

The Influence of AI-Driven Factors on Customer Satisfaction and Loyalty in E-commerce: A Case Study of Taobao Users in China

อิทธิพลของปัจจัยที่ขับเคลื่อนด้วย AI ต่อความพึงพอใจและความภักดีของลูกค้าในอีคอมเมิร์ซ:
กรณีศึกษาของผู้ใช้ Taobao ในประเทศจีน

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Abstract

This research, distant from the ubiquitous siloed AI scenario, investigates how customer satisfaction and loyalty are jointly shaped by different AI-driven factors in B2C e-commerce. We conducted a cross-sectional online survey through the Wenjuanxing platform, collecting data from 405 active Taobao users in China. A 5-point Likert scale was employed to measure the instrument; content validity was assessed using IOC values (0.67–1.00); and reliability for each construct was confirmed with Cronbach's alpha > 0.83. Proposed hypotheses were tested using Pearson correlation and multiple linear regression. The results demonstrated that perceived synergistic AI personalization (PSAP), perceived warmth (PW), perceived procedural value (PPV), AI competence (AIC), and information quality (IQ) all had significant positive effects on CS; and PSAP and TAI significantly predicted CL. PSAP ($\beta = 0.170$, $p < 0.001$) was the dominant predictor of customer satisfaction, with PW ($\beta = 0.147$, $p < 0.01$), IQ ($\beta = 0.145$, $p < 0.01$), PPV ($\beta = 0.144$, $p < 0.01$), and AIC ($\beta = 0.119$, $p < 0.04$); for exploratory behavior, PSAP ($\beta = 0.263$, $p < 0.001$) and TAI ($\beta = 0.240$, $p < 0.001$). From an applied perspective, the results suggest that Taobao and other AI-backed commerce platforms should pursue closer integration of chatbots and recommendation systems, plan for more personable and transparent AI interactions, and elevate trust-building features including clearer policies on data usage and human escalation as first-order drivers of long-term loyalty.

Keywords: AI Personalization, Customer Satisfaction, Customer Loyalty, Trust in AI, E-Commerce

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บทคัดย่อ

งานวิจัยนี้มีวัตถุประสงค์เพื่อศึกษาถึงปัจจัยขับเคลื่อนด้วยปัญญาประดิษฐ์(AI)แต่ละประเภทที่ส่งผลร่วมกันอย่างไรต่อความพึงพอใจและความภักดีของลูกค้าในธุรกิจอีคอมเมิร์ซ B2C โดยงานนี้แตกต่างจากแนวคิดเดิมที่มีมุมมองการทำงานของ AI แบบแยกส่วน (AI Silos) ผู้วิจัยเก็บรวบรวมข้อมูลด้วยการสำรวจออนไลน์แบบภาคตัดขวางผ่านแพลตฟอร์ม Wenjuanxing จากกลุ่มตัวอย่างที่เป็นผู้ใช้ Taobao ในจีนที่มีการใช้งานต่อเนื่อง จำนวน 405 ราย เครื่องมือที่ใช้คือแบบสอบถามมาตรวัดลิเคิร์ต 5 ระดับ ซึ่งผ่านการตรวจสอบคุณภาพแล้ว โดยมีค่าดัชนีความสอดคล้อง (IOC) อยู่ระหว่าง 0.67–1.00 และค่าสัมประสิทธิ์แอลฟาของครอนบาค (Cronbach's Alpha) สูงกว่า 0.83 ในทุกด้าน แสดงให้เห็นถึงความตรงและความเชื่อมั่นที่ดี สถิติที่ใช้ทดสอบสมมติฐาน ได้แก่ ค่าสหสัมพันธ์แบบเพียร์สัน และการวิเคราะห์การถดถอยเชิงเส้นพหุคูณ

ผลการวิจัย ปัจจัยที่มีอิทธิพลเชิงบวกต่อความพึงพอใจของลูกค้าอย่างมีนัยสำคัญ ได้แก่ การรับรู้การปรับแต่งเฉพาะบุคคลด้วย AI (PSAP), การรับรู้ความอบอุ่น (PW), การรับรู้คุณค่าเชิงกระบวนการ (PPV), ความสามารถของ AI (AIC) และคุณภาพของข้อมูล (IQ) โดยตัวแปรที่มีอิทธิพลสูงสุดคือ PSAP ($\beta = 0.170, p < .001$) รองลงมาคือ PW ($\beta = 0.147$), IQ ($\beta = 0.145$), PPV ($\beta = 0.144$) และ AIC ($\beta = 0.119$) ตามลำดับ ส่วนปัจจัยที่สามารถทำนายความภักดีของลูกค้าได้อย่างมีนัยสำคัญมีเพียง 2 ตัวแปร คือ PSAP ($\beta = 0.263, p < .001$) และความไว้วางใจใน AI หรือ TAI ($\beta = 0.240, p < .001$)

