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ChatGPT Made Me Buy it: The Role of AI Recommendation Tools in Shaping Generation Z Consumers' Trust and Purchase Intentions

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Abstract

The advent of artificial intelligence (AI) in electronic shopping has caused a major shift , and the creation of personalized recommendation systems that provide customized consumer services in a targeted manner has played a key role in this development. These digital tools, for the so-called Generation Z, who are the tech-savvy and a generation fully immersed in it, are not only the conveniences they can't do without, but also the advisors that can help them and guide them to making purchases. In spite of the growing use of recommendation systems in e-commerce, the psychology and behavior models that these systems exercise in shaping consumer behavior are yet to be exhaustively studied. This paper will analyze the effect of AI-based recommendation tools in trust-building and purchase decision among the Generation Z customers, especially focusing on the intervening role of trust in this relationship. Through an empirical TAM (Technology Acceptance Model) and trust-based consumer decision model application on a structured survey of 200 Gen Z consumers in Malaysia.Most of the 200 respondents are students from UKM schools in Malaysia. this study aims at revealing the dynamics involved in these. These conclusions would be applicable to the marketers and the developers of the technology who are working towards improving the user experience and ensuring the consumer trust in the AI-enabled e-commerce applications.

Keywords: Artificial Intelligence, Recommendation Systems, Generation Z, Trust in AI, Purchase Intention

Introduction

"I wasn't planning to buy anything, but ChatGPT said I should."

That statement sums up the fact that one of the business generations who most often use AI-driven digital platforms is Generation Z—people born between the mid-90s and early 2010s. In an era when intelligent algorithms navigate people's music preferences, travel itineraries, and even more, AI's effect on consumer behavior is significant and wide-reaching. However, nowhere is this more visible than in internet shopping, where platforms like Shopee and TikTok Shop, along with conversational bots such as ChatGPT, have an increasingly powerful role in what shoppers see, think about, and ideally buy.

AI recommendation tools are designed to customize the shopping experience by analyzing user data, preferences, and behavioral patterns to suggest products that align with individual tastes. These systems promise to reduce choice overload, improve shopping speed, and increase customer satisfaction (Pappas et al., 2017). For Generation Z—an age group known for its technological fluency, short attention spans, and preference for hyper-personalized interactions—such systems are particularly attractive (Priporas et al., 2017). However, while personalization is often viewed as a strength, its effectiveness hinges on a critical factor: trust. Without trust in the accuracy, fairness, and intentions of these AI systems, even the most sophisticated recommendations may be dismissed or ignored (Gefen et al., 2003).

Nowadays advancements in AI have sparked widespread discussions about the ethics, transparency, and psychological impact of algorithmic recommendations. Then, empirical evidence on how young consumers perceive and respond to such systems remains limited. Especially under explored is the mediating role of trust—whether perceived personalization enhances trust, and in turn, whether trust increases the likelihood of purchase.

This study aims to address this gap by examining how perceived personalization in AI recommendations influences purchase intentions among Generation Z consumers, with trust serving as a potential mediating factor. Anchored in the Technology Acceptance Model (TAM) developed by Davis (1989) and the Trust-Based Consumer Decision Model, the research seeks to contribute both theoretical insights and practical guidance for businesses seeking to optimize AI-driven marketing strategies.

Problem Statement

Artificial intelligence (AI) has become a fundamental component of modern digital commerce, with recommendation systems serving as core tools to enhance personalization, streamline decision-making, and influence consumer behavior (Kumar et al., 2019). These systems, increasingly embedded in platforms such as Shopee, TikTok Shop, and conversational agents like ChatGPT, leverage machine learning to analyze consumer preferences and deliver bespoke suggestions. While this level of personalization is designed to improve user satisfaction and conversion rates, its effectiveness largely depends on how users interpret and trust the recommendations they receive (Pappas et al., 2017; Gefen et al., 2003).

Although the widespread adoption of AI recommendation tools in e-commerce, there is a notable gap in empirical research examining their influence on Generation Z—a cohort defined by its digital nativity, hyperconnectivity, and preference for personalized experiences (Priporas et al., 2017). Although Generation Z is considered highly responsive to AI technologies, existing studies often overlook consumer responses without considering generational differences in trust formation and decision-making. Especially, the role of trust as a middle-link between perceived personalization and purchase intention remains underexplored in this demographic group.

Additionally, much of the literature has focused on traditional recommendation algorithms (e.g., collaborative filtering or content-based systems), whereas conversational AI platforms such as ChatGPT represent a more dynamic and autonomous recommendation style. These tools not only recommend products but also engage users in real-time dialogue, potentially changing the way trust is built and maintained (Ali & Freimann, 2021). However, few studies have addressed how this newer form of AI-mediated interaction affects consumers' psychological acceptance and behavioral intentions.

Research Objective

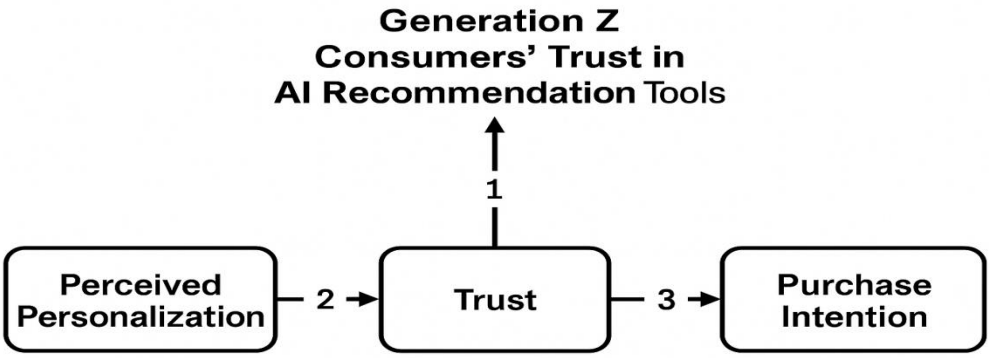
This study is research for the influence of AI-powered recommendation systems on the purchasing behavior of Generation Z consumers in Malaysia. And the important of mediating role of trust [Priporas et al., 2017; Ali & Freimann, 2021].The objectives are following these points:

To examine Generation Z consumers' trust in AI recommendation tools. This objective focuses on evaluating the level of trust Generation Z users place in AI systems when interacting with digital shopping platforms. It means if users trust the AI recommendation tools' reliable, accurate, and secure in suggesting products or not [Gefen et al., 2003].

