European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
http://eelet.org.uk

AI-Driven Personalization In E-Commerce: Impact On Consumer Purchase Intention And Trust

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Abstract
This research examines the impact of artificial intelligence-driven personalization strategies on consumer purchase intention and trust in e-commerce platforms. Through a mixed-methods approach combining quantitative surveys (n=847) and qualitative interviews (n=32), this study investigates how personalization mechanisms influence consumer behavior. Results indicate that AI-driven personalization significantly enhances purchase intention ($\beta=0.68$, $p<0.001$) while simultaneously presenting complex trust dynamics. The study reveals that transparency in data usage ($\beta=0.54$, $p<0.001$) and perceived control over personalization ($\beta=0.47$, $p<0.01$) mediate the relationship between personalization and consumer trust. Findings suggest that while personalization increases conversion rates by approximately 31%, concerns about data privacy can diminish trust by 23% when personalization is perceived as invasive. This research contributes to the literature by proposing a conceptual framework integrating Technology Acceptance Model (TAM) with Privacy Calculus Theory, offering practical implications for e-commerce practitioners balancing personalization benefits with privacy considerations.

Keywords: AI personalization, e-commerce, consumer trust, purchase intention, privacy concerns, machine learning, recommendation systems

Introduction
The global e-commerce market has experienced exponential growth, reaching $5.7 trillion in 2023, with projections estimating $7.4 trillion by 2025. Within this landscape, artificial intelligence (AI) has emerged as a transformative force, fundamentally altering how businesses interact with consumers. AI-driven personalization represents a paradigm shift from traditional

mass marketing to individualized consumer experiences, leveraging machine learning algorithms, natural language processing, and predictive analytics to tailor product recommendations, content, and user interfaces to individual preferences.

Personalization in e-commerce encompasses various dimensions including product recommendations, dynamic pricing, customized search results, personalized email marketing, and adaptive website interfaces. Major e-commerce platforms such as Amazon, Alibaba, and Netflix have demonstrated the commercial viability of AI personalization, with Amazon attributing 35% of its revenue to recommendation engines and Netflix estimating that personalization saves approximately $1 billion annually through reduced churn.

Research Problem

Despite the widespread adoption of AI personalization, the relationship between personalization intensity and consumer responses remains inadequately understood. While personalization can enhance user experience and purchase likelihood, it simultaneously raises significant privacy concerns that may erode consumer trust. This privacy paradox—where consumers simultaneously desire personalized experiences and fear privacy intrusion—creates a complex decision-making environment for both consumers and businesses.

Current literature presents conflicting findings regarding personalization effectiveness. Some studies report substantial increases in conversion rates and customer satisfaction, while others highlight negative consequences including perceived manipulation, privacy concerns, and algorithmic distrust. This inconsistency suggests moderating variables and boundary conditions that warrant systematic investigation.

Research Objectives

This study addresses the following research objectives:

1. To quantify the impact of AI-driven personalization on consumer purchase intention in e-commerce contexts
2. To examine the relationship between personalization and consumer trust, identifying mediating and moderating factors
3. To investigate the role of transparency and perceived control in mitigating privacy concerns
4. To develop a comprehensive framework explaining the mechanisms through which AI personalization influences consumer behavior
5. To provide actionable recommendations for e-commerce practitioners implementing personalization strategies

Research Questions

RQ1: To what extent does AI-driven personalization influence consumer purchase intention in e-commerce platforms?

RQ2: How does AI-driven personalization affect consumer trust, and what factors mediate this relationship?

RQ3: What role do transparency and perceived control play in moderating the relationship between personalization and trust?

RQ4: How do different types of personalization (product recommendations, interface customization, dynamic pricing) differentially impact purchase intention and trust?

Significance of the Study

This research contributes to both academic literature and practical application by:

- Providing empirical evidence quantifying personalization effects on purchase behavior
- Integrating multiple theoretical frameworks to explain complex consumer responses
- Identifying specific personalization strategies that maximize benefits while minimizing privacy concerns
- Offering evidence-based guidelines for ethical AI implementation in e-commerce
- Advancing understanding of the privacy-personalization trade-off in digital environments

Conceptual Framework and Hypotheses

Conceptual Model

The proposed conceptual framework integrates Technology Acceptance Model, Privacy Calculus Theory, and Social Exchange Theory to explain the relationships among AI personalization, purchase intention, and trust. The model posits that AI personalization directly influences purchase intention while also affecting trust through multiple pathways. Transparency and perceived control mediate the relationship between personalization and trust, while privacy concerns moderate these relationships.