คำสำคัญ: การปรับแต่งเฉพาะบุคคลด้วย AI, ความพึงพอใจของลูกค้า, ความภักดีของลูกค้า, ความไว้วางใจใน AI, อีคอมเมิร์ซ

Introduction

AI Personalization, Customer Satisfaction, Customer Loyalty, Trust In AI, E-Commerce. The international e-commerce industry has continued to grow at an incredibly quick pace. Industry-wide estimates put 2025 global retail e-commerce sales at around USD 6.9 trillion, with the figure expected to surpass USD 8 trillion by 2027 (Statista, 2024; eMarketer, 2024). This rapid growth has driven increased competition among online platforms, shifting the basis of differentiation from price and assortment to a customized customer experience. AI, particularly in the form of conversational agents and recommendation systems, has now become a means to make this personalization a reality – it enables high-volume behavioral data analysis and allows for customization of interactions almost in real time.

Despite this widespread adoption, a persistent limitation remains in how AI technologies are deployed in practice. Chatbots are typically optimized for conversational support and problem resolution, while recommendation engines emphasize predictive accuracy. The two systems rarely share state. We refer to this fragmented deployment as the siloed AI problem, in which independently operating AI components fail to learn from one another, thereby delivering disjointed experiences for the customer. The academic literature mirrors this fragmentation: prior studies tend to examine AI applications in isolation—chatbot efficiency on the one hand, recommendation accuracy on the other—without considering how integrating multiple AI systems can generate compounded value (Adam et al., 2021; Huang & Rust, 2021). The multidimensional nature of AI-enabled customer experience encompassing functional performance, procedural fairness, and emotional connection therefore remains underexplored, and theoretical frameworks suited to explaining such holistic value creation, including Service-Dominant Logic (Vargo & Lusch, 2016) and the Three-Layer Value Pyramid (Wang & Prompanyo, 2020), have not yet been fully leveraged in AI-driven e-commerce.

There are several distinct gaps in this fractured landscape. First, although the idea of perceived synergistic AI personalization—the complementary interaction between chatbots and recommendation systems—has been identified, more empirical study is required to determine its impact on actual consumer happiness and loyalty (Riemer & Peter, 2021). Second, the significance of perceived warmth in AI interactions—examined through social cognition theory, based on human-AI interaction research—in providing users with peaceful comfort (Kim et al., 2022) and adequate comprehension in an e-commerce scenario has not yet been fully investigated. Third, the effectiveness, openness, and equity of procedural aids in AI-enabled service delivery have received less attention than outcome-based evaluations (Shin, 2021). Fourth, although data quality and AI process competency are regarded as functional qualities (DeLone & McLean, 2016; Huang & Rust, 2021), their combined impact in an all-encompassing multi-dimensional model has not been examined. Finally, because of the ethical and comparative aspects of AI-mediated space, the direct and independent impact of confidence in AI on loyalty would require careful examination (Glikson & Woolley, 2020; Lankton et al., 2015).

In response to these gaps, this study offers an integrated view of AI-enabled personalization. Instead of assessing individual AI tools in isolation, it examines customers' responses to synergistic AI personalization the combined functionality of chatbots and recommendation systems that yield frictionless, personalized, and contextualized experiences. Besides, the study devises a detailed customer satisfaction-and-loyalty model comprising socio-relational factors (perceived warmth, procedural value, and trust in AI) as well. The research seeks to provide empirical testing of this model and contribute to the theoretical understanding of how AI alters consumer outcomes, and also offer practical insights for practitioners involved with AI-powered e-commerce platforms through data from Taobao users in China.