To determine the effect of perceived personalization on purchase intention. This objective aims to assess how tailored recommendations influence the intention to purchase among Generation Z consumers. The important of this objective is if AI-generated suggestions and perceived personalization on purchase intention have positive affect or not [Pappas et al., 2017].

To assess the mediating role of trust between personalization and purchase intention. This objective explores whether trust serves as a mediator in the relationship between perceived personalization and the consumer's purchase intention. It investigates the relationship of trust personalized customization and purchase intention.

By addressing these objectives, the research will contribute to a deeper understanding of how AI-driven personalization and trust interact to shape online shopping behaviors among young digital consumers[Komiak & Benbasat, 2006].



Research Questions

This study aims to explore the behavioral and psychological mechanisms that influence how Generation Z consumers engage with AI-powered recommendation systems in online shopping environments. This study is focuses on the role of perceived personalization, trust and purchase intention. The research questions are following these points:

How do Generation Z consumers perceive the trustworthiness of AI recommendation tools? This question seeks to understand the level of trust that Gen Z users place in AI recommendation systems.

What is the relationship between perceived personalization and purchase intention? This question seeks to understand the level of trust that Gen Z users place in AI recommendation systems.

Does trust in AI mediate the relationship between personalization and purchase intention? This question examines whether trust plays a mediating role between perceived personalization and purchase intention.

Literature Review

Introduction

The literature review provides the conceptual and empirical basis for this research, which focuses on the impact of AI-based recommendation systems on the purchasing behavior of Generation Z, particularly with regard to perceived personalization, trust, and purchase intention. The section begins by contextualizing the development of AI recommendation tools in e-commerce, followed by a discussion on Generation Z as a consumer segment. Subsequently, the constructs of perceived personalization, trust in AI, and purchase intention are examined within the framework of the Technology Acceptance Model (TAM) and the Trust-Based Consumer Decision Model.5.2 AI Recommendation Systems in E-Commerce

Artificial intelligence, especially machine learning and natural language processing, is changing digital commerce by implementing a recommendation system, which adjusts product recommendations according to users' past behaviors, preferences and interactions.

Recommendation systems are divided into collaborative filtering, content-based filtering and hybrid models (Ricci, etc.). Recently, conversational artificial intelligence platform (such as ChatGPT) has become an interactive recommendation agent (Zhang et al.) that dynamically customizes product recommendations using generation models. By 2020).

Artificial intelligence recommendation system provides better decision-making, reduces the cost of selection, and increases the perceived value through relevance and contextualization (Pappas, etc.). These systems can not only help retailers increase revenue, but also improve customer participation and loyalty. According to Kumar and others. In 2019, an effective recommendation system can have a significant impact on the conversion rate of consumers. However, users' acceptance of this system depends not only on the accuracy of technology, but also on their perception of transparency, reliability and intention (Zanker et al. 2019).

In addition, Kanapathipillai and others point out that. By 2024, artificial intelligence may improve the quality and convenience of customer service in Malaysia's e-commerce environment by realizing seamless interaction and instant response. Their discovery will help to integrate artificial intelligence into the contact point of customer journey, thus improving brand loyalty.

Generation Z as Digital Consumers

Generation Z is usually defined as people born in the mid-1990s and early 21st century, and is considered as the first generation of real digital natives. This group is characterized by a high degree of technical mobility, a desire for instant satisfaction, a preference for personalized experience and participation in multiple digital platforms (Williams et al.). Author: Priporas et al.,2017).

In Malaysia, Generation Z constitutes a large part of e-commerce platforms such as Shopee,Lazada and TikTok. These consumers are more likely to be influenced by social media, user-generated content and AI-based recommendations in their purchase decisions (Lim et al. Your digital consumption behavior is not only influenced by convenience and price sensitivity, but also by authenticity, relevance and credibility (Turner,2015).

According to Salam et al. In 2024, Generation Z places high value on digital marketing strategies in line with its values and lifestyle, including trusted, personalized and ethical artificial intelligence applications. These characteristics make it easier for people to identify and be loyal to the brand if they participate properly.

Sensitive Personalization in Recommendation System

Perceived personalization refers to the degree to which users think that the content or service they receive is based on their specific needs and preferences (Tam&Ho,2006). In the context of e-commerce, personalized recommendation is regarded as enhancing the shopping experience by combining product recommendation with consumers' personal taste and purchase history.

Research shows that perceived personalization has a positive impact on customer satisfaction, participation and purchase intention (Bleier&Eisenbeiss,2015). When consumers find suggestions relevant and personalized, they are more likely to regard the system as useful and attractive. However, personalization must strike a balance between relevance and perception of intrusiveness (Awad&Krishnan,2006).

For Generation Z, personalization is not just a function, but an expectation. According to Priporas et al. (2017) This group is particularly sensitive to the marketing of personal feelings. Personalized content increases their sense of control and satisfaction, which in turn leads to deeper participation. However, when personalization is characterized by excessive manipulation or invasion, it may undermine trust and backfire (Aguirre et al. , 2016).

