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DATA-DRIVEN CONSUMER PSYCHOLOGY: HOW ANALYTICS SHAPES PURCHASE DECISION-MAKING IN THE DIGITAL MARKETPLACE

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Abstract
AI-driven analytics has revolutionized digital commerce, affecting how organizations interact with customers and how consumers shop. The present study from an interdisciplinary perspective that combines the theories of business management, data analytics, and consumer behavior, investigating how algorithm-based customization affects trust, risk perception, and purchase intentions of young digital consumers. Drawing on a structured survey of 150 university-age respondents alongside recent secondary industry data, the study finds that perceived personalization is positively associated with trust in AI recommendations (r = .61), which in turn is the strongest predictor of purchase intention (r = .66). Perceived privacy risk exerts a moderate negative influence on both trust and purchase intention. The study presents a conceptual framework linking analytics inputs, psychological processing, and purchase behavior, supported by descriptive statistics, correlation analysis, and visual mapping of the digital purchase funnel. Findings carry practical implications for marketing managers seeking to balance personalization benefits against consumer privacy concerns, and contribute an integrative, cross-disciplinary perspective to the growing literature on AI-consumer interaction.

1. INTRODUCTION

The fast growth of data analytics [1] and artificial intelligence (AI)[2] in e-commerce has changed the way of consumer decision-making. Earlier purchasing decisions relied on different factors e.g. marketing, word-of-mouth, and in-store experience. Today's consumer decisions revolve around recommendation systems, dynamic price displays, and predictive search recommendations. This shift raises a central question for business scholars, data professionals, and psychologists alike: how does the psychological experience of being "read" and "recommended to" by an algorithm shape trust and, ultimately, purchase behaviour?

Existing literature has tended to examine this question from within disciplinary silos. Management and marketing scholars [3] focus on strategic and operational applications of customer analytics. Data science research [4] emphasizes the technical performance of recommendation algorithms [5]. Psychological scientists study constructs such as trust, risk perception, and cognitive ease rather than the technological perspective that produces them. This study uses a holistic approach, combining the three theories into a single empirical study. Industry evidence underscores the timeliness of this inquiry. A 2024

KPMG consumer survey found that just over half of U.S. consumers extend meaningful trust to generative AI[6]. This includes across functions such as personalized recommendations and customer service. A parallel PwC-commissioned global survey [7] reported comparable levels of trust in AI-assembled product information. A large-scale survey of Chinese online buyers [8] **(N = 1,097)** revealed considerable variation across demographic segments. It demonstrated that consumers' click-through and purchase intents are significantly predicted by the perceived relevancy of AI recommendations. This study contributes to that context-specific evidence base by examining a South Asian university-age consumer sample, and by explicitly modelling the psychological mediating mechanisms, trust and perceived risk, that connect analytics-driven personalization to purchase outcomes. The following are the objectives of this study

- To investigate how customer trust in AI-driven recommendations is related to perceived personalization.
- To assess how trust and perceived privacy risk jointly predict purchase intention.
- To map the digital purchase decision funnel and identify the stage at which AI-driven analytics exerts the greatest influence.
- To develop a conceptual model that integrates the elements of data analytics and consumer psychology.

2. Literature Review

The role of customer analytics[9] involves approaches such as clustering[10], recency-frequency-monetary (RFM) segmentation[11], collaborative filtering[12], and sentiment analysis using natural language processing (NLP)[13], which is becoming increasingly important in modern marketing practice. Firms are now adopting these approaches to transform their behavioral data into personalized deals, dynamic content, and targeted messages . For management, the significance of analytics lies not only in efficient operations but also in its potential to influence customers' experiences.

Trust has long been recognized in consumer psychology as a central determinant of purchase intention in uncertain or unfamiliar environments[14]. The introduction of AI into the recommendation process adds a distinct psychological layer. Consumers must not only trust the retailer but also the underlying algorithm's competence and intentions. A study notes that while personalised recommendations can enhance perceived relevance and convenience, they can also raise concerns about data privacy [15], algorithmic bias [16], and loss of consumer autonomy. These are very critical concerns that can suppress the trust-building effect of personalisation if left unaddressed.