Research Objectives

Based on the identified research gaps, the objectives of this study are as follows:

1. To examine the influence of perceived synergistic AI personalization on customer satisfaction and customer loyalty in B2C e-commerce.
2. To investigate the effects of perceived warmth, perceived procedural value, AI competence, and information quality on customer satisfaction.
3. To analyze the influence of trust in AI on customer loyalty.
4. To develop and empirically validate an integrated multi-dimensional model of AI-driven customer satisfaction and loyalty grounded in Service-Dominant Logic and the Three-Layer Value Pyramid.

Conceptual Framework

Service-Dominant Logic and AI as an Operant Resource

SDL holds that value is not anchored in physical outputs but rather co-created through actor-to-actor interactions (Vargo & Lusch, 2016). Chatbots and recommendation systems are examples of operant resources in AI-powered e-commerce that use data as input and link the customer and algorithmic process to co-create value. Asserting that interactive, adaptive learning across touchpoints is the route to co-creation enabled in intelligent systems, SDL has expanded into digital and AI-enabled services (Hollebeek et al., 2021; Verma et al., 2021). On the other hand, when AI systems are implemented without this form of

coordination, they are rarely able to integrate resources efficiently, and the consumer experience typically seems fragmented.

Siloed AI versus Synergistic AI Personalization

The term "siloe AI" refers to the isolated implementation of distinct AI applications that do not exchange behavioral or contextual data with other deployed AI solutions. Chatbots and recommendation systems, treated as separate processes, have been the main focus of prior research on the use of AI in e-commerce (Adomavicius & Tuzhilin, 2005; Adam et al., 2021). These studies show improvements in individual performance, but they largely ignore coordination across AI systems, which can increase perceived value. According to a second study focused on digital transformation, in order to enhance customer experience, connected personalization necessitates coupled and amplified integration across the technologies (Edelman & Abraham, 2022; Riemer & Peter, 2021). The current study expands on this idea by examining perceived synergistic AI personalization as a separate consumer impression. Thus, this research suggests:

H1: Perceived synergistic AI personalization has a positive effect on customer satisfaction.

H2: Perceived synergistic AI personalization has a positive effect on customer loyalty.

Functional Value: AI Competence and Information Quality

Functional Value: This is about utility: how well this performs a task and whether it looks quite decent while doing it or not. AI competence in AI-mediated environments is the perceived ability of an AI system to do a variety of activities competently, while information quality is the objective quality (DeLone & McLean, 2016). Good recommendations and good responses minimize the effort for decision-making and increase perceived utility. AIX and IQ are also acknowledged as key value drivers of customer satisfaction in online service research (Huang & Rust, 2021; Pillai et al., 2020). Wherefore:

H3: AI competence has a positive effect on customer satisfaction.

H4: Information quality has a positive effect on customer satisfaction.

Procedural Value and AI-Enabled Service Processes

Procedural value refers to the quality of the service process rather than the final result. It mainly involves whether the process is efficient, open, and fair to customers (Parasuraman et al., 2005). In AI-based e-commerce platforms, procedural value is reflected in how quickly the system responds, whether the process is easy to understand, and whether customers receive a stable and consistent service experience. Studies have shown that when AI systems work in unclear or inconsistent ways, customers may feel the process is unfair, which can reduce their satisfaction (Shin, 2021; Lee, 2018). However, when the process is simple, organized, and transparent, customers are more likely to understand how the system works, feel less uncertain, and complete their shopping more comfortably (Schäfer et al., 2019). So:

H5: Perceived procedural value has a positive effect on customer satisfaction.

Emotional Value, Perceived Warmth, and Trust in AI

This emotional value is the feelings that are obtained from interpersonal service interaction. Social agents are assessed on their qualities and behaviors across two key dimensions: warmth and competence (Fiske et al., 2007). Previous studies have shown that in human-AI interaction, perceived warmth through polite language (e.g., polite advice), empathy (e.g., expressing sympathy with the user), and human-like tendencies (e.g., a smiling face) significantly improve user comfort and satisfaction with AI use. Previous research related to conversational AI suggests that a friendlier communication style can often lead to a

higher overall perceived service quality and satisfaction after the encounter (Kim et al., 2022; Roy & Naidoo, 2021). AI trust, through reducing perceived risk and relational commitment online, improves emotional value (Gefen et al., 2003; Glikson & Woolley, 2020). Perceived warmth and trust are two of the most crucial elements in making AI-driven experiences turn into long-term consumer loyalty. As a result:

H6: Perceived warmth has a positive effect on customer satisfaction.

H7: Trust in AI has a positive effect on customer loyalty.

