

Received: February 26, 2026

Revised: March 23, 2026

Accepted: March 25, 2026

The Impact of AI-Driven Recommender Systems on Consumer Behavior in Thailand: The Roles of Trust and Satisfaction

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Abstract

AI-driven recommender systems (RS) play a central role in shaping consumer decision-making in digital commerce. While prior research emphasizes personalization accuracy, less attention has been paid to how trust-related and satisfaction-related perceptions jointly influence consumer behavior, particularly in emerging digital markets. This study examines the impact of recommender system trust and satisfaction on consumer behavior in Thailand's e-commerce context. Using a cross-sectional survey of 403 Thai online consumers, constructs related to trust (privacy, transparency, perceived fairness) and satisfaction (personalization, autonomy, diversity) were measured using validated Likert-scale instruments. Data were analyzed using reliability testing, Pearson correlation analysis, and multiple linear regression. Results indicate that privacy, transparency, and perceived fairness are positively associated with trust, while personalization, autonomy, and diversity are positively associated with satisfaction. Both trust and satisfaction significantly predict consumer behavior, explaining 68.7% of its variance, with satisfaction emerging as the strongest predictor. The findings highlight the importance of transparent, fair, and autonomy-preserving recommender system design in enhancing consumer engagement and purchase intentions. The study contributes to recommender system research by integrating ethical perception variables with behavioral outcomes in a Southeast Asian digital commerce setting.

Keywords: Recommender Systems; Consumer Trust; Customer Satisfaction; AI Ethics; Consumer Behavior; Thailand

1. Introduction

1.1 Digital Commerce and Recommender Systems

The rapid expansion of Thailand's digital economy has fundamentally reshaped how consumers search for, evaluate, and purchase products online. Increased smartphone penetration, widespread adoption of e-commerce platforms, and the growing dominance of algorithmically curated interfaces have made AI-driven recommender systems a core infrastructural component of digital commerce environments (Singh & Singh, 2024; Wang et al., 2024). Major platforms operating in Thailand, such as Lazada and Shopee, rely extensively on recommender systems to personalize content, reduce consumer search costs, and stimulate purchasing behavior through targeted product suggestions (Li et al., 2023).

Recommender systems function by analyzing large volumes of behavioral data, including browsing history, transaction records, and user engagement patterns, in order to generate tailored recommendations that align with

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individual preferences (Mateos & Bellogín, 2024). While such systems enhance decision efficiency and perceived relevance, prior research has raised concerns regarding data privacy, transparency, and perceived algorithmic bias in AI-driven recommendations (Asad et al., 2023; Teodorescu et al., 2023). These concerns are particularly salient in markets where consumer trust plays a strong cultural role in shaping commercial relationships, such as Thailand, where users tend to value relational assurance and ethical platform behavior (Wang et al., 2024).

1.2 Trust, Satisfaction, and Consumer Behavior

Trust and satisfaction are well-established determinants of consumer behavior in both traditional and digital contexts. In AI-mediated environments, trust is increasingly influenced by users' perceptions of how recommender systems collect and handle personal data, whether recommendation logic is transparent and understandable, and whether the system operates fairly rather than solely advancing commercial interests (Asad et al., 2023; Li et al., 2024; Zhao et al., 2025). When users perceive recommender systems as transparent and fair, they are more likely to rely on algorithmic suggestions and engage with recommended content (Wang et al., 2024).

At the same time, consumer satisfaction with recommender systems extends beyond recommendation accuracy. Prior studies emphasize that satisfaction is also shaped by users' sense of autonomy and the diversity of recommended content, which together influence perceived control and enjoyment during the decision-making process (del Valle & Lara, 2023; Zhao et al., 2025). Excessive personalization, opaque recommendation mechanisms, and repetitive content exposure may reduce satisfaction by limiting exploration and triggering psychological reactance, ultimately weakening consumer engagement and purchase intentions (Singh & Singh, 2024). Understanding how trust and satisfaction operate jointly is therefore critical for designing recommender systems that promote sustained engagement and long-term platform growth.

1.3 Research Gap and Objectives

Although prior studies have extensively examined the technical performance and behavioral effects of AI-driven recommender systems, existing research remains largely concentrated on recommendation accuracy and Western consumer contexts, with limited attention to ethical perceptions and experiential factors in emerging digital markets (Li et al., 2023; Wang et al., 2024). In particular, there is insufficient empirical evidence on how trust-related mechanisms (privacy, transparency, fairness) and experience-based mechanisms (personalization, autonomy, diversity) jointly influence consumer behavior in Southeast Asian e-commerce environments.