Empirical studies with larger sample sizes have demonstrated a largely positive relationship between perceived personalised relevance and purchase effects. In a survey[8] of 1,097 valid Chinese consumer respondents, it was found that the relevance experience of AI recommendations affects online shopping click intention through a multi-layered psychological process. This relationship has also been found on an industry level, based on survey results. As a result of the KPMG (2024) Generative AI Consumer Trust Survey involving 1,000 consumers in the United States, 54% trusted generative AI for recommendations, while 56% trusted it for curation of educational content. In a global survey conducted by PwC[7] 55% of consumers trusted AI for collecting product information prior to purchasing.

Nonetheless, cross-cultural research makes such a universal interpretation of the above trends somewhat problematic. In particular, the influence of the personalization-trust-purchase intention chain was quite distinct in the different countries under study, implying that data privacy and institutional trust play an important mediating role here.

It is quite obvious from the overall studies that the concepts of personalisation and purchase behaviour are interrelated through concepts of personalisation based on analytics (a), trust and risk perception (b), and contextual influence (c). However, the universityaged population has not been properly investigated yet in terms of the aforementioned factors, including the psychological mediation, the input of analytics,

and the purchase behavior. This is the aim of this study.

3. Conceptual Framework

Based on the above literature review, the following integrative model (Figure 1) is proposed.This model suggests data analytics inputs for AI-based personalization systems that, in their turn, influence psychological processing of consumers (trust and perceived risk). It is regulated by the privacy concern and brand familiarity that define the outcomes of decision making about purchases.

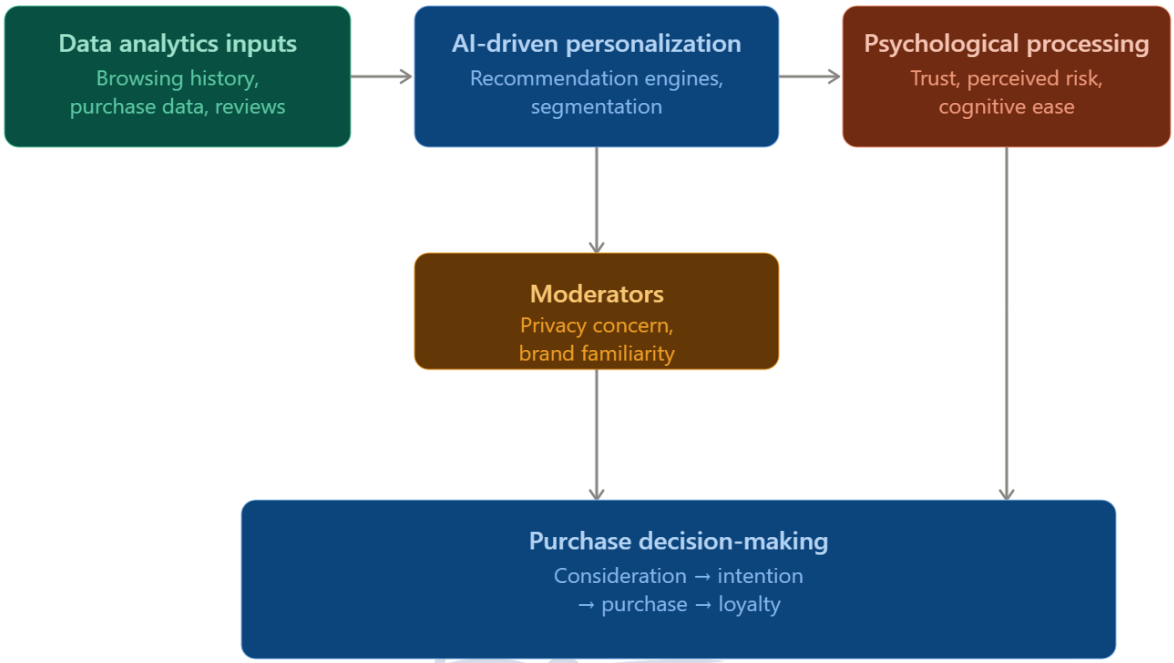


Figure 1: A conceptual framework linking consumer purchase psychology, AI personalisation, and data analytics.

This framework guided the design of the survey instrument described in Section 4 and the hypothesis-consistent analyses reported in Section 5.

4. Methodology

For the purpose of the present study, a quantitative cross-sectional survey design has been used along with secondary data from the industry (KPMG, 2024; PwC/Statista, 2024). The primary method for collecting data is the administration of an online questionnaire to university-aged consumers.