The proposed conceptual framework is presented in Figure 1.

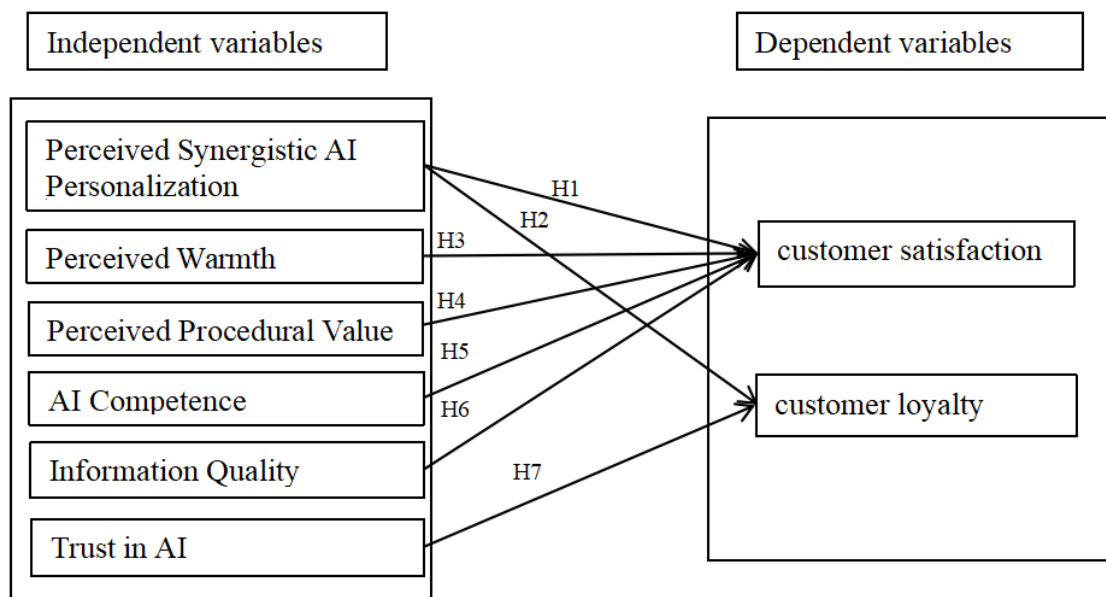


Figure 1: Conceptual Framework

Research Methodology

Research Design and Sample

The hypotheses were tested using a quantitative survey design with a cross-sectional approach. The sample was active B2C e-commerce consumers in mainland China who had experience using AI tools on the Taobao platform. As per the latest annual report of the operator (Alibaba Group, 2024), Taobao has more than 900 million monthly active users in China. Based on the platform engagement statistics, the population eligible for this study, i.e., those who actively interacted with either or both of Taobao's chatbots and recommendation algorithms, was estimated to be around 600 million users. Eligibility requirements were: (1) Aged 18–60 years; (2) made at least three transactions on Taobao in the last six months; (3) used Taobao's chatbots and/or recommender systems in the last three months.

The minimum sample size was determined using the Yamane (1973) formula at a 95% confidence level and a 5% margin of error, giving a required minimum of 400. The recruitment approach was based on convenience sampling. Convenience sampling was chosen because a complete sampling frame of eligible Taobao users is not publicly accessible, and because the research is directed at a population that is already

inherently active online. Convenience sampling has been broadly endorsed in similar e-commerce/digital-services research where probability sampling is not viable (Etikan et al., 2016). To address the known limitations of this technique, we intentionally broadened recruitment across multiple Chinese social-media channels (WeChat, Weibo, and Xiaohongshu), posted invitations at various times of the day to capture different user segments, and used screening questions to verify eligibility prior to respondents entering the main survey. The questionnaire was administered online in Q4 2025 via the Wenjuanxing platform; the use of a unique-link method prohibited multiple submissions, and respondents who failed any screening question were immediately filtered out of the survey. After the data cleaning process, 405 valid replies were kept for analysis.

