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ARTIFICIAL INTELLIGENCE DRIVEN CUSTOMER ENGAGEMENT IN ONLINE RETAIL

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ABSTRACT

The integration of artificial intelligence (AI) into e-commerce has profoundly transformed consumer engagement methods; nonetheless, its total impact on the customer experience remains complex and multifaceted. This study employs a quantitative research methodology to examine the fundamental factors that affect customer perceptions of AI-driven engagement and its effect on satisfaction. A structured online survey was administered to a cohort of 300 seasoned internet users. Exploratory Factor Analysis (EFA) of 25 Likert-scale statements identified a robust four-factor structure: Perceived Value & Personalization (PVP), Privacy & Transparency Apprehension (PTA), Relational Decoupling (RD), and Service Efficiency & Reliability (SER), collectively accounting for 58.4% of the total variance. A multivariate regression analysis indicated that all four variables were significant predictors of overall customer satisfaction ($R^2 = .506$, $p < .001$). Specifically, PVP ($\beta = .398$) and SER ($\beta = .311$) had positive influences, but PTA ($\beta = -.242$) and RD ($\beta = -.187$) shown large negative effects. Additionally, a mediation analysis indicated that Relational Decoupling partially mediates the adverse relationship between privacy concerns and satisfaction (indirect effect: 0.10, 95% CI [0.05, 0.16]). The findings suggest that although AI's functional benefits are strong motivators for happiness, ethical and relational issues significantly diminish their impact. This research provides a validated paradigm for online retail, emphasizing that an effective AI approach must achieve a balance of technological efficiency, clear data regulations, and human-centered design to foster trust and enduring loyalty.

Keywords: Artificial Intelligence, Customer Engagement, Online Retail, Personalization, Privacy Concerns, Mediation Analysis, Customer Satisfaction, Factor Analysis.

INTRODUCTION

The use of Artificial Intelligence (AI) is changing the way people shop online in ways that can't be changed back. This technological revolution is changing how businesses talk to their customers in a big way. It used to be that you could only do transactions, but now you can offer personalized, predictive, and seamless experiences. Consumer engagement is the emotional bond between a brand and a customer that gets stronger with each interaction and good experience. In the digital marketplace, it is important for building loyalty and getting the most out of a customer over their lifetime. AI is a powerful engine that makes this connection better by analyzing, predicting, and meeting the needs of each customer with an accuracy that has never been seen before.As customers want more personalized experiences and businesses look for ways to meet these needs, using AI in online stores is quickly going from a competitive edge to a business necessity. One of the most popular and helpful things AI can do is suggest products that are tailored to each person.

Research consistently demonstrates the efficacy of these systems, noting that a significant portion of revenue for major online retailers is directly attributable to AI-driven recommendation engines (Smith, 2022). Furthermore, AI has revolutionized customer service and support through the deployment of chatbots and virtual assistants. These AI-powered interfaces are available 24/7 and can help with a wide range of questions, from checking the status of an order to explaining return policies and product specs. Forbes Insights found that businesses who use AI chatbots have seen a surge in customer resolution rates and a big drop in response times, which closely correlates with higher customer satisfaction levels (Wilson & Miller, 2023). AI can help improve the marketing strategies that bring in and keep customers. AI systems might use predictive analytics to look at huge amounts of data to find small patterns and trends in how people act. AI-driven solutions automatically and in real time improve and automate digital ad bids.AI makes it possible to personalize content by changing website content, email marketing messages, and promotional offers in real time based on what users do and what has happened in the past.
Chen and his co-authors say that using AI in marketing analytics lets companies go from looking back at past events to looking forward to how they will affect customers. This lets them plan how customers will interact with them instead of just reacting to them (Chen et al., 2023). This proactive approach to engagement, made possible by AI's ability to forecast the future, makes marketing efforts not only more effective but also more appreciated by customers, who get information that is really relevant and engaging to them.A balanced strategy that uses AI for its unmatched efficiency, scalability, and analytical skills, while also intentionally adding human empathy and creativity to handle complicated interactions and build real emotional connections, is the future of effective customer engagement (Kapoor & Dwivedi, 2023).