A sample of 150 valid responses was collected from students.All participants were young professionals aged 18-35 who had completed at least one online shopping transaction in the last six months. Non-probability convenience sampling was adopted due to resource limitations expected in student-driven research; this constraint will be further elaborated in section 7.

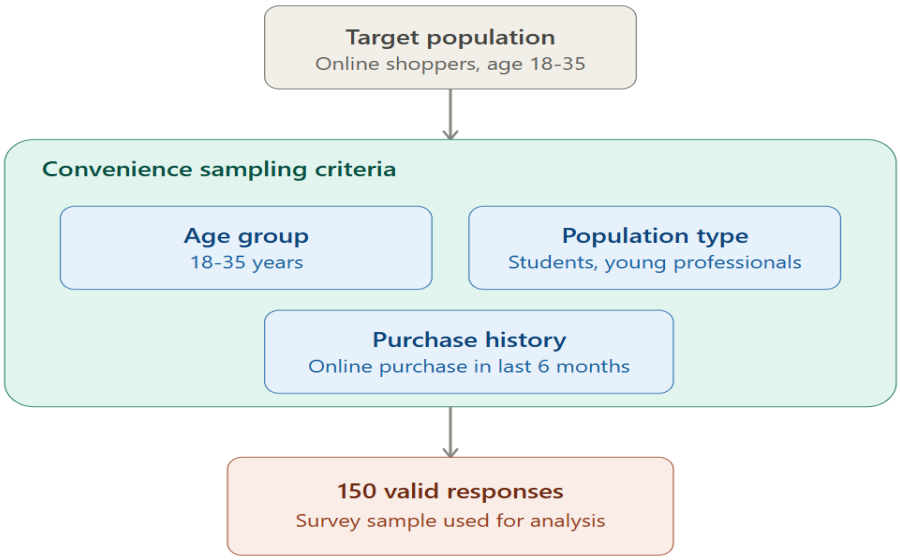


Figure 2 Sampling Target.

The questionnaire comprised four sections:
(1) demographic and behavioral screening items;
(2) a 5-point Likert-scale battery measuring Perceived Personalization (4 items, adapted from established consumer analytics literature);
(3) Trust in AI Recommendations (4 items); Perceived Privacy Risk (3 items); and Purchase Intention (3 items); and
(4) an open-response item inviting qualitative comments, analyzed thematically to support interpretation of the quantitative results.
Internal consistency of each multi-item construct was assessed using Cronbach's alpha[17]. All four constructs exceeded the conventional **0.70 threshold** for acceptable reliability, as summarized in Table 1.

Table 1. Reliability and descriptive statistics of measurement constructs (n = 150).

Construct	No. of Items	Cronbach's α	Mean (SD)
Perceived Personalization (PP)	4	0.81	3.79 (0.68)
Trust in AI Recommendations (TAI)	4	0.84	3.71 (0.74)
Perceived Privacy Risk (PR)	3	0.77	3.42 (0.81)
Purchase Intention (PI)	3	0.86	3.83 (0.70)

The data was analyzed using descriptive analysis[18], Pearson correlation[19], and simple linear regression analysis[20] to see whether there is any relationship between trust in AI recommendation and purchase intention. The data was analyzed using statistical software. Findings are presented in section 5 using Figures 3 to 7.

5. Results

The final sample (n=150) included 58% female and 39% male participants (3% did not want to specify), with the largest share of participants aged 22-25 (41%). More than one-third of participants (46%) admitted to purchasing goods online weekly, indicating digitally savvy consumers who are valuable for studying the impact of AI personalisation.