Measurement and Instrument

All constructs were measured with multi-item measures adapted from the extant literature and minimally adjusted to the e-commerce environment. Responses were recorded on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Items on Perceived Synergistic AI Personalization (PSAP) were adopted from Riemer and Peter (2021) and Adam et al. (2021). Items measuring perceived warmth (PW) were derived from Fiske et al. (2007) and Kim et al. (2022). Items measuring perceived procedural value (PPV) were modified from Parasuraman et al. (2005) and Shin (2021). Items for AI competency (AIC) and information quality (IQ) were adapted from DeLone and McLean (2016) and Huang and Rust (2021). Items for TAI were modified from Lankton et al. (2015) and Glikson and Woolley (2020). The items of customer satisfaction (CS) and customer loyalty (CL) were adapted from Wang and Prompanyo (2020) and Oliver (1999). The questionnaire comprised: (1) screening items to verify eligibility; (2) core construct scale PSAP (4 items), PW (4 items), PPV (4 items), AIC (4 items), IQ (4 items), TAI (4 items), CS (4 items), CL (4 items); and (3) a demographic section (age, education, shopping frequency). Sample items include: "The chatbot and recommendation system on Taobao work well together to understand my needs" (PSAP) and "The AI interactions on Taobao feel friendly and approachable" (PW).

Reliability and Validity Assessment

The Item-Objective Congruence (IOC) Index, with a minimum value of 0.50 as recommended by Rovinelli and Hambleton (1977), was used to assess the item content validity, in which each item was rated by three subject-matter experts, and both together were retained at a value of 0.5 or higher. The resulting IOC values ranged from 0.67 to 1.00, with an overall mean of 0.81. Cronbach's alpha revealed internal consistency reliability was satisfactory, as all construct values exceeded 0.83, avoiding the normal threshold of 0.70 proposed by Nunnally and Bernstein (1994).

A principal component analysis with varimax rotation exploratory factor analysis (EFA) was performed to confirm the construct structure. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was acceptable (0.799), and Bartlett's test of sphericity also indicated that the data in this instance were appropriate for factor analysis ($\chi^2 = 6,981.200$; $df = 496$; $p < 0.001$), suggesting the adequacy of data for factor analysis (Hair et al., 2019). The exploratory factor analysis (EFA) produced a clean eight-factor solution corresponding to the expected theoretical model and explained 67.4% of cumulative variance. All items loaded above 0.71 on the intended factors, with no cross-loadings exceeding 0.40, confirming both convergent and discriminant validity. Table 1 shows the EFA results in detail.

Table 1: Exploratory Factor Analysis Results

Construct	No. of Items	Loading Range	Eigenvalue	% Variance	Cumulative %	Cronbach's α
PSAP	4	0.781 – 0.852	4.21	13.16	13.16	0.871
PW	4	0.762 – 0.834	3.07	9.59	22.75	0.851
PPV	4	0.755 – 0.829	2.78	8.69	31.44	0.844
AIC	4	0.748 – 0.821	2.62	8.19	39.63	0.836
IQ	4	0.741 – 0.819	2.49	7.78	47.41	0.832
TAI	4	0.736 – 0.812	2.31	7.22	54.63	0.838
CS	4	0.728 – 0.808	2.15	6.72	61.35	0.851
CL	4	0.713 – 0.802	1.93	6.03	67.38	0.847

Note: KMO = 0.799; Bartlett's test $\chi^2 = 6,981.200$ (df = 496), $p < 0.001$.

Research Results

Sample Profile and Analytical Strategy

Data analysis was performed using SPSS in a systematic multi-stage process: (1) descriptive statistics to profile the sample; (2) Pearson correlation analysis to examine bivariate relationships among variables; and (3) two multiple linear regression analyses to test the hypotheses. The first regression used CS as the dependent variable with PSAP, PW, PPV, AIC, and IQ as predictors (testing H1, H3, H4, H5, H6); the second used CL as the dependent variable with PSAP and TAI as predictors (testing H2 and H7).

The sample was dominated by young, educated, and experienced Taobao users: 41.98% were aged 26–30; 59.75% held a bachelor's degree or higher; and 77.53% had used Taobao for more than seven years. This profile is consistent with the core user base of AI-integrated platforms in China.

Table 2 shows the descriptive statistics for the eight variables in this study. As all means lie above the scale midpoint (3.00), ranging from 3.84 to 4.06 on a five-point Likert-type scale, this indicates that respondents hold overall positive perceptions of Taobao's AI-enabled service. Standard deviations range from 0.62 to 0.74, suggesting a moderate level of variation, while skewness/kurtosis are within ± 1 , which provides support for the assumption of approximate normality for parametric analyses (Hair et al., 2019).