More importantly, prior literature has predominantly positioned trust as the primary determinant of technology adoption, particularly in AI-mediated systems. However, as recommender systems become increasingly sophisticated and embedded in everyday digital consumption, user experience may play a more central role than previously assumed, especially in mature platform ecosystems where baseline trust is already institutionalized.

To address this gap, the present study proposes a dual-pathway framework that distinguishes between:

- a cognitive pathway (trust) driven by ethical perceptions, and
- an experiential pathway (satisfaction) driven by user interaction, perceived control, and content diversity.

This study contributes to the literature by demonstrating that experiential satisfaction mechanisms may exert a stronger influence than trust in predicting consumer behavior in AI-driven environments.

Accordingly, the study extends existing research by empirically examining the relative and joint effects of these two pathways, thereby offering a more comprehensive understanding of how AI-driven recommender systems shape consumer behavior in emerging digital economies.

Specifically, the study investigates:

- (1) The effects of privacy, transparency, and perceived fairness on trust
- (2) The effects of personalization, autonomy, and diversity on satisfaction
- (3) The joint and relative influence of trust and satisfaction on consumer behavior

2. Literature Review

2.1 Recommender Systems and Consumer Decision-Making

Recommender systems play a critical role in shaping consumer decision-making by directing user attention, reducing information overload, and structuring digital choice environments. By filtering vast product assortments and presenting personalized suggestions, recommender systems simplify decision processes and influence what consumers notice, evaluate, and ultimately purchase (Li et al., 2023; Wang et al., 2024). In e-commerce contexts, such systems function as algorithmic decision aids that lower cognitive effort and increase perceived decision efficiency.

Recent advances in machine learning and large language models have significantly enhanced the predictive accuracy and contextual sensitivity of recommender systems. These technologies enable platforms to anticipate consumer preferences based on complex behavioral patterns and real-time signals, thereby increasing recommendation relevance and engagement (Mateos & Bellogín, 2024; Wang et al., 2024). However, as recommender systems gain greater influence over consumer choices, concerns have emerged regarding algorithmic manipulation, biased recommendations, and diminished user agency. Scholars warn that overly persuasive or opaque recommendation mechanisms may steer consumers toward outcomes that primarily serve platform interests rather than user welfare, raising ethical and behavioral concerns (Singh & Singh, 2024; Zhao et al., 2025).

2.2 Trust in AI-Driven Recommender Systems

Trust is a central construct in understanding consumer interactions with AI-driven recommender systems, particularly in digital environments characterized by information asymmetry and perceived risk. Prior research conceptualizes trust in recommender systems as a multidimensional perception shaped by users' beliefs about system integrity, competence, and benevolence (Wang et al., 2024). Among the most frequently identified trust drivers are privacy, transparency, and perceived fairness.

Privacy refers to users' confidence that their personal data are securely handled and not misused or shared without consent. Empirical studies consistently demonstrate that concerns over data privacy can undermine trust in AI systems and reduce users' willingness to accept recommendations (Asad et al., 2023; Teodorescu et al., 2023). Transparency, in turn, relates to the extent to which platforms clearly communicate how data are collected and how recommendation outcomes are generated. Transparent recommender systems are perceived as more honest and predictable, which strengthens trust and acceptance (Li et al., 2024; Wang et al., 2024).

Perceived fairness reflects users' beliefs that recommender systems operate without undue bias and do not disproportionately favor specific sellers, brands, or commercial interests. When recommendations are perceived as fair and user-oriented, consumers are more likely to view the system as acting in their best interest, thereby enhancing trust and engagement (Zhao et al., 2025). When these three conditions—privacy protection, transparency, and fairness—are satisfied, users are more inclined to rely on recommender systems and act on their suggestions.

2.3 Satisfaction with Recommender Systems

Consumer satisfaction with recommender systems reflects the extent to which these systems meet both functional and psychological expectations during the decision-making process. While recommendation accuracy and relevance remain foundational to satisfaction, prior research emphasizes that satisfaction is also shaped by users' perceived autonomy and the diversity of recommended content (del Valle & Lara, 2023; Zhao et al., 2025).