Hypotheses Development

H1: AI-driven personalization positively influences consumer purchase intention.
Rationale: Personalization enhances shopping efficiency, product discovery, and perceived relevance, thereby increasing purchase likelihood. Tailored recommendations reduce information overload and cognitive effort, facilitating decision-making.

H2: AI-driven personalization positively influences consumer trust.
Rationale: Effective personalization signals competence and attentiveness, demonstrating the platform's ability to understand and serve consumer needs. This competence enhances trust dimensions of ability and benevolence.

H3: Transparency in data usage mediates the relationship between AI personalization and consumer trust.
Rationale: Transparency reduces uncertainty and perceived risk, addressing privacy concerns that might otherwise diminish trust. When consumers understand how their data is used, they are more likely to perceive personalization as beneficial rather than intrusive.

H4: Perceived control over personalization mediates the relationship between AI personalization and consumer trust.
Rationale: Control mitigates feelings of manipulation and vulnerability. When consumers can adjust personalization settings, they maintain autonomy, reducing psychological reactance and enhancing trust.

H5: Privacy concerns moderate the relationship between AI personalization and purchase intention, such that the positive effect is weaker for consumers with high privacy concerns.
Rationale: Privacy-concerned consumers experience greater cognitive conflict when confronted with personalization, as benefits are offset by privacy risks. This tension reduces purchase intention.

H6: The positive relationship between AI personalization and trust is stronger for consumers with higher technology innovativeness.
Rationale: Technology innovators exhibit greater comfort with new technologies and more positive attitudes toward AI, making them more receptive to personalization and more likely to trust AI systems.
H7: Different personalization types (product recommendations, interface customization, dynamic pricing) have differential effects on purchase intention and trust.
Rationale: Personalization types vary in intrusiveness and perceived benefit. Product recommendations are generally viewed positively, while dynamic pricing may trigger fairness concerns, resulting in divergent effects.

Research Methodology

Research Design

This study employs a sequential mixed-methods design combining quantitative surveys with qualitative interviews. The quantitative phase tests hypotheses and quantifies relationships, while the qualitative phase provides deeper understanding of consumer perspectives and decision-making processes.

Phase 1 (Quantitative): Online survey distributed to e-commerce consumers
Phase 2 (Qualitative): Semi-structured interviews with survey participants

Sampling Strategy

Quantitative Sample

Target Population: Adult consumers (18+) who have made online purchases within the past six months
Sampling Method: Stratified random sampling ensuring representation across age, gender, income, and geographic location
Sample Size: n = 847 respondents

Qualitative Sample

Sampling Method: Purposive sampling selecting respondents representing diverse perspectives on personalization
Sample Size: n = 32 participants
Selection Criteria: Varied personalization acceptance levels, demographic diversity, technology proficiency

Data Analysis

Quantitative Analysis

Preliminary Analysis:

- Descriptive statistics and frequency distributions
- Missing data analysis and treatment
- Normality assessment (Kolmogorov-Smirnov test)
- Reliability analysis (Cronbach's alpha)

Main Analysis:

- Confirmatory Factor Analysis (CFA) assessing measurement model
- Structural Equation Modeling (SEM) testing hypothesized relationships

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
http://eelet.org.uk

- Mediation analysis using bootstrapping procedures (5,000 iterations)
- Moderation analysis using Hayes PROCESS macro
- Multi-group analysis comparing personalization types

Qualitative Analysis

Interview transcripts were analyzed using thematic analysis:

1. **Familiarization:** Reading transcripts multiple times
2. **Coding:** Identifying meaningful units and assigning codes
3. **Theme Development:** Grouping codes into themes
4. **Review:** Refining themes for coherence
5. **Interpretation:** Relating themes to research questions

Validity and Reliability

Construct Validity: Ensured through established scales and expert review **Content Validity:** Survey items reviewed by three e-commerce experts **Convergent Validity:** Average Variance Extracted (AVE) > 0.50 **Discriminant Validity:** Square root of AVE exceeds inter-construct correlations **Internal Consistency:** Cronbach's alpha > 0.70 for all constructs **Test-Retest Reliability:** Two-week interval with subset (n=97), correlation > 0.85

Ethical Considerations

The study received institutional review board approval. Participants provided informed consent, were assured of anonymity, and could withdraw without penalty. Data was encrypted and stored securely. No deception was employed.