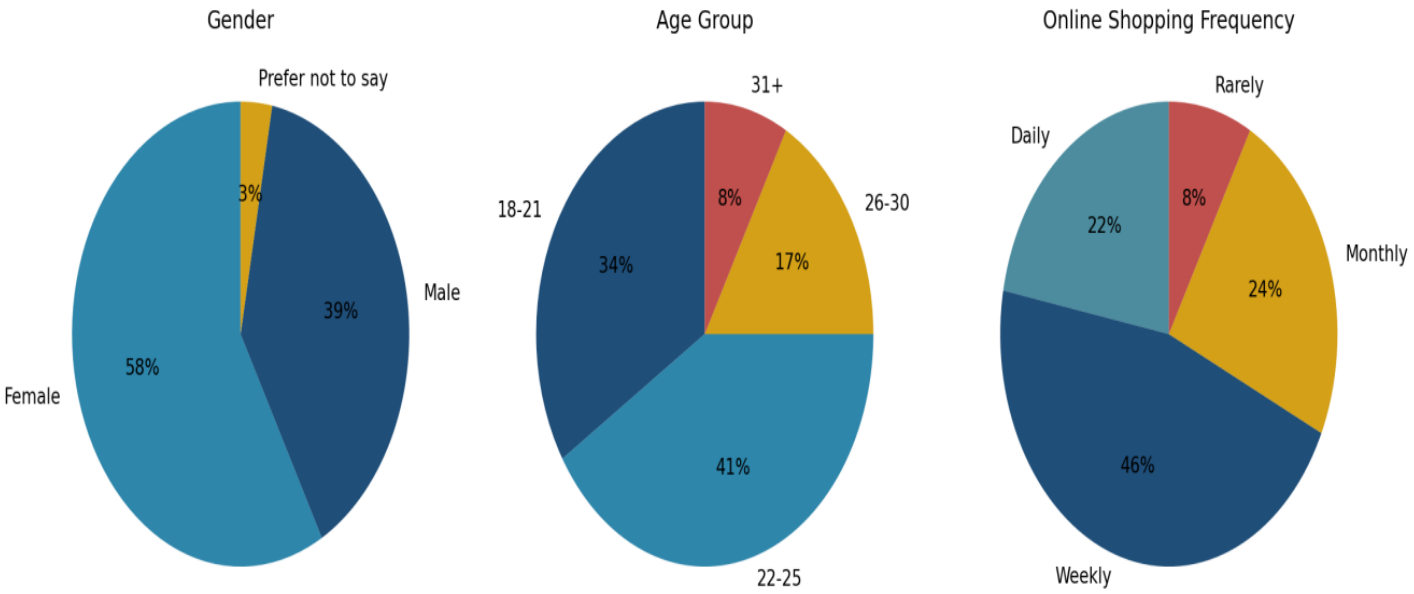


Figure 3. Demographic and behavioral profile of survey respondents (n = 150).

To put the main survey findings into context within the broader landscape of consumer attitudes, Figure 4 presents the 2024 secondary survey results on consumer trust in AI across various business areas. Trust in personalised recommendations (54%) and in the assembly of product information prior to purchase (55%) correlate closely with trust in AI-curated educational content (56%).