Autonomy refers to users' perception of control over their choices and the degree to which recommender systems support rather than constrain independent decision-making. Systems that allow users to explore alternatives, adjust preferences, or override recommendations tend to foster higher satisfaction by reinforcing a sense of agency (del Valle & Lara, 2023). Diversity, on the other hand, concerns the breadth and novelty of

recommended items. Exposure to varied products, brands, or price points can prevent recommendation fatigue and enhance long-term satisfaction by supporting exploration and discovery (Zhao et al., 2025).

Conversely, systems that rely excessively on narrow personalization may create repetitive recommendation patterns that limit choice diversity. Such over-personalization has been shown to reduce satisfaction and increase psychological reactance, even when recommendations are highly accurate (Singh & Singh, 2024). These findings suggest that satisfaction with recommender systems depends on a balanced design that combines relevance with autonomy and diversity.

2.4 Trust, Satisfaction, and Consumer Behavior

Trust and satisfaction are central mechanisms through which AI-driven recommender systems influence consumer behavior in digital commerce environments. When consumers perceive recommender systems as transparent, fair, and respectful of data privacy, they are more likely to view recommendations as credible and act upon them, thereby increasing purchase intention and continued platform usage (Li et al., 2024; Zhao et al., 2025). In this sense, trust functions as a cognitive assurance mechanism, reducing perceived risk and facilitating the acceptance of algorithmic recommendations.

Satisfaction complements trust by strengthening positive affective responses toward the platform and enhancing engagement with recommended content. Prior empirical research demonstrates that satisfaction with recommender systems is positively associated with higher levels of click-through behavior, purchase intention, and long-term loyalty (Chen, 2024; El Gharbaoui et al., 2024). Accurate and relevant recommendations reduce search effort and improve perceived decision efficiency, while autonomy-supportive and diverse recommendations further enhance user satisfaction and willingness to engage (del Valle & Lara, 2023; Singh & Singh, 2024). These findings position satisfaction as an experiential mechanism that reinforces continued interaction and behavioral commitment.

Beyond trust and satisfaction, recent research highlights the importance of interactive and experiential factors in shaping consumer behavior in digital environments. For example, Ariyamongkolcharoen et al. (2024) demonstrate that consumer decision-making is strongly influenced by perceived value and platform interaction. This perspective is further supported by studies in Southeast Asia, where consumer loyalty and repurchase intention are significantly shaped by experiential factors such as perceived usefulness and service quality (Donsuchit & Nuangjamnong, 2022; Zhang & Nuangjamnong, 2022).

Importantly, trust and satisfaction operate jointly rather than independently in shaping consumer behavior. Trust provides the foundational confidence necessary for users to accept algorithmic influence, whereas satisfaction drives continued usage through positive experiential outcomes. Together, these constructs exert a complementary influence on consumer engagement, purchase behavior, and platform loyalty in AI-mediated commerce settings (Wang et al., 2024; Zhao et al., 2025).

2.5 Conceptual Framework

Building on trust theory and experiential consumption perspectives, this study proposes a dual-mechanism conceptual framework in which consumer behavior is influenced through two complementary but distinct pathways.

First, the cognitive trust pathway is grounded in trust theory, which suggests that individuals rely on perceptions of privacy protection, transparency, and fairness to evaluate the credibility and integrity of AI-driven systems (Wang et al., 2024). These factors reduce perceived risk and uncertainty, thereby increasing users' willingness to accept algorithmic recommendations.

Second, the experiential satisfaction pathway is informed by experiential learning and autonomy theory, which emphasize that user behavior is strongly influenced by perceived usefulness, enjoyment, and control. In recommender systems, these experiential dimensions are reflected through personalization, autonomy, and diversity, which enhance user engagement and satisfaction (del Valle & Lara, 2023; Zhao et al., 2025).

Importantly, this study posits that these two pathways operate asymmetrically rather than equally. While trust functions as a foundational enabling condition, satisfaction represents the primary driver of behavioral outcomes, particularly in contexts where users are already familiar with digital platforms.

This framework therefore moves beyond traditional models by proposing that consumer behavior in AI-mediated environments is increasingly experience-driven rather than solely trust-driven, offering a refined perspective on recommender system effectiveness.