Results and Analysis

Descriptive Statistics

Table 1: Descriptive Statistics and Correlations

Variable	**Mean**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1. AI Personalization	4.82	1.23	(.91)						
2. Purchase Intention	5.14	1.18	.64**	(.89)					
3. Consumer Trust	4.56	1.34	.58**	.72**	(.93)				
4. Transparency	3.98	1.45	.52**	.49**	.67**	(.88)			
5. Perceived Control	4.21	1.38	.44**	.46**	.61**	.73**	(.86)		
6. Privacy Concerns	4.87	1.41	-.31**	-.28**	-.43**	-.52**	-.48**	(.90)	
7. Tech Innovativeness	4.65	1.29	.48**	.41**	.38**	.34**	.39**	-.22**	(.87)

Note: **p < .01; Values in parentheses are Cronbach's alpha coefficients; n = 847

Key findings from descriptive statistics:

- Purchase intention exhibited highest mean (M=5.14), indicating generally positive purchase inclinations
- Transparency received lowest mean (M=3.98), suggesting consumer desire for greater data usage clarity
- All constructs demonstrated adequate internal consistency (α > 0.85)
- Strong positive correlation between personalization and purchase intention (r=.64)
- Moderate positive correlation between personalization and trust (r=.58)
- Negative correlations between privacy concerns and all outcome variables

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Measurement Model Assessment

Confirmatory Factor Analysis evaluated measurement model fit:

Table 2: Model Fit Indices

Index	Recommended Value	Obtained Value	Evaluation
χ^2/df	< 3.0	2.47	Acceptable
CFI	> 0.90	0.94	Good
TLI	> 0.90	0.93	Good
RMSEA	< 0.08	0.06	Good
SRMR	< 0.08	0.05	Good

All fit indices met recommended thresholds, indicating acceptable measurement model fit.

Convergent Validity: All factor loadings exceeded 0.70, and Average Variance Extracted (AVE) values ranged from 0.64 to 0.78, exceeding the 0.50 threshold.

Discriminant Validity: The square root of AVE for each construct exceeded its correlations with other constructs, confirming discriminant validity.

Structural Model and Hypothesis Testing

Structural Equation Modeling tested the hypothesized relationships:

Table 3: Hypothesis Testing Results

Hypothesis	Path	β	SE	t-value	p-value	Result
H1	Personalization → Purchase Intention	0.68	0.04	17.24	<.001	Supported
H2	Personalization → Trust	0.36	0.05	7.82	<.001	Supported
H3	Transparency → Trust (mediation)	0.54	0.05	11.47	<.001	Supported
H4	Perceived Control → Trust (mediation)	0.47	0.05	9.86	<.001	Supported

H1 (Personalization → Purchase Intention): Strongly supported (β=0.68, p<.001). AI personalization explained 52% of variance in purchase intention, indicating substantial influence. For every one standard deviation increase in personalization, purchase intention increased by 0.68 standard deviations.

H2 (Personalization → Trust): Supported (β=0.36, p<.001). Personalization positively influenced trust, though with moderate effect size. Combined with mediators, the model explained 48% of variance in trust.

H3 (Transparency Mediation): Strongly supported (β=0.54, p<.001). Transparency significantly mediated the personalization-trust relationship. Bootstrapping analysis revealed significant indirect effect (β=0.19, 95% CI [0.15, 0.24]).

H4 (Perceived Control Mediation): Strongly supported (β=0.47, p<.01). Perceived control significantly mediated the personalization-trust relationship. Indirect effect was significant (β=0.17, 95% CI [0.12, 0.22]).

Mediation Analysis

Table 4: Mediation Effects

Path	Direct Effect	Indirect Effect	Total Effect	Mediation Type
Personalization → Trust	0.36***	-	0.36***	-

Personalization → Transparency → Trust	0.36***	0.19***	0.55***	Partial
Personalization → Control → Trust	0.36***	0.17***	0.53***	Partial
Personalization → Both → Trust	0.18**	0.36***	0.54***	Partial

Note: **p < .01, ***p < .001; Bootstrap samples = 5,000

Results indicate partial mediation. Transparency and perceived control account for substantial variance in the personalization-trust relationship, but direct effects remain significant, suggesting additional mechanisms operate. Combined mediation analysis revealed that transparency and perceived control together mediate 67% of the total effect of personalization on trust, demonstrating their critical importance.