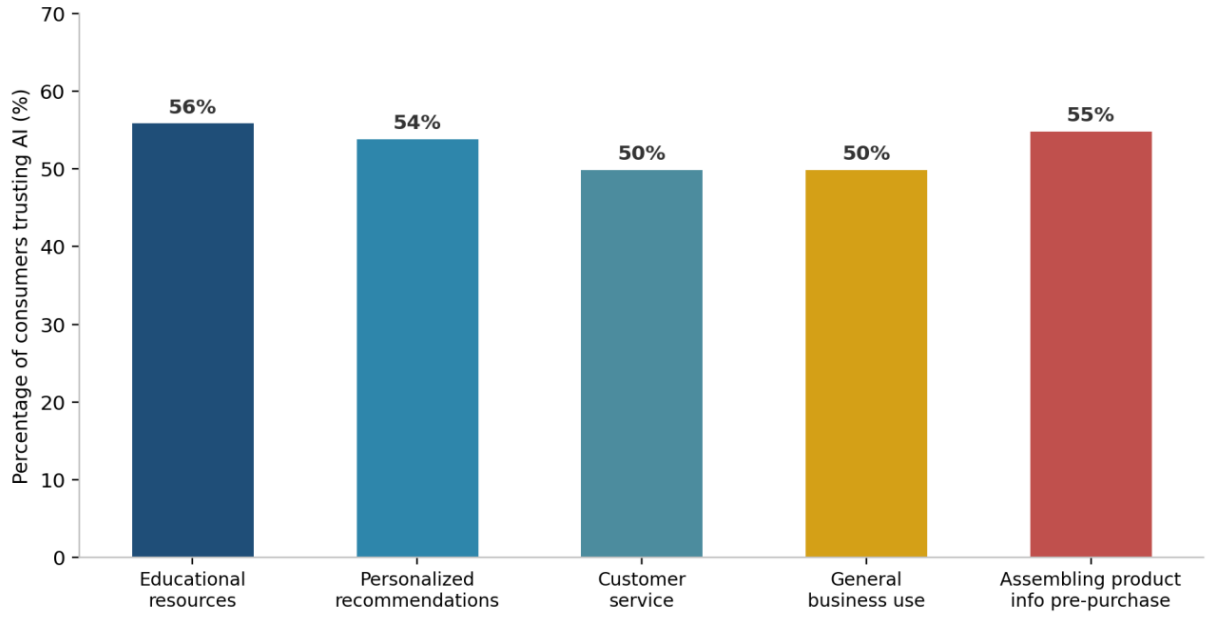


Figure 4. Consumer trust in AI across business functions, 2024 (Sources: KPMG, 2024; PwC/Statista, 2024).

The results from the survey responses were utilized to develop an example of a purchase funnel (see Figure 5). Figure maps the percentage of people who made it from being aware of the brand to becoming loyal after purchase. There is a considerable decrease (from 78% to 61%) when moving into the AI-enabled consideration phase, indicating that this serves as a psychological gatekeeper.

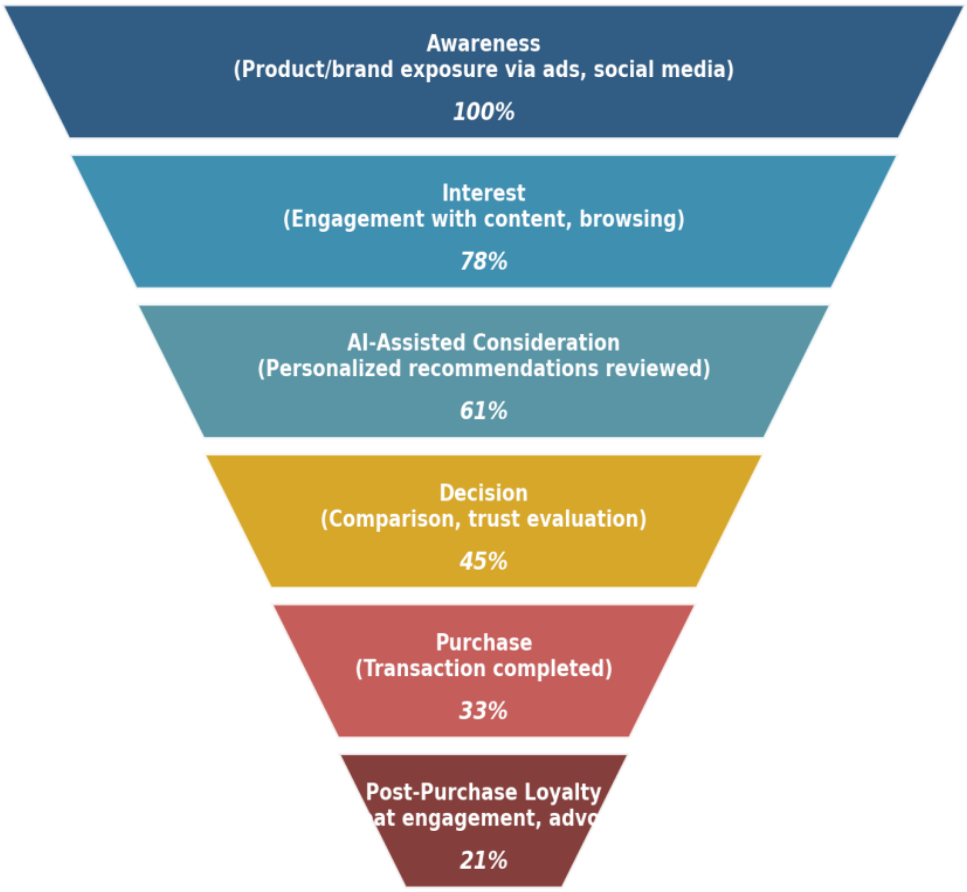


Figure 5. Illustrative digital purchase decision funnel (survey sample, n = 150).