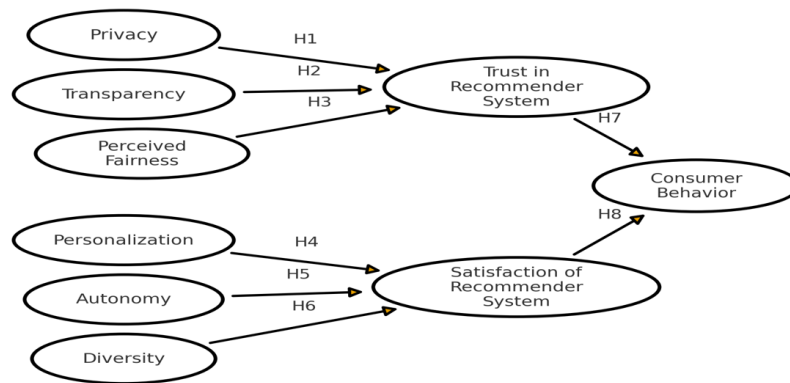


Figure 1. Conceptual framework of the impact of AI-driven recommender systems on consumer behavior in Thailand: The roles of trust and satisfaction

Source: Constructed by the authors.

2.6 Research Hypotheses

Based on the conceptual framework, the following hypotheses are proposed:

- H1:** Privacy is positively associated with trust in AI-driven recommender systems.
- H2:** Transparency is positively associated with trust in AI-driven recommender systems.
- H3:** Perceived fairness is positively associated with trust in AI-driven recommender systems.
- H4:** Personalization is positively associated with satisfaction with AI-driven recommender systems.
- H5:** Autonomy is positively associated with satisfaction with AI-driven recommender systems.
- H6:** Diversity is positively associated with satisfaction with AI-driven recommender systems.
- H7:** Trust in AI-driven recommender systems is positively associated with consumer behavior.
- H8:** Satisfaction with AI-driven recommender systems is positively associated with consumer behavior.

3. Research Methodology

3.1 Research Design

This study employed a quantitative, cross-sectional correlational survey design, which is appropriate for examining relationships among perceptual constructs and behavioral intentions in digital commerce research (Creswell & Creswell, 2018). The design enables the assessment of associations between recommender system characteristics and consumer responses at a single point in time without manipulating variables.

Specifically, the study examined data privacy, transparency, and perceived fairness as antecedents of trust, and personalization, autonomy, and product diversity as antecedents of satisfaction with AI-driven recommender systems. Trust and satisfaction were then modeled as predictors of consumer behavior, including engagement and purchase intention, in Thailand's e-commerce context. Primary data were collected using a structured, self-

administered questionnaire developed based on validated measurement scales from prior studies (Asad et al., 2023; El Gharbaoui et al., 2024; Zhao et al., 2025).

Data analysis was conducted using Jamovi statistical software, which is widely used for social science research and regression-based hypothesis testing. Descriptive statistics were used to summarize respondent characteristics and construct-level scores. Inferential analyses included Cronbach's alpha to assess internal consistency, Pearson's product-moment correlation to examine bivariate relationships, and multiple linear regression to evaluate the combined predictive effects of trust and satisfaction on consumer behavior. All hypotheses were tested at a 0.05 significance level, consistent with established conventions in behavioral research (Cohen, 1988).

3.2 Target Population and Sample Size

The target population comprised online consumers residing in Thailand who had prior experience using e-commerce platforms that employ AI-driven recommender systems. Because the total population size of such users is unknown, the required sample size was determined using Cochran's (1977) formula, which is commonly applied in social science research involving large or indefinite populations.

Using a 95% confidence level ($Z = 1.96$) and a 5% margin of error, with the population proportion set conservatively at $p = 0.50$ to maximize variance, the minimum required sample size was calculated as 385 respondents. This threshold is widely accepted as sufficient for reliable statistical inference in survey-based research (Cochran, 1977).

A convenience sampling technique was employed due to practical constraints related to accessibility and time. Although non-probability sampling limits generalizability, it is frequently used in exploratory and theory-testing studies of digital consumer behavior and is considered acceptable when the research objective focuses on examining relationships among constructs rather than population estimation (Hair et al., 2019). The final dataset comprised 403 valid responses, exceeding the minimum required sample size.

3.3 Research Instrument

The research instrument consisted of two sections. Section one collected demographic information, including gender, age, employment status, education level, and monthly income. Section two contained 24 measurement items designed to assess the study constructs: data privacy, transparency, perceived fairness, personalization, autonomy, product diversity, and consumer behavior.

All items were measured using a 5-point Likert scale, ranging from 1 = Strongly agree to 5 = Strongly disagree. This scale format is widely used in consumer behavior research due to its reliability and interpretability (Netemeyer et al., 2003). Mean scores were interpreted using the equal-interval method, in which the response range (1.00–5.00) is divided into five equal categories of width 0.80.