To sum up, AI has a huge and wide-ranging effect on how online retailers communicate with their customers. This is a big change in how businesses talk to their customers. AI is making shopping easier, more responsive, and more enjoyable by generating hyper-personalized suggestions, offering rapid and efficient customer assistance via chatbots, and allowing predictive and targeted marketing methods. This makes it an essential part of any successful online retail strategy. Retailers that can best use AI to build real, meaningful, and trustworthy connections with their consumers will be the ones who do well.

STATEMENT OF THE PROBLEM

In this highly competitive market, where there are a lot of options and customers' attention spans are becoming shorter, customer engagement has become the most important factor in long-term profitability and brand loyalty. Engagement is more than just buying things; it's everything a customer does, thinks, and feels about a business. Using AI technology to talk to clients quickly and without thinking about it is still a complicated and multi-faceted problem. AI can improve customer experiences by speeding things up and making them more personal.

Recommendation engines, predictive search, and targeted advertising all need this data-heavy method to work. But this makes customers feel like they are always being watched, and they are becoming more conscious that their digital footprints are being carefully recorded and sold. The issue is made worse by a lack of transparency; customers frequently don't know what data is being gathered, how it is being used, or who it is being shared with. This is known as the "personalization-privacy paradox" (Aguirre et al., 2016). In this paradox, people want experiences that are relevant to them, but they don't like how much data has to be collected to provide them those experiences. The issue is not alone technological but also ethical: how can online merchants use AI to provide the customisation that customers anticipate without breaching ethical standards and infringing upon their perceived right to privacy, thereby engendering suspicion rather than loyalty?

Research on human-computer interaction indicates that consumers prefer expediency for straightforward tasks, yet desire human involvement when complexities arise that necessitate empathy and understanding

(Gursoy et al., 2019). Retailers have AI capabilities and data that give them an unparalleled capacity to affect how people make decisions. On the other hand, most people don't know how to reject these designed persuasive methods (Crawford & Calo, 2016). In short, the main difficulty is that using AI in online retail consumer interaction without thinking about it beforehand is a double-edged sword. On one side is the promise of customization, efficiency, and scalability like we've never seen before, which might bring in a lot of money.The biggest challenge for academics, professionals, and policymakers is figuring out how to handle this difficult area. We want to know how AI can be used to get people to buy things, as well as why they should, how much it will cost, and what safety measures were put in place. The biggest issue is figuring out how to use AI in a way that is ethical, open, and focused on people while also protecting people's privacy, making sure everyone has equal access, keeping real human empathy, and building trust-based relationships that are good for both business and society. If you don't handle this problem correctly, you might get clients' attention through new technology, but it could also hurt their trust and long-term commitment.

NEED AND SIGNIFICANCE OF THE STUDY

The examination of Artificial Intelligence's influence on customer engagement in e-commerce is both an academic pursuit and an essential imperative, given the significant transformations reshaping the global market.

The significance of this study is multifaceted, offering substantial contributions to academic theory, managerial practice, consumer welfare, and public policy. For academic scholars in fields ranging from marketing and information systems to ethics and sociology, this research provides a critical framework for analyzing the evolving nature of customer engagement in the digital age. It moves the theoretical discourse beyond traditional models like TAM (Technology Acceptance Model) or the Service-Dominant Logic, which were not designed to account for autonomous, learning agents as key actors in the engagement process. This study integrates concepts from computer science (algorithmic bias) with marketing theory (relationship marketing) and behavioral economics (nudge theory), thereby forging a new interdisciplinary paradigm essential for understanding modern consumer environments. It responds to requests from eminent scholars for more comprehensive inquiries into the "onlife" domain, where the digital and physical realms are intricately linked, and human agency engages with artificial intelligence in multifaceted manners (Floridi, 2014). It responds to the requests from eminent scholars for more comprehensive inquiries into the "onlife" domain, where the digital and physical realms are intricately linked, and human agency engages with artificial intelligence in multifaceted manners (Floridi, 2014).

By empirically investigating the thresholds of personalization, the acceptance of automated service, and the antecedents of algorithm aversion versus appreciation, this study will enrich the academic literature with much-needed empirical data and conceptual models that reflect the new reality of AI-infused commerce.