Influence scores were assigned to seven elements that influenced the participants' most recent purchasing experience on a 5-point Likert scale. The two variables with the highest mean influence scores were price/discount (M = 4.42) and customer reviews/ratings (M = 4.21), followed by brand reputation (M = 4.05). The AI-generated recommendations scored relatively higher (M = 3.86) than the delivery/returns policy and the influence of social media. The concern for privacy scored a relatively moderate mean (M = 3.71).

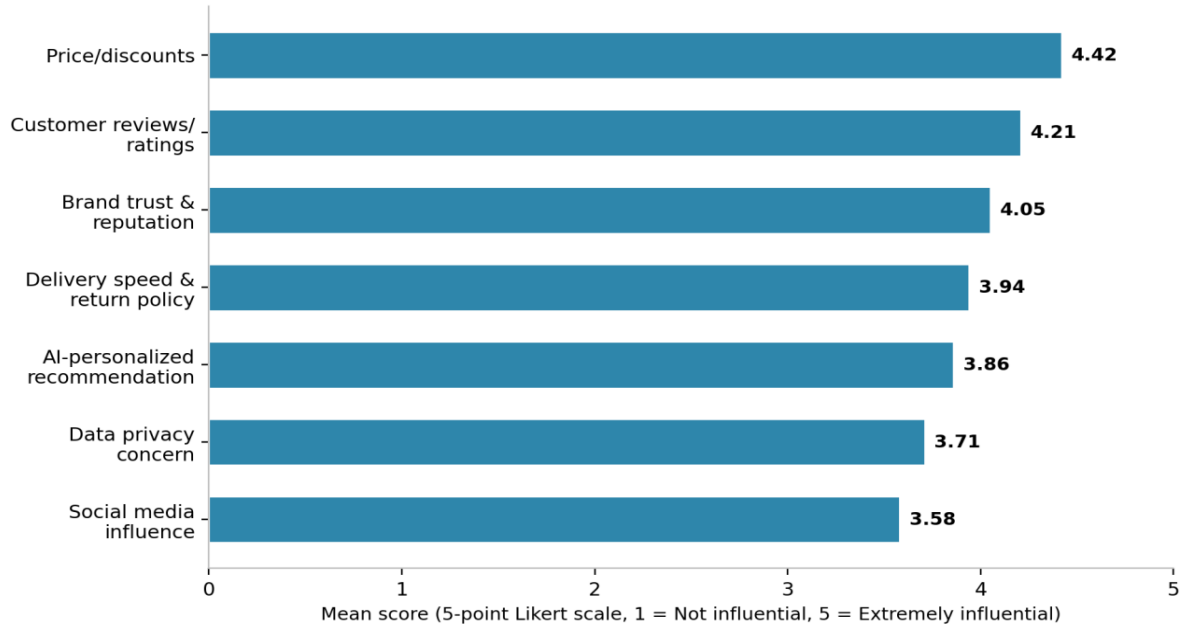


Figure 6. Mean influence scores of factors shaping online purchase decisions (n = 150).

Pearson correlation matrix for the four core variables is depicted in Table 2 and Figure 7. Perceived Personalization[22] showed positive moderate to high correlations with Trust in AI (r = .61, p < .001) and Purchase Intention (r = .57, p < .001). Among all bivariate correlations in the model, the relationship between Trust in AI and Purchase Intention had the highest positive correlation (r = .66, p < .001). On the other hand, Perceived Privacy Risk negatively correlated with Trust in AI (r = -.41) and Purchase Intention (r = -.35).

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Table 2. Pearson correlation matrix of key constructs (n = 150). *p < .05, **p < .001.

Construct	1. PP	2. TAI	3. PR	4. PI
1. Perceived Personalization	1.00	0.61**	-0.28*	0.57**
2. Trust in AI	0.61**	1.00	-0.41**	0.66**
3. Perceived Privacy Risk	-0.28*	-0.41**	1.00	-0.35**
4. Purchase Intention	0.57**	0.66**	-0.35**	1.00