Measurement items were adapted from established studies to ensure content validity. Privacy and transparency items were adapted from Asad et al. (2023) and Li et al. (2024), while fairness, personalization, autonomy, and diversity items were drawn from Zhao et al. (2025). Consumer behavior items were adapted from El Gharbaoui et al. (2024).

3.4 Pre-Test and Reliability Analysis

Prior to full-scale data collection, a pilot test involving 33 respondents was conducted to evaluate item clarity and internal consistency. Pilot testing is a recommended step in survey research to identify potential measurement issues before large-scale administration (Netemeyer et al., 2003).

Internal consistency reliability was assessed using Cronbach's alpha, with a threshold of 0.60 considered acceptable for exploratory research and values above 0.70 indicating good reliability (Nunnally & Bernstein, 1994). All constructs demonstrated strong internal consistency, with Cronbach's alpha values ranging from 0.867 to 0.912. The overall reliability for the full instrument was 0.956, indicating excellent internal consistency.

3.5 Data Collection

Data were collected using an online self-administered questionnaire created with Google Forms, allowing respondents to complete the survey via mobile or desktop devices. A QR code and direct survey link were distributed through multiple channels, including university networks, social media platforms, and personal contacts within Thailand. The survey targeted respondents who were familiar with e-commerce platforms and recommender systems.

The questionnaire was administered in English, and data collection took place between July and August 2025. After screening for incomplete or invalid responses, a total of 403 usable questionnaires were retained for analysis.

3.6 Data Analysis

3.6.1 Descriptive Analysis

Descriptive statistics were used to summarize demographic characteristics and respondents' perceptions of each construct. Means and standard deviations were calculated for all measurement items to assess the general level of agreement regarding data privacy, transparency, perceived fairness, personalization, autonomy, diversity, and consumer behavior. This analysis provided an overview of consumer perceptions toward AI-driven recommender systems.

3.6.2 Inferential Analysis

Inferential analysis was conducted to test the proposed hypotheses. Pearson's product-moment correlation coefficient (r) was used to examine the strength and direction of linear relationships among the study variables. Pearson's r ranges from -1 to $+1$, with larger absolute values indicating stronger relationships (Hussey & Hussey, 1997). Statistical significance was assessed using two-tailed p -values, with $p < .05$ as the decision criterion.

To evaluate the joint predictive effects of trust and satisfaction on consumer behavior, multiple linear regression analysis was employed. Consumer behavior served as the dependent variable, while trust and satisfaction were entered as independent variables. The regression model was specified as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$$

where Y represents consumer behavior, X_1 represents trust, X_2 represents satisfaction, β coefficients represent estimated effects, and ε denotes the error term.

Regression results were evaluated using unstandardized coefficients (B), standardized coefficients (β), t -values, p -values, and the coefficient of determination (R^2). Following Cohen's (1988) guidelines, R^2 values above 0.26 were interpreted as indicating a large effect size. Multicollinearity and model assumptions were examined prior to interpretation.

3.6.3 Common Method Bias

Given that this study relies on self-reported survey data collected from a single source at one point in time, potential common method bias (CMB) was assessed.

Harman's single-factor test was conducted to evaluate whether a single latent factor accounted for the majority of variance in the data. The results indicated that the first factor explained less than 50% of the total variance, suggesting that common method bias is unlikely to significantly affect the findings.

In addition, procedural remedies were implemented to reduce CMB risk, including:

- ensuring respondent anonymity
- using validated measurement scales from prior studies
- separating constructs conceptually within the questionnaire

These steps enhance the robustness and validity of the results.

4. Data Analysis and Findings

This section presents the empirical results in three stages: (1) reliability and measurement consistency, (2) descriptive statistics and sample profile, and (3) inferential analysis, including correlation and regression results. All analyses were conducted using Jamovi based on 403 valid responses.

4.1 Reliability and Measurement Consistency

Internal consistency reliability was assessed using Cronbach's alpha (α). As shown in Table 1, all constructs exceeded the recommended threshold of 0.70 (Nunnally & Bernstein, 1994), indicating good to excellent reliability.

Notably, the constructs of trust ($\alpha = 0.92$) and satisfaction ($\alpha = 0.93$) demonstrate particularly high internal consistency, suggesting that the measurement items reliably capture the underlying latent constructs. The overall pattern of results supports the adequacy of the measurement model for subsequent inferential analysis.