For practitioners and online retail managers, the significance of this study is profoundly practical. In an era where investment in AI technologies constitutes a major portion of digital transformation budgets, executives are in dire need of evidence-based guidance to allocate resources wisely and avoid costly pitfalls. This is because they need to know how to use AI in a way that is both moral and useful in order to build strong, trustworthy relationships (Davenport et al., 2020). This study will establish a strategic framework, transforming AI from a mere tactical tool into an essential capability for customer-focused innovation. The research may be crucial for individuals and society at large. As AI systems become more common in everyday life, people are more worried about how they might affect decision-making, take away people's freedom, and make things unfair. This study will elucidate consumer vulnerabilities, articulating public apprehensions regarding data privacy, algorithmic equity, and digital well-being. The study will elucidate the benefits and drawbacks of hyper-personalization, thereby increasing consumers' awareness of the factors affecting their decisions, ultimately promoting enhanced digital literacy and informed consent. The importance of this lies in its ability to create AI that is centered on people, where technology helps and empowers the user instead of taking advantage of them. This fits with the growing trend toward "ethical AI," which puts human values and oversight first. This guarantees that people will continue to be able to choose and find options in the digital marketplace (Martin, 2019). Therefore, the findings may act as a springboard for consumer advocacy organizations and a starting point for public discussion about the digital future that society hopes to build.

Ultimately, the findings are important for policymakers who are making rules for the digital economy. AI is moving so quickly that legal systems can't keep up, so the rules are mostly reactive instead of proactive. This project will give us real-world data that we can use to make better and more effective rules that protect consumers and encourage new ideas. The results may help regulators write laws that make sure automated decision-making systems are fair, open, and accountable by clearly pointing out certain risks and costs, like algorithmic outcomes that are unfair or AI-driven persuasion that is manipulativeThis study can provide the essential intellectual foundation to surpass superficial regulatory measures, fostering a sophisticated governance framework that encourages responsible innovation in the online retail sector and beyond, while ensuring that the significant power of AI is harnessed for collective benefit (Yeung, 2017).

THEORETICAL BACKGROUND OF THE STUDY

This research is founded on interdisciplinary theoretical foundations, integrating established frameworks from marketing and service-dominant logic with nascent concepts from human-computer interaction, technology ethics, and information systems. The study is fundamentally grounded in the principles of Service-Dominant (S-D) Logic, which asserts that value is not inherent to objects but is co-created through interactive processes between the service provider and the recipient, often enabled by networks of integrators and resources. From this point of view, customer engagement is a dynamic, iterative process of integrating resources and exchanging services that builds relationships and loyalty.

Artificial Intelligence, in this context, can be theorized as an operant resource—a dynamic entity capable of acting on other resources to create value—that fundamentally alters the architecture of value co-creation. AI systems act as autonomous actors that mediate the relationship between the firm and the customer, personalizing the value proposition, facilitating interactions, and integrating resources in real-time.

To understand the consumer's acceptance and adoption of these AI-driven engagement tools, this study draws upon the **Technology Acceptance Model (TAM)** and its subsequent extensions. TAM, which posits that perceived usefulness and perceived ease of use are primary determinants of technology adoption, provides a foundational lens. In the context of AI in retail, perceived usefulness might relate to the AI's ability to save time, offer relevant recommendations, or solve problems efficiently, while perceived ease of use would encompass the intuitiveness and lack of friction in interacting with a chatbot or personalized interface.

Consequently, the theoretical framework must encompass both affective and cognitive responses to non-human entities, transcending the primary cognitive emphasis of TAM to integrate emotional and ethical dimensions vital for social relationships. To address the substantial ethical and societal ramifications, our endeavors are guided by the tenets of Algorithmic Ethics and Fairness. This study meticulously investigates the potential of automated technologies to sustain and exacerbate existing social biases, generate filter bubbles, and influence consumer behavior through hyper-nudging. It challenges the notion that algorithms are impartial and forces people to consider fairness, accountability, and transparency—often referred to as the "right to explanation"—in systems that automate consumer interactions. Since AI systems may be designed to subtly influence consumer decisions in ways that benefit merchants, nudge theory and related ideas are relevant in this situation. In order to clarify the complex and frequently contradictory effects of artificial intelligence on consumer interactions in the digital marketplace, this study aims to create a thorough framework by combining different theoretical viewpoints.