Moderation Analysis

H5 (Privacy Concerns Moderation): Supported (β=-0.23, p<.01). Privacy concerns significantly moderated the personalization-purchase intention relationship. Simple slopes analysis revealed:

- Low privacy concerns: β=0.78, p<.001
- Medium privacy concerns: β=0.68, p<.001
- High privacy concerns: β=0.55, p<.001

The positive effect of personalization on purchase intention decreased by 29% from low to high privacy concern levels.

H6 (Technology Innovativeness Moderation): Supported (β=0.19, p<.05). Technology innovativeness moderated the personalization-trust relationship:

- Low innovativeness: β=0.41, p<.001
- Medium innovativeness: β=0.58, p<.001
- High innovativeness: β=0.71, p<.001

Technology innovators exhibited 73% stronger personalization-trust associations compared to low innovativeness consumers.

Comparative Analysis of Personalization Types

H7 (Differential Effects): Partially supported. Multi-group analysis compared four personalization types:

Table 5: Personalization Type Effects

Type	Purchase Intention Effect	Trust Effect	Acceptance Rate
Product Recommendations	β=0.72***	β=0.61***	87%
Search Personalization	β=0.69***	β=0.58***	81%
Interface Customization	β=0.64***	β=0.54***	79%
Dynamic Pricing	β=0.51***	β=0.32**	62%

Note: **p < .01, ***p < .001

Chi-square difference tests confirmed significant differences ($\Delta\chi^2$ = 47.32, p<.001). Product recommendations exhibited strongest effects, while dynamic pricing showed weakest effects and lowest acceptance.

Qualitative data revealed dynamic pricing concerns:

- "I don't like feeling they're charging me more than others" (Participant 14)
- "Price changes based on my browsing feels manipulative" (Participant 27)

Additional Findings

Purchase Conversion Analysis: Respondents reporting high personalization exposure (top quartile) demonstrated 31% higher purchase completion rates compared to low exposure (bottom quartile): 73% vs. 56% completion.

Trust Erosion: Among respondents experiencing privacy violations (n=147, 17.4%), trust decreased by 23% on average, with 64% reducing platform usage.

Transparency Effects: Platforms providing detailed privacy policies and data usage explanations received 42% higher trust ratings than those with minimal disclosure.

Control Preferences: 78% of respondents desired greater control over personalization features, with specific preferences for:

- Opt-in/opt-out toggles (89%)
- Data deletion capabilities (84%)
- Personalization intensity adjustment (76%)
- Data usage visibility (81%)

Qualitative Findings

Thematic Analysis Results

Qualitative analysis identified five major themes explaining consumer perspectives on AI personalization:

Theme 1: Perceived Value and Convenience

Participants appreciated personalization primarily for efficiency and discovery benefits:

"It saves me so much time. Instead of scrolling through hundreds of products, I see exactly what I'm looking for." (P8, Female, 29)

"I've discovered products I didn't know existed but absolutely love. The recommendations understand my style." (P19, Male, 34)

Subthemes:

- Time savings (mentioned by 28/32 participants)
- Reduced cognitive load (24/32)
- Product discovery (26/32)
- Shopping enjoyment enhancement (18/32)

Theme 2: Privacy Concerns and Data Anxiety

Despite appreciating benefits, participants expressed significant privacy concerns:

"It's creepy how much they know about me. I searched for something once, and now it's everywhere." (P3, Female, 42)

"I worry about what happens to my data. Who else has access? Could it be sold?" (P16, Male, 51)

Subthemes:

- Surveillance discomfort (22/32)
- Data breach fears (27/32)
- Third-party sharing concerns (25/32)
- Lack of control over data (20/32)

Participants distinguished between acceptable and invasive data collection. Browsing history and purchase data were viewed as reasonable, while location tracking and social media integration raised concerns.

Theme 3: Trust Through Transparency

Transparency emerged as crucial for trust development:

"When they explain how they use my data and give me options, I feel more comfortable. It shows they respect me." (P11, Female, 37)

"I trust Amazon more than others because they're upfront about why they recommend products." (P24, Male, 45)

Participants valued:

- Clear privacy policies (29/32)
- Explanation of recommendation algorithms (23/32)
- Notification of data collection (26/32)
- Regular communication about data practices (18/32)

Theme 4: Control and Autonomy

Perceived control significantly influenced acceptance:

"I don't mind personalization as long as I can turn it off or adjust it. Having that choice makes all the difference." (P7, Female, 31)

"I like that I can delete my history and see what data they have on me. That transparency and control builds trust." (P21, Male, 39)

Desired control mechanisms:

- Granular privacy settings (31/32)
- Easy opt-out options (28/32)
- Data deletion capabilities (30/32)
- Personalization intensity adjustment (25/32)

Theme 5: Personalization Quality and Relevance

Personalization quality significantly impacted perceptions:

"Sometimes the recommendations are so off, it makes me question if they understand me at all. Bad recommendations actually make me trust them less." (P5, Female, 28)

"When recommendations are spot-on, it feels like magic. When they're wrong, it feels invasive and pointless." (P18, Male, 43)

Quality dimensions:

- Accuracy of recommendations (31/32 mentioned)
- Diversity vs. filter bubbles (19/32)
- Timeliness and context-appropriateness (22/32)
- Personalization consistency (16/32)

Privacy Calculus in Action

Interviews revealed sophisticated privacy calculus processes. Participants evaluated:

Benefits Side:

- Time savings
- Better product matches
- Exclusive offers

- Enhanced shopping experience

Costs Side:

- Privacy loss
- Potential data misuse
- Feeling surveilled
- Reduced anonymity

Decision-making varied by:

- **Context:** Participants accepted more data collection from trusted brands
- **Data Type:** Sensitive data (financial, health) triggered stronger privacy concerns
- **Alternatives:** Availability of non-personalized alternatives influenced tolerance
- **Past Experience:** Previous data breaches reduced acceptance

Trust Development Process

Participants described trust as evolving through stages:

Stage 1: Initial Skepticism New platforms faced high skepticism. Users employed protective behaviors (fake information, minimal disclosure).

Stage 2: Cautious Exploration Positive initial experiences encouraged gradual information sharing and personalization engagement.

Stage 3: Conditional Trust Repeated positive interactions built trust, but remained conditional on continued positive performance and no privacy violations.

Stage 4: Established Trust Long-term positive relationships generated stable trust, though vulnerable to single negative incidents.

Stage 5: Trust Degradation Privacy violations, data breaches, or perceived manipulation rapidly eroded trust, often irreversibly.

6.4 Platform-Specific Perspectives

Participants differentiated platforms:

Amazon:

Highest trust (26/32 rated 6-7 on 7-point scale), attributed to transparency, recommendation accuracy, and established reputation.

Netflix:

High trust for entertainment recommendations (23/32 rated 6-7), but lower stakes perceived compared to financial transactions.

Social Commerce Platforms:

Moderate trust (14/32 rated 5-7), with concerns about data sharing between social and commercial contexts.

Smaller E-Commerce Sites:

Lowest trust (8/32 rated 5-7), requiring more explicit transparency and control features to gain acceptance.

Discussion

Principal Findings

This research provides comprehensive evidence that AI-driven personalization significantly influences consumer purchase intention and trust in e-commerce contexts, while revealing complex mediating and moderating mechanisms.

Direct Effects of Personalization

The finding that AI personalization strongly predicts purchase intention (β=0.68, p<.001), explaining 52% of variance, provides robust quantitative support for personalization efficacy. This effect size substantially exceeds previous estimates in the literature, which typically report correlations of 0.40-0.55. The stronger effect observed in this study may reflect:

1. **Technological Advancement:** Modern AI systems provide more accurate personalization than earlier systems studied in previous research
2. **Consumer Adaptation:** Consumers have become more accustomed to and receptive toward personalization
3. **Comprehensive Measurement:** This study assessed multiple personalization dimensions simultaneously, capturing cumulative effects

The 31% increase in purchase conversion rates among highly personalized experiences translates to substantial business value. For a platform with 1 million monthly visitors and 5% baseline conversion, implementing effective personalization could generate 15,500 additional purchases monthly—a transformative impact.

The Trust Paradox

While personalization positively influences trust (β=0.36, p<.001), this effect is notably weaker than its impact on purchase intention. This discrepancy suggests consumers may purchase despite trust concerns, driven by convenience and perceived value—a troubling finding with long-term implications.

Qualitative data illuminated this paradox. Participants described compartmentalized thinking: "I don't fully trust them, but the deals are too good to pass up" (P13). This pragmatic acceptance may create vulnerable consumer-platform relationships susceptible to disruption by privacy incidents.

The 23% trust erosion following privacy violations confirms trust fragility. Once broken, trust proves difficult to rebuild, with 64% of affected consumers reducing platform engagement. This finding underscores the asymmetry between trust building (gradual) and trust destruction (rapid).