The latest discovery from Achim et al. (2024) further shows that the combination of personalization, convenience and clarity has greatly improved the purchase intention of Z generation consumers in Malaysia.

Trust in Artificial Intelligence

Trust is a complex structure and plays a vital role in human-computer interaction. Under the background of artificial intelligence recommendation system, trust includes the ability to believe in the system, honesty (honesty and fairness) and kindness (acting in the best interests of users) (Geng, etc. Author: McKnight et al.,2002).

Trust in artificial intelligence is particularly important for Generation Z, whose digital experience enables them to recognize the benefits and risks of algorithmic decision-making. Factors that affect the trust in AI include system transparency, perceptual accuracy, interpretability and previous experience (Wang&Benbasat,2007). If consumers believe that the AI system is reliable, safe and interested in them, they are more likely to follow their suggestions (Komiak&Benbasat,2006).

Trust is not automatic. Such as Lankton et al. (2015) found that the initial trust was influenced by the interface design and brand reputation, while the lasting trust was influenced by the interaction results. In AI systems such as ChatGPT or stores, fluency of conversation and perceived empathy also contribute to users' confidence (Zhao et al. 2023).

Afroogh et al。 Building long-term trust in artificial intelligence requires not only technical reliability, but also compliance with ethical rules, especially in markets such as Malaysia, where there are huge differences in privacy and digital education.

Purchase Intention and Digital Behavior

Purchase intention refers to the likelihood of consumers buying products or services according to their attitudes and opinions (Fishbein&Ajzen,1975). In digital transactions, purchase intention is strongly influenced by perceived practicality, usability, social influence and trust (Davis,1989). (Pavlou,2003)

For Generation Z, the buying habits are strongly influenced by mobile applications and social platforms, and the buying path is not linear. The suggestion of artificial intelligence system can be used as a clue to stimulate curiosity, explore and finally stimulate transactions (Lim et al. If suggestions generated by artificial intelligence are considered relevant and credible, they can have a positive impact on purchasing decisions.

In addition, trust is a psychological bridge between personalized advice and behavioral intention (Kim&Peterson,2017). Without trust, consumers may even refuse to accept highly personalized advice, so it is very important to study the interaction between personalization, trust and intention to understand how artificial intelligence shapes consumer behavior.

Wulandari&Rasyid(2022) believes that trust and perceived risk are the most influential factors in online purchase decision, which highlights the necessity of creating a reliable artificial intelligence ecosystem for the Z-generation e-commerce platform.

Technology Acceptance Model (TAM)

The technology acceptance model (TAM) developed by Davis(1989) holds that two main factors-perceived utility (PU) and perceived usability (PEOU)-determine individuals' intention to use technology. Over the years, TAM has been widely used to understand users' acceptance of information systems, including applications powered by artificial intelligence.

Under the background of recommendation system, the chip may be influenced by how artificial intelligence adjusts its suggestions, while the chip may be influenced by user interface and system interactivity. Researchers extend TAM to the concepts of trust, personalization and fun to better predict users' behaviors in e-commerce (Venkatesh&Davis,2000). (Pavlou,2003)

TAM is still a useful model for Generation Z, but it must take into account the social and emotional aspects of digital interaction. AI tools that are regarded as user-friendly and useful are more likely to be accepted and adopted (Wang&Benbasat,2007).

Rahmiati and Yuannita(2020) pointed out that the combination of PU and e-commerce trust is a particularly powerful indicator of purchase intention, indicating the changing nature of TAM in online consumer behavior.

Trust-Based Consumer Decision Model

The trust-based consumer decision-making model extends the traditional decision-making framework and regards trust as an important intermediary (Kim et al. In this model, trust acts as a filter that affects how consumers process information and make decisions. Especially in the online environment without personal clues, trust is very important to reduce perceived risk.

The model is applied to artificial intelligence recommendation system, which shows that personalized perception increases confidence, which in turn increases purchase intention. If consumers trust artificial intelligence to understand their needs and act in a transparent way, they will be more likely to accept their suggestions. In contrast, without trust, personalization is unlikely to promote shopping (Beldad et al. in 2010).

Yincharoen et al. (2022) continues to support this framework, and shows that buyers' confidence in the digital market significantly affects the decision-making process and plays an intermediary role between perceived personalization and purchase intention.

The Defects of Literature

Although the existing literature has covered all aspects of artificial intelligence recommendation system and digital consumer behavior, there is still a considerable gap. First of all, limited empirical research is specifically aimed at the Z generation in Southeast Asia, especially in Malaysia. Cultural background plays a role in trust and personalized perception, and the discovery of western background cannot be directly applied (Hofstede,2001).

Secondly, most studies have studied AI recommendation tools in isolation, without considering the overall user experience, including chat bots, social media and peer influence. Integrating conversational artificial intelligence into recommendation system is a new field, which deserves further study (Zhao et al.). 2023).

Thirdly, many existing studies rely on horizontal design, which can capture the attitude of consumers at a specific time. Longitudinal research is needed to study how trust develops in repeated interaction with artificial intelligence systems, especially in personalization and purchase behavior. Finally, it is necessary to use structural equation model and longitudinal design to test trust as an intermediate variable more accurately. This will better understand how trust develops and how it affects the long-term effectiveness of recommendation systems.

Hypotheses

This section introduces the hypotheses put forward in this study, which are derived from the literature review of the relationship between personal perception, reliance in AI tools and purchase intention of Malaysian Z generation consumers. This study integrates the technology acceptance model (TAM) and the decision-making model based on consumer confidence to examine how the artificial intelligence recommendation system affects consumer behavior. Based on this theory, we study four hypotheses.