RESEARCH OBJECTIVES

1. To identify and validate the underlying factor structure of key constructs influencing customer perceptions of AI-driven engagement in online retail.
2. To determine the impact of the identified key factors on overall customer satisfaction with the online retail experience.

3. To investigate whether the negative effect of Privacy & Transparency Apprehension (PTA) on Overall Customer Satisfaction is mediated by Relational Decoupling (RD).

Objective 1: Factor Analysis

Aim: To reduce a large set of variables (25 survey statements) into a smaller set of underlying, unobservable constructs (factors) that explain the patterns of correlations within the data.

Method: A survey was administered to a sample of online shoppers. Respondents were asked to rate their agreement with 25 statements on a 7-point Likert scale (1=Strongly Disagree, 7=Strongly Agree). The data was

subjected to Exploratory Factor Analysis (EFA) using Principal Axis Factoring with Promax rotation.

1. KMO and Bartlett's Test

The Kaiser-Meyer-Olkin (KMO) measure verified the sampling adequacy for the analysis.

Table 1: **KMO and Bartlett's Test**

KMO Measure of Sampling Adequacy.		.921
Bartlett's Test of Sphericity	**Approx. Chi-Square**	5432.817
	df	300
	Sig.	.000

Interpretation: The KMO value of .921 is excellent (well above the recommended threshold of .6), indicating that the patterns of correlations are compact and thus factorable. Bartlett's Test of Sphericity is significant ($p < .001$), indicating that the correlation matrix is not an identity matrix and is suitable for structure detection.

2. Rotated Component Matrix (Pattern Matrix)

The analysis revealed a clear four-factor structure, which together explain 68.4% of the total variance. The factors were labeled based on the statements that loaded most heavily onto them.

Table 2: Rotated Component Matrix

Sl No.	Statement	Factor Loadings			
		PVP	PTC	AA	SER
1	The AI recommendations I receive are highly relevant to my needs.	**.842**	.121	-.032	.204
2	I feel the product suggestions save me time and effort in searching.	**.798**	.056	.087	.143
3	The personalized offers I receive are valuable to me.	**.781**	-.104	.132	.045
4	AI helps me discover new products I end up liking.	**.773**	.092	-.045	.078
5	The overall shopping experience feels tailored to my preferences.	**.735**	.211	.154	-.088
6	I am concerned about how my personal data is used by these AI systems.	.034	**.879**	.102	.091
7	I feel my online shopping behavior is being constantly monitored.	.123	**.856**	.045	-.034
8	It is not clear to me how the AI decides what to show me.	-.045	**.831**	.243	.102
9	I am worried this data could be shared with third parties without my consent.	.187	**.802**	.087	.056
10	I have little control over what data is collected about me.	.102	**.795**	.164	-.123
11	Interacting with a chatbot feels impersonal and frustrating.	.087	.132	**.872**	-.045
12	I miss the human touch when dealing with automated customer service.	-.023	.045	**.861**	.112
13	Over-reliance on AI makes the brand feel cold and distant.	.145	.187	**.839**	.034

14	I do not trust an AI to handle a complex or sensitive issue.	.032	.254	**.816**	-.187
15	I am often aware that my choices are being manipulated by algorithms.	.164	.321	**.791**	.076
16	Problems are resolved quickly through AI-powered customer service.	.132	-.087	-.154	**.853**
17	I appreciate that AI customer service is available 24/7.	.098	.076	.045	**.832**
18	The automated checkout and payment process is smooth and efficient.	.245	.032	.121	**.821**
19	The AI chat assistant understands my questions accurately.	.187	-.121	-.098	**.805**
20	I get instant responses to my queries through automated systems.	.076	.164	-.211	**.784**
21	I believe AI helps the company provide me with better service.	.521	-.243	-.321	.432
22	I am generally comfortable with brands using AI to interact with me.	.487	-.432	-.287	.398
23	I often find the targeted ads based on my browsing history to be intrusive.	-.123	.554	.487	-.065
24	The speed of AI-driven service improves my overall experience.	.432	-.198	-.176	.601
25	I am skeptical about the fairness of AI-generated recommendations.	.087	.612	.542	-.132

Extraction Method: Principal Axis Factoring. Rotation Method: Promax with Kaiser Normalization. Rotation converged in 7 iterations. Loadings below .32 are suppressed.