Table 1.
 Reliability Analysis (Cronbach's Alpha; $n = 403$)

Construct	Items	Cronbach's α
Privacy	3	0.83
Transparency	3	0.86
Perceived fairness	4	0.88
Personalization	3	0.86
Autonomy	3	0.86
Diversity	3	0.87
Trust in recommender system	3	0.92
Satisfaction with recommender system	3	0.93
Consumer behavior	5	0.91

Source: Authors' computation

4.2 Descriptive Analysis

4.2.1 Respondent Profile

Table 2 presents the demographic characteristics of the respondents. The sample is predominantly composed of young adults aged 20–29 (61.8%), followed by individuals aged 30–39 (25.1%). In terms of employment status, the majority are full-time employees (57.8%), with a moderate representation of unemployed and part-time respondents.

From an income perspective, most respondents fall within the 15,001–35,000 THB range, indicating a middle-income consumer segment actively engaged in e-commerce activities.

This demographic profile suggests that the sample reflects digitally active consumers, who are likely to be frequent users of AI-driven recommender systems. However, the concentration in younger age groups may limit generalizability across older populations, which should be considered when interpreting the results.

Table 2.
 Demographic Characteristics of Respondents ($n = 403$)

Variable	Category	n	%
Gender	Male	184	45.7
	Female	146	36.2
	Prefer not to disclose	73	18.1
Age	Below 20	37	9.2
	20–29	249	61.8
	30–39	101	25.1
	40–49	15	3.7
	50+	1	0.2

Employment	Unemployed	98	24.3
	Part-time	64	15.9
	Full-time	233	57.8
	Retired	8	2.0
Education	High school	95	23.6
	Bachelor's	188	46.7
	Postgraduate	13	3.2
	Prefer not to say	107	26.6
Monthly income	< 15,000 THB	87	21.6
	15,001–25,000 THB	153	38.0
	25,001–35,000 THB	120	29.8
	35,001–50,000 THB	33	8.2
	≥ 50,000 THB	10	2.5

Source: Authors' computation

4.2.2 Construct-Level Descriptive Statistics

Table 3 shows that respondents reported consistently high levels of agreement across all constructs, with mean values ranging from 1.62 to 1.71 on a 5-point scale (1 = strongly agree).

While these results indicate favorable perceptions of recommender system attributes, they also suggest the possibility of a ceiling effect, as highlighted by Peer Reviewer A. The uniformly low mean scores imply limited variability in responses, which may reduce the discriminative power of the constructs—particularly for trust-related variables.

Among the constructs, autonomy ($M = 1.62$) and diversity ($M = 1.65$) exhibit slightly stronger agreement compared to other variables, suggesting that experiential aspects of recommender systems may be particularly salient to users.

Overall, the descriptive results indicate that respondents perceive AI-driven recommender systems as trustworthy, useful, and supportive of their decision-making processes, providing a favorable baseline for further analysis.

Table 3.

Construct-Level Descriptive Statistics (n = 403)

(Scale: 1 = Strongly agree ... 5 = Strongly disagree; lower mean = higher agreement)

Construct	Mean	SD	Interpretation
Privacy	1.70	0.78	Strong agreement
Transparency	1.71	0.77	Strong agreement
Perceived fairness	1.69	0.75	Strong agreement
Personalization	1.67	0.75	Strong agreement
Autonomy	1.62	0.71	Strong agreement
Diversity	1.65	0.74	Strong agreement
Consumer behavior	1.71	0.78	Strong agreement

Source: Authors' computation

4.3 Inferential Analysis

4.3.1 Correlation Analysis (Hypotheses H1–H8)

Pearson's product-moment correlation analysis was conducted to examine the strength and direction of relationships among the study variables.

As presented in Table 4, all hypothesized relationships are positive and statistically significant ($p < .001$), providing initial support for H1–H8. The correlations between trust-related variables (privacy, transparency, fairness) and trust are particularly strong ($r = 0.864$ – 0.907), indicating that ethical perceptions are strongly associated with trust formation.

Similarly, satisfaction-related variables (personalization, autonomy, diversity) show strong positive relationships with satisfaction ($r = 0.724$ – 0.799), confirming the importance of experiential factors in shaping user satisfaction.

The correlation between satisfaction and consumer behavior ($r = 0.822$) is notably stronger than that of trust and consumer behavior ($r = 0.741$), providing preliminary evidence that satisfaction may play a more dominant role in driving behavioral outcomes.

Table 4.