Theoretical Framework

In this study, the conceptual basis is rooted in two established models: TAM developed by Davies (1989) and mcknight's trust-based consumer decision-making model. (2002). These frameworks are integrated to explain the role of perceived personalization and trust in artificial intelligence tools in shaping the purchase intention of Malaysian Z consumers when interacting with artificial intelligence-based recommendation systems.

This section explains the theoretical basis of this study by combining the structures discussed in the hypothesis part (Perceived Personalization (PP), Confidence in Artificial Intelligence Tools (T) and Willingness to Buy (PI)) with relevant theoretical records. It also provides a visual conceptual model to illustrate the hypothetical relationship.

Technical acceptance model (TAM)Technology adoption model is one of the most influential theoretical models to predict and explain technology adoption. According to Davis (1989), TAM assumes two key beliefs-perceived practicality and perceived usability-as the decisive factors of individuals' intention to use specific technologies.

In this study, Perceptual Personalization (PP) is considered to be useful, similar to Perception, because it reflects the degree to which AI recommendation system adjusts content according to users' specific needs and preferences, thus improving decision-making efficiency and user satisfaction. When users believe that the technology meets their personal needs, it will increase the perceived practicality of the system (Sundar&Marathe,2010). Therefore, according to TAM, PP should have a positive impact on purchasing intention (PI), because highly personalized recommendation can make users' shopping experience more effective and enjoyable.

Overview of Key Structure

Before making any assumptions, it is important to define the main construct and its expected role in the proposed framework:

Perceived Personalization (PP) is the degree to which consumers assume that AI recommendation system customizes its content, recommendation and experience according to personal preferences, behaviors and backgrounds.

Trust in AI Tools (T) tools indicates users' trust, security and confidence in the ability and intention of recommendation system.

Purchase Intention (PI) reflects the possibility of consumers making a purchase decision after receiving the recommendation of AI tools.

The following assumptions are based on previous empirical results and theoretical framework.

H1: Perceived Personalization is Positively Associated with Purchase Intention

This assumption posits that when consumers perceive the advice provided by the AI system in a highly personalized way, they intend to increase their purchases. Personalization can improve user contentment by providing content related to consumer preferences, and increase the gratification of participation and follow-up.Generation Z pays special attention to customization experiences due to their familiarity with digital technology and their expectation of instant, tailored content. Prior research has demonstrated that personalization has a significant positive effect on purchase-related behaviors (Xu et al., 2020; Ho & Bodoff, 2014).The underlying mechanism is explained by the technology acceptance model, in which the perceived usefulness leads to behavioral intention. Personalized suggestions reduce information overload and decision fatigue, and provide an effective way for product discovery and procurement. Hens, the following assumptions have been published:
H1: *Perceived personalization is positively associated with purchase intention.*

H2: Perceived Personalization is Positively Associated with Trust in AI Tools

Trust plays a key role in the digital environment, especially in the interaction in which technology entrusts human judgment. When AI system provides relevant and accurate advice, users are more likely to think that the system is intelligent, capable and trustworthy. Customization may mean that the system already knows the user, thus improving reliability and security.

Based on the decision-making model grounded in consumer trust, personalization has been shown to enhance both cognitive confidence and emotional trust. Empirical studies by Awad and Krishnan (2006), as well as Wang and Emurian (2005), support this relationship, demonstrating that customized content can effectively strengthen users' trust in online systems.Thus, this study hypothesizes:
H2: *Perceived personalization is positively associated with trust in AI tools.*

H3: Trust in AI Tools is Positively Associated with Purchase Intention

In digital transactions, trust reduces perceived risks and uncertainties, and encourages users to continue buying. Especially in the environment driven by artificial intelligence, the recommendation system can run in the black box, and users need to trust the integrity and decision-making ability of the system.

Trust acts as mediator between technical interaction and consumer events. When consumers trust artificial intelligence tools, they are more likely to believe that suggestions are in their best interests, which leads to higher commitment and willingness to buy. Although Generation Z is usually proficient in technology, they are cautious about data misuse and algorithm distortion. Therefore, it is essential to build trust through transparency and consistency.

For the above reasons, the study suggests:

H3: Trust in AI tools is positively associated with purchase intention.

H4: Trust Mediates the Relationship Between Personalization and Purchase Intention

This hypothesis combines the relationship between H1 and H3, and assumes that trust plays an bridging role between connection personalization and purchase intention. Although personalization can directly affect the purchase intention, it can also foster trust, thus increasing the possibility of purchase.

For studies support the mediating role of trust in the relationship between personalization and consumer behavior. For instance, Kim and Peterson (2017) identified trust as the key mechanism through which personalized interactions influence consumer responses. Also, Bleier and Eisenbeiss (2015) found that personalization enhances users' trust in the recommendation platform, which in turn significantly increases their willingness to act on the recommendations provided.

By combining explicit and implicit pathways, this study aims to more accurately understand the consumer behavior in the artificial intelligence-mediated environment:

H4: *Trust in AI tools mediates the relationship between perceived personalization and purchase intention.*

Proposed Conceptual Framework

To visually represent the relationships among the variables, the following conceptual framework is proposed:

Figure 1: Research Framework

The relationship of H1, H2, H3 and H4

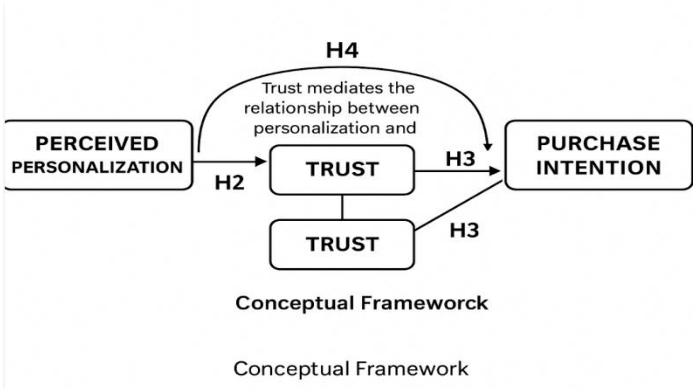


Figure 1: Conceptual Framework linking Personalization, Trust, and Purchase Intention

Summary of Hypotheses

Hypothesis	Description
H1	Perceived personalization is positively associated with purchase intention.
H2	Perceived personalization is positively associated with trust in AI tools.
H3	Trust in AI tools is positively associated with purchase intention.
H4	Trust in AI tools mediates the relationship between personalization and purchase intention.