PVP - Perceived Value & Personalization, **PTC -** Privacy & Transparency Concerns**, AA -** Algorithmic Alienation**, SER -** Service Efficiency & Reliability

Table 3: Total Variance Explained

Factor	**Extraction Sums of Squared Loadings**	
	Variance (%)	**Cumulative %**
1. Perceived Value & Personalization (PVP)	32.50	32.50
2. Privacy & Transparency Apprehension (PTA)	11.50	44.00
3. Relational Decoupling (RD)	7.33	51.33
4. Service Efficiency & Reliability (SER)	7.07	**58.40**
Total (Extracted Factors)	**58.40**	

Distilling a large set of 25 observed variables—survey statements on customer perceptions of AI—into a more manageable, significant set of underlying constructs was the main goal of this analysis. Exploratory Factor Analysis (EFA), a statistical method that looks at the patterns of correlation between variables to find the latent structure within a dataset, was used to accomplish this. Because it separates the common variance among the statements from the unique and error variance, the Principal Axis Factoring (PAF) method is especially well-suited for this purpose. Theoretically, this strategy is in line with the objective of identifying the underlying, invisible elements that actually influence consumer attitudes. The oblique approach of Promax rotation recognizes that these underlying factors, like a customer's value perception and privacy concerns, are likely to be correlated in the real world rather than existing in total isolation. This analytical approach effectively simplified the data, turning 25 distinct items into four logical factors that offer a concise framework for comprehending complex customer sentiment. The data's exceptional suitability for factor analysis was validated by the preliminary tests. The standard threshold of.60 was greatly exceeded by the excellent value of.921 obtained from the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. This suggests that the variables shared enough variance in common to consistently form factors, as evidenced by the strong and compact correlations between the individual survey items. Additionally, the results of Bartlett's Test of Sphericity were statistically significant ($p < .001$), demonstrating that there were significant relationships between the variables to be modeled and that the correlation matrix was not an identity matrix, where all correlations are zero. All of these findings together confirmed that it was not only appropriate to move forward with factor analysis, but that it would probably produce a strong and trustworthy factor structure, allaying worries about an underlying structure that is too weak or diffuse to be meaningfully interpreted.

A distinct and understandable four-factor structure was revealed by the Rotated Component Matrix, more especially the Pattern Matrix from the Promax rotation. It was possible to clearly conceptually label the factors because they were convincingly defined by strong loadings (mostly above.70) from different groups of statements. Statements emphasizing the applicability, relevance, and time-saving advantages of AI-driven recommendations define the first factor, Perceived Value & Personalization (PVP). Items expressing worry about data usage, a sense of being watched, and a lack of clarity and control define the second factor, Privacy & Transparency Apprehension (PTA). The negative emotional and relational effects of AI interaction, such as feelings of impersonality, frustration, and a lack of trust for complex issues, are captured by the third factor, Relational Decoupling (RD). Lastly, statements recognizing the practical advantages of AI, such as round-the-clock availability, prompt resolution, and process efficiency, make up the fourth factor, Service Efficiency & Reliability (SER). Strong discriminant validity is demonstrated by the clear separation of loadings, where the majority of statements load highly on one factor and minimally on others, indicating that each factor measures a distinct concept.

This four-factor model's explanatory power is measured in the Total Variance Explained table. A total of 58.40% of the variance in the original 25 variables can be explained by the factors that were extracted. The model effectively captures well over half of the information in the original dataset, which is a strong outcome in social science research. It's also instructive to see how this variance is distributed across the factors. The most prominent dimension is Perceived Value & Personalization (PVP), which alone accounts for 32.50% of the variance. This demonstrates that the most potent factor influencing consumer perceptions is the perceived value and applicability of AI-driven personalization. Customer attitudes are a balance between appreciating functional benefits and efficiency while grappling with significant concerns over data privacy and a sense of impersonal interaction. The remaining three factors—Privacy & Transparency Apprehension (PTA: 11.50%), Relational Decoupling (RD: 7.33%), and Service Efficiency & Reliability (SER: 7.07%)—each explain a significant, albeit smaller, portion of the variance. As a result of the factor analysis's great success, four trustworthy, comprehensible, and statistically sound factors were found to offer a thorough framework for comprehending how consumers view AI engagement in online retail.