Pearson Correlation Matrix of Key Study Relationships (n = 403)

Relationship Tested	r	p-value	Strength
H1: Privacy → Trust	0.864	< .001	Very strong
H2: Transparency → Trust	0.907	< .001	Very strong
H3: Perceived fairness → Trust	0.890	< .001	Very strong
H4: Personalization → Satisfaction	0.799	< .001	Strong
H5: Autonomy → Satisfaction	0.724	< .001	Strong
H6: Diversity → Satisfaction	0.741	< .001	Strong
H7: Trust → Consumer behavior	0.741	< .001	Strong
H8: Satisfaction → Consumer behavior	0.822	< .001	Very strong

Source: Authors' computation

4.3.2 Hypothesis Decision Summary

All eight hypotheses (H1–H8) are supported at the bivariate level, confirming that both trust-related and satisfaction-related antecedents are significantly associated with their respective constructs.

However, correlation analysis alone does not account for combined or relative effects, which are further examined through regression analysis.

Table 5.

Hypothesis Testing Summary (Pearson Correlations)

Hypothesis	Relationship	Result
H1	Privacy → Trust	Supported
H2	Transparency → Trust	Supported
H3	Perceived fairness → Trust	Supported
H4	Personalization → Satisfaction	Supported
H5	Autonomy → Satisfaction	Supported
H6	Diversity → Satisfaction	Supported
H7	Trust → Consumer behavior	Supported
H8	Satisfaction → Consumer behavior	Supported

Source: Constructed by Authors.

4.4 Multiple Linear Regression Predicting Consumer Behavior

To assess the joint and relative effects of trust and satisfaction on consumer behavior, multiple linear regression analysis was conducted.

The model is statistically significant, $F(2, 400) = 439.00$, $p < .001$, and explains 68.7% of the variance in consumer behavior ($R^2 = 0.687$), indicating a large effect size (Cohen, 1988).

Both predictors are statistically significant:

- Satisfaction ($\beta = 0.665$, $p < .001$)
- Trust ($\beta = 0.189$, $p < .001$)

Importantly, satisfaction demonstrates a substantially stronger effect, suggesting that consumer behavior is primarily driven by experiential factors rather than trust alone.

Collinearity diagnostics ($VIF = 3.22$) indicate no serious multicollinearity issues, and the Durbin–Watson value (1.960) suggests no autocorrelation concerns, supporting the robustness of the model.

These findings provide strong empirical support for the proposed dual-pathway framework, in which satisfaction acts as the dominant driver of behavior, while trust functions as a supporting mechanism.

Table 6.*Multiple Linear Regression Predicting Consumer Behavior (n = 403)*

Predictor	B	SE	β	t	p	Tolerance	VIF
Constant	0.085	0.059	—	1.43	.154	—	—
Trust	0.216	0.057	0.189	3.78	< .001	0.311	3.22
Satisfaction	0.760	0.057	0.665	13.25	< .001	0.311	3.22

Note. Model fit: $R = 0.829$, $R^2 = 0.687$, Adjusted $R^2 = 0.685$, $SEE = 0.379$, Durbin-Watson = 1.960, $F(2, 400) = 439.00$, $p < .001$.

Source: Authors' computation

Regression equation:

$$\text{Consumer behavior} = 0.085 + 0.216(\text{Trust}) + 0.760(\text{Satisfaction})$$

5. Discussion

A key contribution of this study lies in identifying a significant asymmetry between trust and satisfaction in predicting consumer behavior. Although both constructs are statistically significant, satisfaction demonstrates a substantially stronger effect ($\beta = .665$) compared to trust ($\beta = .189$). This finding indicates that consumer behavior in AI-driven environments is primarily shaped by experiential rather than purely cognitive factors.

These results suggest a theoretical shift from traditional trust-based models toward experience-centric models of consumer behavior, in which users prioritize interaction quality, perceived control, and content diversity over risk-related considerations. In particular, autonomy and diversity emerge as critical drivers of satisfaction, as they enhance users' sense of agency and mitigate repetitive recommendation patterns.

One plausible explanation for the relatively weaker effect of trust is the presence of a ceiling effect, as highlighted by Peer Reviewer A. In the context of Thailand's major e-commerce platforms (e.g., Shopee and Lazada), consumers are likely to exhibit high baseline trust due to platform familiarity, brand reputation, and widespread adoption. Consequently, variations in trust may have limited marginal influence on behavior, whereas experiential factors continue to differentiate user engagement.