Table 2: Descriptive Statistics of All Study Variables (n = 405)

Variable	Mean	SD	Min	Max	Interpretation
PSAP	4.06	0.62	1	5	High
PW	3.92	0.68	1	5	High
PPV	3.97	0.65	1	5	High
AIC	3.89	0.71	1	5	High
IQ	3.95	0.66	1	5	High
TAI	3.84	0.74	1	5	High
CS	4.01	0.63	1	5	High
CL	3.96	0.69	1	5	High

Note: Means in the range 3.41–4.20 are interpreted as "High" on the 5-point Likert scale.

Correlation Analysis

Pearson correlation coefficient results in Table 3 revealed significant positive correlations ($p < 0.01$) between all independent variables and the dependent variables (CS and CL), providing preliminary support for the hypothesized relationships. PSAP, for example, was significantly correlated with both CS ($r = 0.254$) and CL ($r = 0.283$), and CS and CL were positively correlated ($r = 0.259$, $p < 0.01$).

Table 3: Pearson Correlation Matrix

	PSAP	PW	PPV	AIC	IQ	TAI	CS	CL
PSAP	1							
PW	0.140**	1						
PPV	0.162**	0.198**	1					
AIC	0.190**	0.132**	0.156**	1				
IQ	0.121*	0.166**	0.137**	0.156**	1			
TAI	0.084	0.225**	0.237**	0.133**	0.132**	1		
CS	0.254**	0.239**	0.239**	0.216**	0.228**	0.242**	1	
CL	0.283**	0.144**	0.234**	0.227**	0.184**	0.262**	0.259**	1

Note: * $p < 0.05$, ** $p < 0.01$.

Hypothesis Testing via Regression Analysis

Determinants of Customer Satisfaction

The regression model with CS as the dependent variable was statistically significant, $F(5, 399) = 16.50$, $p < 0.001$, with an Adjusted R^2 of 0.161 (Table 4). PSAP ($\beta = 0.170$, $p < 0.001$), PW ($\beta = 0.147$, $p < 0.01$), IQ ($\beta = 0.145$, $p < 0.01$), PPV ($\beta = 0.144$, $p < 0.01$), and AIC ($\beta = 0.119$, $p < 0.05$) all had significant positive effects, supporting H1, H3, H4, H5, and H6. Substantively, this implies that for each 1-unit increase in perceived synergistic AI personalization, there is an increase of 0.16 points on the 5-point scale in customer satisfaction when controlling for other variables, and PSAP has the largest standardized effect size among the five predictors. The patterns in the standardized betas show that integrated personalization is the most important factor, but that warmth, information quality, procedural value, and competence all have significant contributions to satisfaction that are roughly similar in size. All VIF values were close to 1, confirming the absence of multicollinearity.

Table 4: Multiple Regression Analysis with Customer Satisfaction (CS) as DV

Predictor	B	Std. Error	Beta	t	p	VIF	Tolerance
Constant	0.740	0.227	–	3.263	0.001**	–	–
PSAP	0.160	0.045	0.170	3.592	0.000**	1.072	0.933
PW	0.150	0.048	0.147	3.110	0.002**	1.079	0.927
IQ	0.144	0.047	0.145	3.082	0.002**	1.062	0.942
PPV	0.139	0.046	0.144	3.039	0.003**	1.082	0.924
AIC	0.118	0.047	0.119	2.516	0.012*	1.077	0.929

$R^2 = 0.171$; Adjusted $R^2 = 0.161$; $F(5, 399) = 16.498$, $p < .001$; Durbin-Watson = 2.146

Note: * $p < 0.05$, ** $p < 0.01$.

Determinants of Customer Loyalty

The regression model with CL as the dependent variable was likewise significant, $F(2, 402) = 31.97$, $p < 0.001$, with an Adjusted R^2 of 0.133 (Table 5). Both PSAP ($\beta = .263$, $p < .001$) and TAI ($\beta = 0.240$, $p < 0.001$) emerged as significant positive predictors, supporting H2 and H7. More specifically, the authors reveal that customers who perceive AI tools on Taobao as working synergistically, and are subsequently more likely to trust those tools, also tend to be significantly more loyal to the platform; integrated personalization shows the largest standardized effect on loyalty of any AI capability evaluated here—implying that in this case at least is better than social proof—suggesting that a combination of complementary/beneficial capabilities drives repeat behavior greater than any individual component examined in this study. VIF values were near 1, indicating no multicollinearity.