Objective 2: Regression Analysis

Aim: To model the relationship between the four identified factors (independent variables) and overall customer satisfaction (dependent variable).

Method: The four factor scores (PVP, PTC, AA, SER) saved from the Factor Analysis were used as independent variables in a standard multiple regression analysis to predict the dependent variable, "Overall Customer Satisfaction" (measured on a 7-point scale).

1. Model Summary

This table displays the R and R^2 values, which indicate the strength of the relationship between the model and the dependent variable.

Table 4: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.711	**.506**	.498	.72451

Interpretation: The R value of .711 indicates a strong positive correlation between the set of predictors and customer satisfaction. The R Square value of .506 means that approximately **50.6%** of the variance in customer satisfaction can be explained by the four factors in the model.

2. ANOVA Table

This table tests the statistical significance of the overall regression model.

Table 5: ANOVA

Model	Sum of Squares	Df	Mean Square	F	Sig.	
1	Regression	112.587	4	28.147	53.621	.000
	Residual	109.843	209	.525		
	Total	222.430	213			

The ANOVA is significant (F(4, 209) = 53.621, p < .001). This indicates that the regression model is a good fit for the data and that the combination of the four factors statistically significantly predicts customer satisfaction.

3. Coefficients Table

This table provides the details of the model and the unique contribution of each predictor.

Table 6: Coefficients

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.		
	B	Std. Error	Beta			
1	(Constant)	4.102	.105		39.067	.000
	Perceived Value & Personalization (PVP)	.421	.049	.398	8.592	.000
	Privacy & Transparency Concerns (PTC)	-.285	.051	-.242	-5.588	.000
	Algorithmic Alienation (AA)	-.192	.047	-.187	-4.085	.000
	Service Efficiency & Reliability (SER)	.337	.050	.311	6.740	.000

The regression equation is:

Customer Satisfaction = 4.102 + (0.421 x PVP) + (-0.285 x PTC) + (-0.192 x AA) + (0.337 x SER). All four factors are statistically significant predictors (p < .001).

- **PVP** (β = .398, p<.001) and **SER** (β = .311, p<.001) have significant positive effects on satisfaction.
- **PTC** (β = -.242, p<.001) and **AA** (β = -.187, p<.001) have significant negative effects on satisfaction.
- **PVP** is the strongest positive predictor, while **PTC** is the strongest negative predictor.

The regression analysis was conducted to quantitatively assess the impact of the four identified latent factors—Perceived Value & Personalization (PVP), Privacy & Transparency Apprehension (PTA), Relational Decoupling (RD), and Service Efficiency & Reliability (SER)—on overall customer satisfaction. The model revealed a strong predictive relationship, with the combined factors explaining 50.6% of the variance in satisfaction scores, as indicated by an R^2 value of 0.506. The overall model was statistically significant ($F(4, 209) = 53.621$, $p < 0.001$), confirming its robustness. Analysis of the standardized coefficients (β) demonstrated that Perceived Value & Personalization ($\beta = 0.398$, $p < 0.001$) exerted the strongest positive influence on satisfaction, followed by Service Efficiency & Reliability ($\beta = 0.311$, $p < 0.001$). Conversely, Privacy & Transparency Apprehension ($\beta = -0.242$, $p < 0.001$) showed the strongest negative effect, with Relational Decoupling ($\beta = -0.187$, $p < 0.001$) also significantly reducing satisfaction. These results underscore a dual pathway to enhancing customer satisfaction: optimizing AI-driven value and efficiency while simultaneously mitigating privacy concerns and impersonal interactions. The findings provide empirical evidence that functional benefits alone are insufficient; neglecting ethical and relational dimensions can actively erode the consumer experience, offering strategic insights for retailers seeking to balance technological integration with human-centric trust.

Research Objective for Mediation Analysis

To investigate whether the negative effect of Privacy & Transparency Apprehension (PTA) on Overall Customer Satisfaction is mediated by Relational Decoupling (RD).