Theoretical and Practical Implications

These assumptions not only extend the technology adoption model and the decision-making model based on consumer trust in the new background of Malaysian Z-Generation artificial intelligence recommendation system, but also have practical significance:
Marketers and application developers should pay attention to clear and privacy-conscious user privacy policies, as this can build trust and stimulate purchases.
Policymakers can consider implementing moral customization policies to ensure trust in artificial intelligence systems.Future researchers: These hypotheses can be tested by using structural equation model to verify the proposed relationship.

Research Methodology

This section introduces the research design, sampling methods, instruments and data analysis techniques used in this study. This method focuses on the quantitative and cross-sectional survey of Z generation consumers in Malaysia to understand how they respond to the AI-based recommendation system.

Research Design

This study adopts quantitative research design and cross-sectional survey. This method allows data to be collected from large samples at any time point, making it an ideal method to study the relationship between perceived personalization, trust in AI tools and consumers' purchase intention of generation Z.

The survey collected data about consumers' views and behavioral intentions on the artificial intelligence recommendation system used in online shopping platforms. This design is suitable for generating quantifiable data, which will be analyzed to test the assumptions made in the study.

Population

The research subjects include Z generation consumers in Malaysia, defined as people born between 1997 and 2012. Generation Z is an important population group because they are highly involved in digital platforms and are familiar with artificial intelligence technology. These groups are highly related to this study, because they are active users of online shopping platforms based on AI, which makes them suitable for studying the influence of AI recommendation system on purchasing behavior.

Samples

A total of 200 respondents were included in the sample. This sample size is considered to be sufficient to ensure the reliability and validity of the results, because it provides enough answers to draw meaningful conclusions. It is enough to represent the target population while maintaining manageable data analysis.

Sampling Method

A convenient sampling method will be used to select participants. This unlikely sampling technique was chosen because it can easily reach qualified interviewees (Z generation consumers in Malaysia).

Instrument Development

To ensure the reliability and validity of the questionnaire, most of the questions were adapted from previous studies with proven content validity. AI experts were consulted to refine the questionnaire, ensuring accuracy and standardization. The questionnaire consists of two sections: Part A includes demographic information, and Part B focuses on the independent variables. Six of the 15 questions pertain to the aspects of artificial intelligence. All variables were measured using a 5-point Likert scale (Strongly disagree to Strongly agree). Table 1.1 outlines the constructs and their corresponding sources.

Table 1.1
Research Model

Constructs	Codes	Measurement items	Sources
Perceived Personalization (PP)	PP1	The product recommendations I receive usually match my interests and preferences.	Tam & Ho (2006)
	PP2	I believe the recommendation system provides suitable suggestions based on my browsing history.	
	PP3	I feel that the recommendation system understands my consumer needs.	
Trust in AI Tools (T)	T1	I trust that the recommended products are beneficial and not misleading.	Gefen et al. (2003)
	T2	I trust the recommendation system to protect my personal information and data.	
	T3	I believe the recommendations are fair,	

		unbiased, and transparent.	
Purchase Intention (PI)	PI1	I am willing to consider purchasing items recommended by the system.	
	PI2	I am willing to consider purchasing items recommended by the system.	Pavlou (2003)
	PI3	If I trust the recommendation system, I am more likely to purchase the suggested items.	

Data Collection

This questionnaire was delivered by online through social media platforms such as WhatsApp and Telegram. The survey was administered to 209 students from the National University of Malaysia (UKM). The most of the respondents are students, with 209 responses collected. To ensure that the sample was representative of the population, respondents were selected from various academic disciplines within the university. The demographic profile of the respondents is presented in Table 1.2. According to the data, the age distribution of the respondents is as follows:16-18 years: 20.1%19-21 years: 30.6% 22-24 years: 30.6% 25 and above: 18.7% Regarding the use of AI-based platforms for shopping, the results show the following usage patterns: Shopee: 34.4% TikTok Shop: 32.1% Lazada: 22.5% ChatGPT product suggestions: 11% These results suggest that Shopee and TikTok Shop are the most frequently used AI-powered shopping platforms among the respondents, with a smaller proportion using ChatGPT for product suggestions. This distribution highlights the growing influence of AI in e-commerce, especially in platforms like Shopee and TikTok Shop.

For these 209 people, all were familiar with artificial intelligence, which confirmed the problem of filtering. This is an important criterion to ensure the validity of the answer, because participants who do not understand artificial intelligence do not provide reliable data. According to the results of dufilter, we determined that all 209 answers were valid and suitable for analysis.

Table 1.2
Demographic profile (n=209)

Demographic Profile	**Frequency (n)**	**Percentage (%)**
Age		
16–18 years	42	20.1
19–21 years	64	30.6
22–24 years	64	30.6
25 and above	39	18.7
AI-based platforms		
Shopee	72	34.4
TikTok Shop	76	32.1
Lazada	47	22.5
ChatGPT product suggestions	23	11

Data Analysis

This part presents the statistical analysis of the study's data, which includes descriptive statistics, normality testing, Pearson correlation, and linear regression. All tests are conducted in line with the proposed hypotheses (H1–H3) and research framework introduced earlier.