Critical Role of Transparency and Control

The strong mediating effects of transparency (β=0.54, p<.001) and perceived control (β=0.47, p<.001) represent this study's most practically significant findings. Together, these factors mediate 67% of personalization's total effect on trust, demonstrating their pivotal importance.

Transparency Mechanisms:

Transparency operates through multiple pathways:

1. **Uncertainty Reduction:** Clear explanations of data usage reduce perceived risk
2. **Fairness Perception:** Transparency signals equitable treatment and respect
3. **Predictability:** Understanding algorithms enables mental model formation
4. **Agency Enhancement:** Knowledge empowers informed decision-making

Importantly, transparency must be meaningful rather than performative. Participants criticized "information dumping" through lengthy, legalistic privacy policies: "They bury everything in 50 pages of legal speak. That's not transparency" (P9). Effective transparency requires accessible language, visual aids, and layered disclosure allowing users to access detail as desired.

Control Mechanisms:
Perceived control addresses fundamental psychological needs for autonomy and self-determination. Control features serve dual functions:
1. **Instrumental:** Enabling actual adjustment of personalization and data practices
2. **Symbolic:** Signaling respect for consumer autonomy even when options aren't exercised

The finding that 78% of participants desired greater control, yet many rarely adjusted settings, suggests control's primary value may be symbolic—providing psychological reassurance rather than active management. This has design implications: control features should be easily accessible but not require constant engagement.

Moderating Factors

Privacy Concerns as Double-Edged Sword

The significant moderation by privacy concerns (β=-0.23, $p<.01$) reveals personalization's differential impact across consumer segments. The 29% reduction in personalization effectiveness from low to high privacy concern levels indicates substantial heterogeneity requiring segmented approaches.

Privacy-concerned consumers don't reject personalization entirely but require additional assurances. They exhibit:
- Higher transparency standards
- Greater need for control features
- More scrutiny of data practices
- Lower tolerance for errors

Platforms can address high privacy concerns through:
- Differential privacy implementations minimizing data exposure
- Federated learning keeping data on user devices
- Explicit consent mechanisms for sensitive data
- Regular privacy audits and certifications

Technology Innovativeness as Amplifier

Technology innovativeness strengthening the personalization-trust relationship (β=0.19, $p<.05$) by 73% suggests early adopters serve as critical advocates for AI personalization. These consumers:
- Provide valuable feedback for system improvement
- Generate positive word-of-mouth
- Tolerate implementation imperfections
- Model adoption for mainstream consumers

However, over-optimizing for innovators risks alienating mainstream consumers with different needs and concerns. Successful platforms balance innovation with accessibility.

Personalization Type Variations

The differential effects across personalization types provide actionable insights:

Product Recommendations (β=0.72 for purchase intention, 87% acceptance): The strongest performer benefits from:
- Clear value proposition (finding relevant products)
- Long usage history building confidence

- Transparency of recommendation basis
- Ability to ignore irrelevant suggestions without consequence

Dynamic Pricing (β=0.51 for purchase intention, 62% acceptance): The weakest performer suffers from:

- Fairness concerns ("Why do others pay less?")
- Perceived manipulation
- Lack of transparency in pricing logic
- Trust erosion when price changes detected

These findings suggest platforms should prioritize recommendation personalization while exercising caution with pricing personalization. When implementing dynamic pricing, transparency becomes especially critical: explaining that prices reflect supply-demand dynamics rather than discriminatory targeting may improve acceptance.

Conclusions

This research provides comprehensive empirical evidence quantifying the impact of AI-driven personalization on consumer purchase intention and trust in e-commerce contexts. Key conclusions include:

1. **Strong Purchase Intention Effects:** AI personalization substantially enhances purchase intention (β=0.68), explaining 52% of variance and increasing conversion rates by approximately 31%.
2. **Complex Trust Dynamics:** While personalization positively influences trust (β=0.36), this effect is weaker than purchase intention effects and highly dependent on transparency and control.
3. **Critical Mediating Factors:** Transparency (β=0.54) and perceived control (β=0.47) mediate 67% of personalization's total effect on trust, highlighting their strategic importance.
4. **Moderating Influences:** Privacy concerns significantly diminish personalization effectiveness, while technology innovativeness amplifies it, indicating substantial consumer heterogeneity.
5. **Personalization Type Variations:** Product recommendations outperform other personalization types, while dynamic pricing raises significant fairness concerns.
6. **Privacy-Personalization Trade-off:** Consumers engage in sophisticated privacy calculus, balancing personalization benefits against privacy costs in context-dependent ways.

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