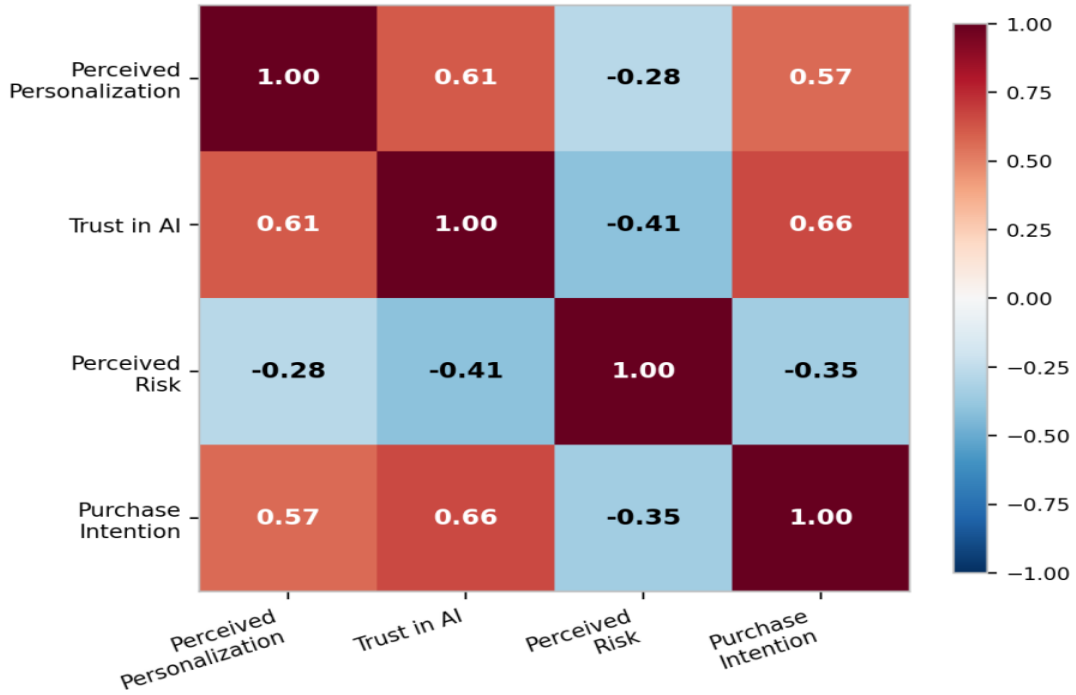


Figure 7. Correlation heatmap of key constructs (n = 150).

The simple linear regression of Purchase Intention on Trust in AI Recommendations was statistically significant. We obtained $F(1, 148) = 114.62$, $p < .001$, explaining about 43% of the variation in purchase intention ($R^2 = .43$). The beta value ($\beta = 0.66$) shows that a one-unit change in trust is associated with a 0.66-unit change in purchase intention.It is reflected from the scatter plot and regression line illustrated in Figure 8.