Descriptive Statistics

Descriptive analysis was performed to evaluate the central tendency and dispersion of the variables: Perceived Personalization (PP), Trust in AI Tools (T), and Purchase Intention (PI).

Table 7.8

Displays the Minimum, Maximum, Mean, and Std.Deviation values for all variables.

Variable	N	Min	Max	Mean	Std. Dev	Skewness	Skew. SE	Kurtosis	Kurt. SE
PP1	209	1	5	3.84	1.011	-0.627	0.168	-0.306	0.335
PP2	209	1	5	3.8	1.035	-0.517	0.168	-0.553	0.335
PP3	209	1	5	3.95	0.984	-0.728	0.168	-0.05	0.335
T1	209	1	5	3.97	0.97	-0.644	0.168	-0.291	0.335
T2	209	1	5	3.98	0.961	-0.816	0.168	0.235	0.335
T3	209	1	5	3.88	1.007	-0.661	0.168	-0.243	0.335
PI1	209	1	5	3.80	1.120	-0.683	0.168	-0.311	0.335
PI2	209	1	5	3.91	1.048	-0.687	0.168	-0.305	0.335
PI3	209	1	5	3.95	1.025	-0.841	0.168	0.277	0.335

All variables showed skewness and kurtosis within the range of ±2, indicating approximate normal distribution (Hair et al., 2014). Thus, the dataset satisfies the assumption for parametric analysis.

Pearson Correlation Analysis

Pearson correlation was used to examine the relationships between PP, T, and PI. The correlation matrix is presented in Table 7.9.

Table 7.9

Correlations

	PPMean	TMean	PIMean
PPMean	1	0.068	0.137*
TMean	0.068	1	0.006
PIMean	0.137*	0.006	1

Pearson correlation analysis was conducted to examine the relationships between perceived personalization (PP), trust in AI tools (T), and purchase intention (PI). The results revealed a significant but weak positive correlation between PP and PI ($r = .137$, $p = .048$), suggesting that personalization may have a minor influence on purchase intention. However, no significant correlation was found between PP and T ($r = .068$, $p = .325$), nor between T and PI ($r = .006$, $p = .931$). Therefore, only hypothesis H1 is supported, while H2 and H3 are not.

Linear Regression Analysis

Linear regression analysis was conducted to test the hypothesized predictive relationships between Perceived Personalization (PP), Trust in AI Tools (T), and Purchase Intention (PI). Each construct was represented by the mean of its corresponding items (i.e., PPMean, TMean, and PIMean).

Model 1

PP Mean → PI Mean (Testing H1)

Indicator	Value
R^2	0.019
β	0.137
p-value	0.048

The regression results indicate that Perceived Personalization significantly and positively predicts Purchase Intention (β = 0.137, p = 0.048). Although the effect size is relatively small, the model explains 1.9% of the variance in Purchase Intention ($R^2 = 0.019$). Therefore, **Hypothesis H1 is supported**.

Model 2

PP Mean → T Mean (Testing H2)

Indicator	Value
R^2	0.005
β	0.068
p-value	0.325

The regression analysis reveals that Perceived Personalization does not significantly predict Trust in AI Tools (β = 0.068, p = 0.325). The model explains only 0.5% of the variance in Trust ($R^2 = 0.005$). Thus, Hypothesis H2 is not supported.

Model 3

T Mean → PI Mean (Testing H3)

Indicator	Value
R^2	0.000
β	0.007
p-value	0.931

Trust in AI Tools does not significantly predict Purchase Intention (β = 0.007, p = 0.931), and the model explains virtually none of the variance in the outcome ($R^2 = 0.000$). Therefore, Hypothesis H3 is not supported.

Although descriptive statistics show that most respondents attach great importance to perceived personalization, trust and purchase intention, Pearson's correlation and regression analysis shows that there is no significant correlation between trust and other variables. This may be due to the limited change of reaction, mainly concentrated in the upper end of Likert scale, which reduces the statistical ability to detect significant differences or trends.

Mediation Analysis (Hypothesis H4)

To examine whether **Trust in AI tools (T Mean)** mediates the relationship between **Perceived Personalization (PP Mean)** and **Purchase Intention (PI Mean)**, a mediation analysis was conducted following the three-step regression approach proposed by Baron and Kenny (1986).

Model Summary: PP Mean → T Mean

Model	R	R Square	Adjusted R Square	Std. Error
1	0.068	0.005	0.000	0.54492

ANOVA: PPMean → TMean

Source	SS	df	MS	F	Sig.
Regression	0.290	1	0.290	0.975	0.325
Residual	61.466	207	0.297		
Total	61.755	208			

Coefficients: PP Mean → T Mean

Variable	B	Std. Error	Beta	t	Sig.
(Constant)	3.765	0.274		15.202	< 0.001
PPMean	0.062	0.062	0.062	0.988	0.325

PP Mean → T Mean

Indicator	Value
R^2	0.005
β	0.068
p-value	0.325

The results show that Perceived Personalization does not significantly predict Trust (β = 0.068, p = 0.325). Thus, path a is not supported.