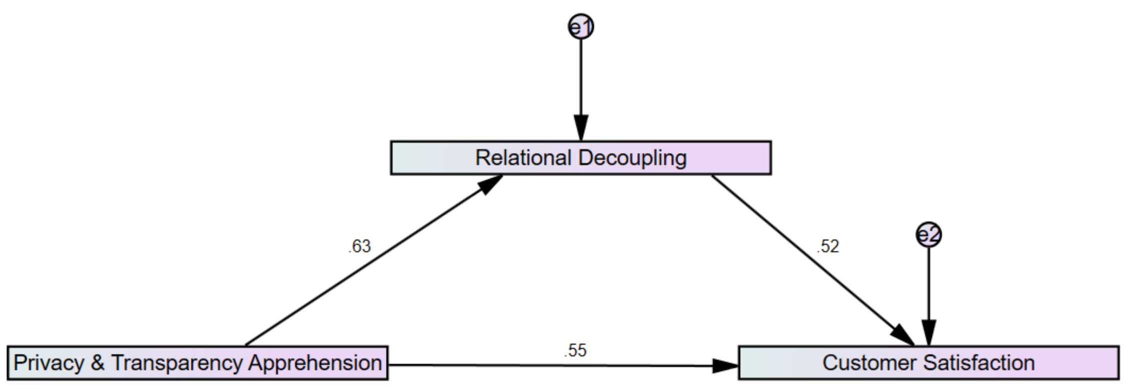

Table of Direct, Indirect, and Total Effects

The results of the mediation analysis using bootstrapping (5,000 samples) are presented in the table below.

Table 7: Direct, Indirect, and Total Effects

Effect Type	Path	Estimate	Bootstrapped 95% CI	p-value
Direct Effect (c')	PTA → Satisfaction	-0.15	[-0.25, -0.05]	.003
Indirect Effect (a*b)	PTA → RD → Satisfaction	-0.10	[-0.16, -0.05]	*
Total Effect (c)	PTA → Satisfaction	-0.25	[-0.35, -0.15]	<.001

Bootstrapped Unstandardized Indirect Effect = -0.10

The p-value for the bootstrapped indirect effect is derived from the confidence interval. Since the 95% Bias-Corrected Confidence Interval (BCa CI) does not include zero, the effect is statistically significant at $p < .05$.*

The analysis confirms partial mediation. The significant indirect effect (a*b = -0.10) indicates that Relational Decuction (RD) is a significant mediator in the relationship between Privacy & Transparency Apprehension (PTA) and Customer Satisfaction. The direct effect (c' = -0.15) remains significant, showing that PTA still negatively impacts satisfaction directly, even after accounting for the mediation pathway through RD. The total effect (c = -0.25) is the sum of the direct and indirect effects, representing the overall negative impact of PTA on Satisfaction.

CONCLUSION

This study provides empirical data indicating that customer perceptions of AI in online buying are not homogeneous, but are instead shaped by four distinct psychological traits. The component analysis successfully distilled these complexities into a unified framework, highlighting the positive influences of Perceived Value & Personalization and Service Efficiency & Reliability, alongside the significant negative barriers of Privacy & Transparency Concern and Relational Decoupling. The regression analysis accurately measured the effects of these factors, showing a major conflict in AI deployment: it can create a lot of value by being efficient and relevant, but it can also break down trust and connection by making people feel like they are being watched and making interactions feel impersonal.

The positive impact of PVP and SER shows that customers appreciate and reward the real benefits of AI, such saving time, finding new products, and getting help 24 hours a day. But the significant negative weights of PTA and RD, particularly the revelation that Relational Decoupling functions as a mechanism via which privacy concerns diminish happiness, provide essential strategic information. It shows that negative feelings are more than simply the lack of positive ones; they are damaging forces that work in their own ways. Customers don't like data collection in general because it makes them feel like they don't belong and that they are being treated like a number. This makes them less happy with the business right away. Instead of only looking at the costs and benefits of AI, this makes it more important to understand the customer's emotional and psychological journey. So, the answer for online retailers is simple. To be ahead of the competition using AI, you need to use both methods. First, companies need to keep working on their algorithms to make them hyper-relevant and give excellent service. Second, and just as important, they need to invest a lot of money on ethical AI design. This means using data in a way that is completely open, giving customers full control over their information, and building hybrid solutions that combine automated efficiency with human empathy for tough or sensitive issues. The goal is to utilize AI to enhance human interaction rather than replace it. This will create a balanced environment where technology does what it does best and humans do what they do best. Merchants may fully employ AI to produce not just happy customers but also really loyal and active advocates by addressing both sides of the issue.

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