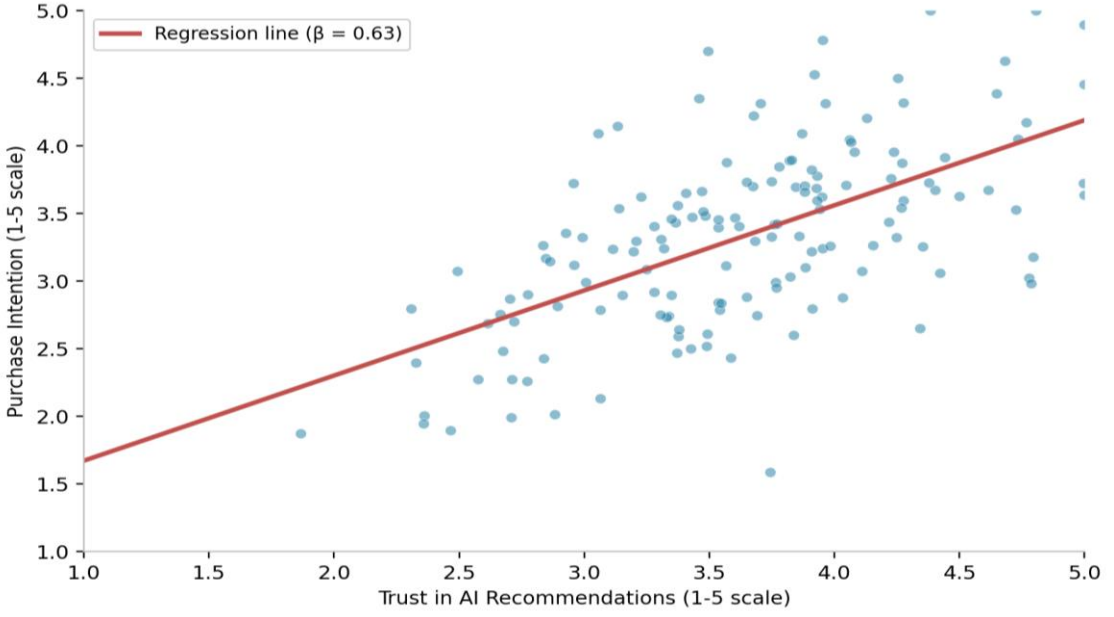


Figure 7. Relationship between trust in AI recommendations and purchase intention (n = 150).

Table 3 below highlights some of the key techniques used for personalization and the common uses and weaknesses associated with these techniques, as documented in the literature. It is a supplementary contribution in relation to business analytics.

Table 3. Comparative overview of consumer analytics techniques referenced in respondent feedback.

Technique	Typical Business Application	Key Strength	Key Limitation
RFM Segmentation	Customer value tiering, loyalty targeting	Simple, interpretable, low computational cost	Ignores qualitative preference signals
Collaborative Filtering	"Customers who bought this also bought" engines	Captures cross-category preference patterns	Cold-start problem for new users/items
NLP Sentiment Analysis	Review mining, brand perception tracking	Extracts unstructured qualitative signal	Sensitive to sarcasm, mixed sentiment
Predictive/Propensity Modeling	Personalized offers, churn prediction	Anticipates future behaviour, not just past	Risk of reinforcing existing biases

6. Discussion

These results show the crucial importance of trust as the most powerful psychological connection between AI-based personalization and intention to purchase. This fact is confirmed by previous research on consumer psychology [21] and more recent research conducted among Chinese consumers [8]. Given that the association between personalisation and trust is moderate (r = .61), one can conclude that the effect of personalisation does not always lead to trust formation. On the contrary, it seems to depend on how personal data protection is handled, as evidenced by the negative association between risk and trust (r = -.41).

For business managers, the large drop in the funnel at the step where recommendations are provided using AI. It clearly indicates that this is the stage on which transparency efforts, such as providing reasons for the particular recommendation, need to focus, and that improvements in algorithms alone would not help increase conversions.

When analyzing data, the comparative summary in Table 3 identifies what aspects of the privacy-personalization relationship are being handled by the existing recommendation technology (collaborative filtering, RFM segmentation, sentiment analysis, and propensity modeling). It becomes clear that none of them directly tackles the privacy issues still identified by participants.

From the psychological point of view, the cross-construct nature of perceived privacy risk implies that trust to AI is not a single-dimensional evaluation of system competencies. It is closely related to other issues concerning data protection, thus supporting the statement by Aldboush and Ferdous (2023), who state that algorithmic trust and data ethics trust are psychologically related.

On the whole, such results prove the integrative approach that is presented in Figure 1: analytics inputs affect personalization, personalization affects trust subject to perceived risk, while trust, and not personalization, affects consumer decisions.

7. Limitations

There are a few limitations of the current study, which are future work. First, the study sample was selected via convenience sampling [23]. It made the process easy, but it may limit the generalizability of the results to university-aged digital consumers in the chosen urban community. Secondly, because the data collection method used is cross-sectional and depends on self-reports, the relationship between personalization, trust, and purchase intention can neither be determined nor validated causally.

Future studies using longitudinal and experimental designs will provide further support for the relationship between the variables under investigation. Thirdly, the purchase funnel illustrated in the figure is hypothetical; it is based on participant reports rather than actual behavioural data recorded on a particular platform. Finally, as far as culture is concerned, the current results should not be generalized across different nations and generations.

8. Conclusion

The current study examined the role of AI-based personalization in influencing decision-making processes in the online setting.It combines the theories related to business management, data analytics, and consumer behavior. Based on a survey conducted among 150 consumers of university age, along with 2024 industry data, it was discovered that consumer trust in AI-based recommendation was more significant than personalization itself as a factor predicting purchase intention. Privacy concerns, on the other hand, were shown to erode this trust. The framework provided in this study, along with the empirical evidence, may be useful for developing new directions of research in this field and for practice in building trustful AI personalization approaches.

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