Model Summary: PP Mean → PI Mean

Model	R	R Square	Adjusted R Square	Std. Error
1	0.137	0.019	0.014	0.63456

ANOVA: PP Mean → PI Mean

Source	SS	df	MS	F	Sig.
Regression	1.599	1	1.599	3.971	0.048
Residual	83.352	207	0.403		
Total	84.951	208			

Coefficients: PP Mean → PI Mean

Variable	B	Std. Error	Beta	t	Sig.
(Constant)	3.330	0.284		11.733	< 0.001
PPMean	0.145	0.073	0.137	1.993	0.048

PP Mean → PI Mean

Indicator	Value
R^2	0.019
β	0.137
p-value	0.048

Perceived Personalization significantly predicts Purchase Intention (β = 0.137, p = 0.048), indicating that the total effect (path c) is supported.

Model Summary: PP Mean & T Mean → PI Mean

Model	R	R Square	Adjusted R Square	Std. Error
1	0.137	0.019	0.009	0.63609

ANOVA: PP Mean & T Mean → PI Mean

Source	SS	df	MS	F	Sig.
Regression	1.600	2	0.800	1.977	0.141
Residual	83.351	205	0.405		
Total	84.951	208			

Coefficients: PP Mean & T Mean → PI Mean

Variable	B	Std. Error	Beta	t	Sig.
(Constant)	3.344	0.414		8.081	<0.001
PPMean	0.145	0.73	0.137	1.987	0.048
TMean	-0.004	0.081	-0.003	-0.049	0.961

PP Mean + T Mean → PI Mean

Path	β	p-value
T Mean → PI Mean	-0.003	0.961
PP Mean → PI Mean	0.137	0.048

When both PPMean and TMean were included as predictors, only Perceived Personalization remained a significant predictor of Purchase Intention, so Trust had no significant effect. Because of path A and path B are not statistically significant, there is no evidence that trust plays an intermediate role. Perceived personalization still has a great direct impact on purchase intention, which shows that there is only a direct relationship. Therefore, assumption H4 is not supported.

Significance of the Study

Artificial intelligence (AI) is no longer a futuristic concept, but a practical and influential force to reshape the digital market. The significance of this research lies in that it provides insights into how recommendation tools based on artificial intelligence affect the purchase behavior of generation Z, one of the most influential consumer groups. The research is helpful to academic theory, technical application and business strategy in several important fields.

Theoretical Contribution

This study combines the technology acceptance model (TAM) and the decision-making model based on consumer trust, providing a dual perspective of how personalization and trust affect consumers' purchase intention. Although TAM is widely used to understand the adoption of digital technology, it is criticized as not fully representing emotional and cognitive factors, such as trust, which is particularly important in an artificial intelligence-mediated environment. By treating trust as a direct and intermediate variable, this study enriches the prediction ability of TAM in artificial intelligence business environment.

In addition, the trust-based consumer decision-making model is usually used in online banking, e-government and traditional e-commerce and other fields. Its application in conversational artificial intelligence tools, such as this research, promotes theoretical

discussion by expanding the trust-based model in the field of digital personalization driven by artificial intelligence, so as to show how trust works or not when artificial intelligence imitates human judgment and autonomy.
In addition, this study tests that these theoretical suggestions-Generation Z in Malaysia-are often underrepresented in global artificial intelligence and e-commerce research. In this way, the study fills an important empirical gap and establishes the cultural-related explanation of the existing western-centered model.

Methodological Contribution
In an orderly way, this study provides a structured and repeatable method to analyze the psychological mechanism of digital trust and personalization through quantitative and cross-sectional design. The questionnaire tool was developed by adjusting and synthesizing the scales previously obtained from TAM (Davis, 1989), Trust Documents (Guy, etc.) and other sources. , 2003) and e-commerce behavior intention (Pavlou,2003).

The rigor of this method ensures reliability and allows future researchers to establish or improve the current framework. In addition, the sample size of 209 Z-generation respondents in Malaysia ensures sufficient statistical capacity to improve the reliability of regression and mediation analysis. This study also ensures the diversity of the student population representing different disciplines, and increases the universality of the Z-generation subgroup.

Although intermediate analysis provides moderate results, it is still very important in method, because it reveals the limitations of trust measurement tools in today's AI environment. It provides a basis for future longitudinal or mixed studies, which explore deeper cognitive and emotional differences that have not been captured in the traditional Lickert Scale survey.

Practical Contribution to Business and Technology Developers
From a practical point of view, these results provide important insights for e-commerce platforms, artificial intelligence developers and Z-generation digital marketers. This study confirms that even if trust is not mediated by relationships, perceived personalization will significantly affect purchase intentions. This shows that personalization should be the key design principle of AI-driven recommendation engine.

Developers of artificial intelligence systems, especially those integrated with shopping platforms such as Shopee or TikTok, can use this discovery to improve recommendation algorithms by adding user-centered relevance and personalization. The study also shows that efforts to build trust through traditional methods (such as privacy guarantee and privacy policy) may not be effective for Z generation users unless these measures are translated into immediate personalized benefits.

On the other hand, marketers can personalize their marketing activities by emphasizing personalization rather than technical interpretability or credibility. Since trust in artificial intelligence tools will not significantly affect the purchase intention, brands may be more effective if they focus on the information of "know you" rather than "trust us". The emotional resonance generated by personalization seems to have more motivation for consumers (at least in this group) than the guarantee of safety or fairness.

Implications for Policymakers and Ethical Governance

For policy makers and regulators concerned about privacy, artificial intelligence ethics and consumer protection, this study emphasizes the importance of striking a balance between personalization and transparency. Although trust is not the main predictor of purchase intention in this study, it is still the key factor in the development of moral AI. Policymakers should not interpret the findings as evidence of a lack of trust mechanism. Instead, they should pay attention to whether personalized algorithms meet ethical standards without affecting users' autonomy or data sovereignty.

The research has also had an impact on Malaysia's national artificial intelligence strategy, which gives priority to artificial intelligence education, moral governance and technological competitiveness. The results show that the younger generation can participate in artificial intelligence in a more pragmatic and transactional way, emphasizing convenience and personalization rather than abstract trust. This behavioral knowledge can promote the development of digital literacy courses and teach users to combine technical fluency with moral awareness.