Table 5: Multiple Regression Analysis with Customer Loyalty (CL) as DV

Predictor	B	Std. Error	Beta	t	p	VIF	Tolerance
Constant	1.500	0.173	–	8.648	0.000**	–	–
PSAP	0.241	0.043	0.263	5.652	0.000**	1.007	0.993
TAI	0.231	0.045	0.240	5.164	0.000**	1.007	0.993

$R^2 = 0.137$; Adjusted $R^2 = 0.133$; $F(2, 402) = 31.969$, $p < .001$; Durbin-Watson = 1.899

Note: * $p < 0.05$, ** $p < 0.01$.

Table 6: Summary of Hypothesis Testing Results

No.	Hypothesis	β	p-value	Result
H1	PSAP $\rightarrow$ CS	0.170	< 0.001	Supported
H2	PSAP $\rightarrow$ CL	0.263	< 0.001	Supported
H3	AIC $\rightarrow$ CS	0.119	< 0.05	Supported
H4	IQ $\rightarrow$ CS	0.145	< 0.01	Supported
H5	PPV $\rightarrow$ CS	0.144	< 0.01	Supported
H6	PW $\rightarrow$ CS	0.147	< 0.01	Supported
H7	TAI $\rightarrow$ CL	0.240	< 0.001	Supported

Discussion

The findings provide robust support for the integrated multi-dimensional model. Each of the seven hypotheses was supported, and the relative magnitudes of the standardized coefficients are themselves informative.

First, the result that *perceived synergistic AI personalization* is the strongest predictor of both customer satisfaction ($\beta = 0.170$) and customer loyalty ($\beta = 0.263$) directly addresses the siloed AI problem identified in prior research. But, anyway — why is this effect so strong? Another probable reason is that they see chatbots and recommendation systems as one functionality and enjoy a holistic experience with the site. In different AI components, the state is shared in such an avatar; for example, the chatbot could

read that an item is offered as the next recommended, as shown by the recommender, and the customer feels more understood overall, and their satisfaction increases as well. This relational commitment is needed to make loyalty adhere higher. This finding further develops the work by [Edelman and Abraham \(2022\)](#), who theorized the existence of an identifiable driver of customer value greater than backend efficiency, by empirically testing this and taking the Service-Dominant Logic one step further by claiming the AI tool bundle as a co-creating operant resource, not each individual tool.

Second, the findings contribute to Service-Dominant Logic by demonstrating empirically that AI systems provide higher value when used as integrated operant resources rather than separate tools as suggested by [Vargo and Lusch \(2016\)](#). To the best of our knowledge, this is one of the first quantitative demonstrations that an SDL-grounded “AI bundle” perception predicts customer outcomes more strongly than any single AI capability tested individually. This is a theoretical contribution that fills a gap left open by earlier conceptual work on AI in services ([Hollebeek et al., 2021](#)).

Third, the significant effects of AI competence and information quality on satisfaction reinforce the role of functional value in AI-mediated services and align with the [DeLone and McLean \(2016\)](#) information-systems success model. The two effects are roughly equal in magnitude, suggesting that customers do not separate “what the AI knows” from “how well the AI performs tasks” when forming a judgment of satisfaction; they treat both as facets of overall functional competence.

Fourth, the positive impact of perceived procedural value highlights that customers evaluate not only outcomes but also the process by which AI-enabled services are delivered, corroborating service-quality research ([Parasuraman et al., 2005](#); [Shin, 2021](#)). Efficient and transparent procedures appear to lower cognitive load and uncertainty, and so produce more favorable evaluations even when the eventual outcome is the same.

Fifth, the significant role of perceived warmth confirms that emotional value remains important even in automated service encounters. Consistent with social cognition theory ([Fiske et al., 2007](#)), these findings echo prior evidence that human-like, empathetic AI interactions improve user satisfaction ([Kim et al., 2022](#)).

Sixth, the strong effect of trust in AI on customer loyalty ($\beta = 0.240$) underscores trust as a relational mechanism that operates beyond satisfaction. This finding aligns with [Gefen et al. \(2003\)](#) and [Glikson and Woolley \(2020\)](#), reinforcing the view that reliability, security, and transparency are particularly critical for long-term commitment in online B2C environments.

