protection is not important to consumers in general.

6.3.3 Implications for Businesses

Consumer trust should not be an afterthought in AI personalisation for businesses, it should be a core objective. Consistency in service quality, accurate recommendations, secure transactions, responsible handling of data and effective complaints handling can help to build trust. Frequent reviews of personalization systems to ensure the information they provide is current, correct and not too sensitive can help uncover practices that might be perceived as intrusive.

6.3.4 Implications for Policymakers and Regulators

To ensure consumers are not harmed from artificial intelligence in marketing, while at the same time enabling companies to reap the rewards of personalisation technology, policymakers need to foster clear standards of consent, data collection, and acceptable uses of consumers' data, and ensure these are followed in a transparent and ethical manner. Consumer-awareness campaigns geared toward educating users about the data that personalization is based on, and how to adjust their privacy settings, can assist in making more informed choices regarding the trade-offs of personalization.

6.4 Limitations and Future Research

There are some limitations of this study. As a cross-sectional design, data were gathered at one time only; thus, any changes in consumer trust, privacy concern, and purchase intention over time cannot be established and the structural relationships reported here should be interpreted as statistical association instead of causal relationships. The study used self-reported purchase intention and not actual purchase behaviour; that is, respondents can indicate that they intend to purchase, but fail to actually purchase. The sample of 112 respondents was done purposively and by snowball sampling, which is not statistically representative of the social media users in Punjab or other parts of Pakistan and does not allow generalizability.

Additionally, consumers' personalized marketing experience might vary across platforms, product categories, price points, and purchase involvement,

and future research could separate the experience across platforms (e.g., Facebook, Instagram, TikTok) or investigate the differences between low and high involvement purchases. While consumer trust and privacy concern was central to this model, other factors that are relevant were left out and warrant consideration in future research including perceived usefulness, recommendation accuracy, transparency, perceived intrusiveness, platform reputation, consumer control, and AI familiarity. Future studies could examine whether privacy concern also serves as a moderator between the relationship of AI personalization and consumer trust or between the relationship of AI personalization and consumer purchase intention — that is, whether consumer concern with the collection of personal data affects the development of trust and/or purchase intention prior to the formation of trust. This research stream would be strengthened by the use of a longitudinal design, an experimental design, or multigroup analysis; a longitudinal design would allow for the study of the development of trust over time as a function of repeated interactions with AI-personalized systems, an experimental design would allow for direct manipulation of the levels of personalization, transparency, and privacy control, and multi-group analysis would be possible if suitable subgroups were available and large enough to test for differences in the relationships reported here based on gender, age, and online-shopping experience.

Chapter 7: Conclusion

This study investigated the impact of AI personalization on purchase intent among social media consumers in Punjab, Pakistan, the mediation of purchase intent by consumers' trust, and the moderation between the relationship between consumer trust and purchase intent by consumer's privacy concerns. Consumer trust and purchase intention were both positively related to AI personalization, with consumer trust having a larger direct impact on purchase intention than AI personalization did. Consumer trust partially mediated between AI personalization and purchase intention, meaning that there are two pathways between personalization and purchase intention: directly through the relevance and convenience of personalization; indirectly through the trust that is gained.

In terms of indirect effects, the influence of AI personalization on purchase intention via the mediation of consumer trust was not significantly different depending on privacy concern, with coefficients slightly decreasing with increasing privacy concern but not significantly.The relationship between consumers' trust and purchase intention and between AI personalization and purchase intention via consumers' trust was also not significantly moderated by consumers' privacy concern, with some of the indirect effects slightly decreasing with an increase in consumers' privacy concern, but not significantly different. In contrast, privacy concern does not seem to be a significant boundary condition for this specific relationship in this sample, but this is not meant to indicate that privacy issues are not significant to consumers in general.

The study extends the existing literature by testing direct, mediated, moderated, and conditional indirect relationships in a single PLS-SEM model, it contributes to the Commitment-Trust Theory and Privacy Calculus Theory, and it offers a piece of evidence from a context that is underrepresented in literature and where the relationships tested elsewhere do not fully replicate, which is the context of Punjab, Pakistan. Quite literally, the findings indicate that businesses should not equate personalization with trust, but rather, ensure that personalised and accurate recommendations are supported by secure transactions, trustworthy services, transparent data handling, and complaint resolution processes, and also provide consumers with better information on, and control over, personalised recommendations. The lack of significant moderation of the tested relationships because of the privacy concern does not imply that privacy protection does not need to be deprioritized.

The conclusions should be viewed in the context of the cross-sectional design, the use of self-reported survey data, the non-probability sampling technique, and the relatively small sample size (n = 112) of this study, which restricts the capacity for causal inference and generalizability. Future studies need to further investigate the roles of these relationships with larger and more diverse samples, to test actual purchasing behaviour instead of stated intention, and to explore these relationships in other national and platform contexts. Overall, the results indicate

that AI personalization is not a standalone solution to developing purchase intent and that this solution is significantly influenced by the trust that is created. In turn, the degree of trust created is dependent on the service that is provided by platforms and the way they manage consumers' data that is perceived as competent, secure, and responsible.

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