Significance for Future Research

Finally, the study identified several ways for future research. The immaterial discovery of trust has opened an important discussion on how to design and measure trust in the context of AI. This shows that the traditional trust model may not be able to fully capture the subtle differences in the interaction between human beings and artificial intelligence, especially for Z generation users who are used to algorithms to mediate almost all aspects of digital life.
Future research can use qualitative or vertical design to capture trust, as a constantly changing structure, subject to repeated exposure, feedback loop and algorithm transparency. In addition, the study of decomposing trust into secondary dimensions-such as trust in ability, honesty and emotional trust-can reveal more detailed insights that cannot be seen in such a broad analysis.

Expected Outcome

Based on the conceptual framework, the empirical concept of literary criticism and abstract, many research results have been paid attention to. Their participation is based on existing employment opportunities, but it also applies to specific consumer groups in Malaysia.

Perceived Personalization Will Positively Influence Purchase Intention (Supported)

The first and most critical expected outcome was that perceived personalization (PP) would have a significant positive effect on purchase intention (PI). The assumption here is grounded in the Technology Acceptance Model, wherein perceived usefulness is a core predictor of behavioral intention. In this study, perceived personalization is viewed as a proxy for usefulness—if the AI system understands users well and recommends relevant products, users are more likely to act on those suggestions.

The empirical findings supported this hypothesis (H1), with a statistically significant, albeit modest, regression coefficient ($\beta = 0.137$, $p = 0.048$). This suggests that personalized recommendations do indeed nudge Generation Z consumers toward purchase decisions, aligning with previous research (Pappas et al., 2017; Tam & Ho, 2006).

Perceived Personalization Will Positively Influence Trust in AI Tools (Not Supported)
The second expected outcome (H2) posited that increased personalization would foster greater trust in AI tools. This was based on the notion that relevance and user-centricity build cognitive and emotional trust. However, the analysis did not support this hypothesis ($\beta = 0.068$, $p = 0.325$).

This unexpected result breaks the traditional idea that personalization is a trust mechanism, and shows that generation Z users may regard personalization as a standard function rather than a trust signal. It can also show the difference between technical performance and emotional trust-users appreciate relevance, but it is not necessarily interpreted as user-friendly or fair.

Trust in AI Tools Will Positively Influence Purchase Intention (Not Supported)
The third hypothesis (H3) assumed that higher trust would translate into a higher purchase intention. This assumption aligns with established trust literature, particularly in the context of online shopping (Gefen et al., 2003). Surprisingly, this pathway was also unsupported ($\beta = 0.007$, $p = 0.931$), revealing almost no influence of trust on purchase decisions.
This discovery has far-reaching influence. This shows that consumers of Generation Z may not rely on trust when using algorithmic systems-they are either based on basic reliability or trust is irrelevant as long as their functions remain unchanged. This challenges marketers and developers to rethink the way they display and market AI tools: perhaps utility should be more important than credibility.

Trust Will Mediate the Relationship Between Personalization and Purchase Intention (Not Supported)
Finally, the mediation hypothesis (H4) predicted that trust would serve as a mediator between personalization and purchase intention. Based on the combined theoretical framework (TAM + Trust Model), this relationship was thought to be both direct and indirect. However, the mediation analysis using the Baron and Kenny approach found no support for this indirect path.

This outcome reinforces the conclusion that trust does not play a central role in influencing purchase intention among this demographic. Instead, personalization appears to directly shape intention without needing to pass through an emotional or cognitive trust filter.

Overall Implications of the Expected Outcomes
Although three of the four hypotheses are not supported, this study has achieved its goal, that is, to provide empirical information about the psychological and behavioral mechanisms that affect the interaction between Generation Z and AI tools. These findings challenge the traditional trust-based model and show that personalization is more important than trust in the business environment driven by artificial intelligence, especially in the digital native environment.

These results also sounded the alarm for digital platforms and marketers: personalized investment can provide better results than abstract trust. In addition, ethical design should focus on transparency and control, rather than assuming that users just trust artificial intelligence because it works well.

Theoretical and Contextual Significance

This study makes an important contribution to theoretical advances and contextual understanding at the intersection of artificial intelligence (AI), personalization, and consumer behavior. Theoretically, this study extends the existing Technology Acceptance Model (TAM) with the concepts of perceived personalization and trust, which allows for a more nuanced interpretation of digital-native consumers' evaluation and use of AI-based recommendation systems. Whereas the TAM traditionally focuses on perceived usefulness and ease of use, the integration of trust in this study reflects a growing awareness of the growing importance of affective and cognitive perceptions in algorithmic environments.

Importantly, this study questions common assumptions regarding the central role of trust in behavioral outcomes. In contrast to common models that portray trust as a key mediator between personalization and purchase intentions, our results show that for Gen Z consumers with frequent exposure to AI-driven platforms, only personalization has a direct and statistically significant effect on purchase intentions, while trust does not significantly mediate or influence this relationship. The findings highlight a generational gap in the interpretation of digital tools. Younger consumers may be more inclined to take algorithmic personalization for granted rather than perceiving it as a sign of trustworthiness. This nuanced generational analysis enriches existing research and encourages researchers to consider contextual moderating variables such as digital maturity and familiarity with AI tools.

This study fills an important gap in the literature by focusing on Malaysian Gen Z consumers, a population segment underrepresented in global research on AI and recommendation systems. Malaysia's diverse socio-cultural background, increasing engagement in e-commerce, and digital policy framework make the country a fertile environment to explore regional perceptions of AI-powered platforms.

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