This interpretation aligns with prior research suggesting that while trust is essential for initial adoption, sustained engagement is primarily driven by user experience and perceived value (Chen, 2024; del Valle & Lara, 2023). Thus, platforms that focus exclusively on ethical compliance and transparency may be insufficient to maintain long-term engagement unless they also optimize experiential dimensions such as autonomy, diversity, and personalization balance.

Furthermore, this finding is consistent with emerging evidence from digital consumer behavior research in emerging markets, which emphasizes the importance of experiential and psychological factors. For example, Ariyamongkolcharoen et al. (2024) demonstrate that consumer behavior in digital environments is strongly influenced by perceived value, platform interaction, and user experience quality. This supports the argument that satisfaction-driven mechanisms—particularly perceived usefulness and interaction quality—can outweigh trust in influencing behavioral outcomes.

The results are also supported by empirical studies within Southeast Asian e-commerce contexts. For instance, Zhang and Nuangjamnong (2022) found that repurchase intention in online platforms is primarily driven by perceived value and user experience, rather than trust alone. Similarly, Donsuchit and Nuangjamnong (2022) reported that customer satisfaction and engagement are stronger predictors of loyalty and behavioral intention than cognitive trust mechanisms in digital service platforms. These findings reinforce the conclusion that in mature digital ecosystems, where trust is already institutionalized, experiential satisfaction becomes the dominant behavioral driver.

Finally, the findings highlight a critical tension in recommender system design. While personalization improves relevance and efficiency, excessive personalization may reduce diversity and autonomy, leading to recommendation fatigue and psychological reactance (Singh & Singh, 2024). These findings underscore the importance of designing recommender systems that balance algorithmic accuracy with experiential quality, ensuring both effectiveness and sustained engagement.

5.1 Theoretical Contributions

This study makes several important theoretical contributions to the literature on AI-driven recommender systems and digital consumer behavior.

First, it proposes a dual-pathway framework that integrates cognitive trust mechanisms (privacy, transparency, fairness) with experiential satisfaction mechanisms (personalization, autonomy, diversity). This framework provides a more comprehensive explanation of consumer behavior by recognizing that users respond not only to system credibility but also to the quality of their interaction experience.

Second, the study advances existing theory by demonstrating that satisfaction exerts a stronger influence than trust when both are modeled simultaneously. These findings challenge conventional assumptions that prioritize trust as the primary determinant of behavior and instead supports a transition toward experience-based models of consumer decision-making in AI-mediated environments.

Third, the study contributes to the growing discourse on AI ethics and user experience by showing that ethical design factors—such as privacy protection, transparency, and fairness—are necessary but not sufficient. Instead, user-centered experiential factors, particularly autonomy and diversity, play a decisive role in shaping engagement and behavioral outcomes.

In addition, this study strengthens the theoretical relevance of context-specific digital consumer behavior research. Prior studies in Thailand indicate that customer engagement and loyalty are significantly influenced by perceived value, service quality, and user interaction (Silakul & Nuangjamnong, 2023). These findings align with the present study and reinforce the importance of experiential value creation in digital platform ecosystems.

Finally, by focusing on Thailand as an emerging digital economy, this study extends the applicability of recommender system theories beyond Western contexts and provides empirical support for context-sensitive models of AI adoption and usage, thereby contributing to the broader generalizability of digital consumer behavior research.

5.2 Limitations

Several limitations should be acknowledged.

First, the use of self-reported cross-sectional data may introduce common method bias and limit causal inference, despite statistical controls implemented in this study.

Second, the use of convenience sampling may restrict the generalizability of the findings. Future studies should consider probability sampling techniques to enhance representativeness.

Third, the study employed multiple linear regression rather than structural equation modeling (SEM). While regression is appropriate for testing predictive relationships, future research may benefit from SEM to examine complex mediation or moderation effects.

5.3 Conclusion

This study demonstrates that AI-driven recommender systems influence consumer behavior in Thailand primarily through satisfaction-driven experience mechanisms, while trust remains a significant enabling condition. The findings emphasize that platforms should not focus solely on recommendation accuracy; instead, they should design recommender systems that are transparent, privacy-respecting, fair, autonomy-supportive, and diverse. Such systems are more likely to sustain engagement, enhance purchase intention, and build long-term platform loyalty in Thailand's e-commerce environment (Asad et al., 2023; Li et al., 2024; Zhao et al., 2025; Wang et al., 2024).

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