A brief note on the small R^2 values (0.171 for CS and 0.137 for CL) is worth making. While these values are lower than those usually reported in laboratory studies, they are in line with e-commerce studies based on the field, where customer views are affected by many factors such as price, product variety, logistics performance, and social influence that are outside the scope of AI experience and are therefore excluded by design. The low R^2 in this case should not be interpreted as a limitation of the model but rather as a reminder that AI-based factors are just one important set of drivers among others. The substantive significance of the supported effects is retained by their uniform direction and statistical power ([Hair et al., 2019](#)).

Theoretical and Practical Contributions

Theoretical contribution. This paper offers three theoretical contributions. It first engages with the notion of perceived synergistic AI personalization as a construct and provides empirical evidence that customers form a unified perception regarding how well various AI tools perform in unison – which has only been conceptualized but rarely tested. Secondly, it gives its explanation of Service-Dominant Logic as a piecemeal multi-level integrated AI bundle (i.e., no specific singular/narrow/weak-type AI tool is the operant resource for value co-creation in this environment). Third, it combines functional, procedural, and emotional value into a single model to offer an explanation of customer satisfaction and loyalty in AI-mediated services that is situated more holistically than the outcome-centric literature to date. Altogether, these contributions address the research gaps identified in the introduction, particularly that on siloed AI deployment, and connect back to findings with The Three-Layer Value Pyramid (Wang & Prompanyo, 2020).

Practical contribution. The most practical consequence for e-commerce platforms is that integrating components across AI is not a back-office worry but rather a customer-perceived attribute that fosters happiness and loyalty. This means platform administrators should focus on architectural decisions that allow users to see this connection, shared customer state, uniform personalization layers, and consistent dialogue context. The study also identifies particular, lower-cost levers: tweaking the chatbot tone for warmth, revealing the reasons behind algorithmic decisions to promote perceived procedural value, and being transparent with consumers about how AI is utilized and how their data is treated to establish trust.

Conclusion

This study aims to explore how AI-driven factors influence customer satisfaction and loyalty, focusing on Taobao customers in China. We are particularly interested in the value generated when chatbots and recommendation systems work together, rather than independently. The suggested paradigm combines functional, procedural, and emotional drives into one single framework based on Service-Dominant Logic and the Three-Layer Value Pyramid. The empirical results of 405 active Taobao users validate all 7 hypotheses; the best predictor of happiness and loyalty is seen as synergistic AI personalization, and faith in AI reinforces loyalty. This study contributes to the field by giving empirical evidence on synergistic AI personalization as a customer-perceptible phenomenon and extending SDL to AI-driven e-commerce. For practitioners, it emphasizes that integrated AI design that is warm, transparent, and trustworthy is a genuine source of competitive differentiation.

Recommendations

Practical Recommendations

More broadly, e-commerce platforms in China and similar markets need to make integrating chatbots and recommendation systems a strategic priority rather than simply spending too much time on the technical details – shared customer context across them is by far the single biggest lever for both satisfaction and loyalty, this study finds. Secondly, platforms should concentrate on the affective dimension of AI interaction, in particular with regard to conversational design signaling warmth, empathy, and approachability, as warm personality traits were found to have such a high weight when explaining good

encounters. Third, transparency mechanisms (e.g., explanations of why users received those suggestions for improvement or clear escalation paths to human agents using the service and policies governing data use presented clearly) should be deployed to improve perceived procedural fairness and trust. Fourth, customer experience teams should monitor user impressions of AI synergy as an explicit KPI that is separate from the typical happiness or NPS measurements, given the outsized influence it has on loyalty.

Recommendations for Future Research

To test the generalizability beyond the Taobao setting, future studies should test the concept in other platforms and markets beyond China. Second, longitudinal designs would be effective in defining causal direction, notably with respect to trust in AI and loyalty, as well as tracking changes over time between the firm and its consumers following expanded capabilities of AI. Third, the comparatively low R2 values suggest integrating additional constructs (e.g., privacy concerns, perceived AI autonomy, switching costs) and possibly moderators (e.g., generational cohort, past AI experience) into an underlying structural equation model. Fourth, qualitative research methods such as interviews or think-aloud protocols could provide insight into why users regard AI products as “co-working” and assist in finding design clues that lead to this attitude. Future studies may also consider negative or border impacts of AI personalization, such as creepiness, filter bubbles, and algorithm aversion, for instances that go beyond the current investigation but are becoming more prominent in the literature.

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