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The Personalization Paradox in AI-Driven Tourism E-Commerce: Psychological Reactance, Threat-Substitution, and the Moderating Role of Privacy Concerns

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Abstract

AI-driven personalization (AIP) has become a core mechanism of digital commerce platforms, yet its psychological consequences remain theoretically fragmented. Drawing on the Stimulus–Organism–Response (SOR) framework and Psychological Reactance Theory (PRT), this study proposes a Threat-Substitution Mechanism (TSM) to explain how AIP shapes continuance intention in high-involvement online travel decisions. Using survey data from 488 Generation Y and Z users of Chinese online travel agencies and analyzing the model via PLS-SEM, results show that AIP significantly increases usage intention (UI) and reduces psychological reactance. Psychological reactance partially mediates the relationship between AIP and UI, indicating the presence of underlying psychological friction alongside dominant utilitarian benefits. Furthermore, privacy concerns amplify the negative relationship between AIP and reactance, suggesting that privacy-sensitive users exhibit heightened appraisal sensitivity rather than uniform resistance to personalization. By reconceptualizing the personalization paradox as a context-contingent threat appraisal process, this study advances electronic commerce research beyond parallel dual-effect models and clarifies the boundary conditions under which AIP enhances or constrains user continuance. Practical implications highlight the importance of algorithmic precision and autonomy-supportive design in AI-enabled commerce platforms.

Keywords: AI personalization; psychological reactance; privacy concerns; usage intention; tourism e-commerce; Stimulus–Organism–Response (SOR); Threat-Substitution Mechanism (TSM)

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1. Introduction

Artificial intelligence (AI) technologies have rapidly permeated contemporary service ecosystems, transforming firm–consumer interactions across industries [1]. In tourism and electronic commerce, AI-powered systems enable real-time recommendation, dynamic pricing, conversational assistance, and predictive analytics at scale [2]. Algorithmic recommendation engines are now embedded in digital travel platforms, curating hotels, destinations, and itineraries tailored to individual users [3]. Yet user acceptance of AI-driven services is far from uniform. Although Generation Y and Generation Z are often described as digitally native and technologically proficient, empirical evidence reveals considerable heterogeneity in their responses, shaped by privacy sensitivity, perceived surveillance, and varying levels of digital competence [4,5]. These cohorts may value

efficiency while remaining alert to data exploitation risks, producing ambivalent cognitive and emotional reactions toward personalization [4,6]. Despite its rapid diffusion, the psychological implications of AI-driven personalization remain only partially explained in tourism research. Environmental psychology suggests that technological stimuli influence behavior through internal cognitive and affective states [7], whereas motivational perspectives indicate that perceived threats to autonomy can trigger defensive resistance [8]. This tension highlights the need to examine both the enabling and constraining psychological mechanisms involved in AI-mediated tourism contexts.

AI personalization (AIP), defined as a system's capacity to analyze user data and deliver preference-matched, contextually relevant, and predictively accurate recommendations [9], is a central mechanism through which tourism platforms enhance user experience by filtering information, reducing search costs, and improving decision efficiency [10]. These advantages are especially salient in high-involvement tourism decisions characterized by financial risk, experiential uncertainty, and information overload [11,12]. At the same time, such functional benefits do not preclude negative psychological interpretations. Existing studies have largely emphasized positive outcomes, particularly user satisfaction and trust [10,13], while giving less attention to the possibility that highly tailored recommendations may also evoke perceptions of reduced autonomy or algorithmic encroachment [14]. This tension gives rise to the personalization paradox in tourism contexts.

As understood in the present study, the personalization paradox refers to the coexistence of utilitarian benefits and autonomy-related psychological friction in AI-driven personalization [12,15]. These positive and negative responses are not necessarily equally strong; rather, their relative salience depends on how users appraise personalization in context. Existing tourism research has not sufficiently clarified how this appraisal process unfolds in high-involvement decisions. This gap motivates the present study to adopt a process-based perspective centered on the Threat-Substitution Mechanism (TSM). By integrating the SOR framework with PRT through TSM, this study explains how users appraise competing concerns of autonomy loss and decision uncertainty in high-involvement tourism decisions. This approach clarifies when utilitarian benefits outweigh autonomy-related friction. To address this gap, the present study examines AI recommendation systems implemented by major Chinese online travel agencies (OTAs), including Ctrip, Tongcheng, Qunar, and Fliggy. These platforms provide personalized itinerary suggestions, hotel bookings, attraction tickets, and ancillary services based on users' historical behaviors and inferred preferences. This context is especially suitable because China's tourism market is highly digitalized, and Generation Y and Generation Z users increasingly favor technology-mediated and personalized travel experiences [16–19]. At the same time, rising privacy awareness has created a distinctive tension in which users willingly exchange personal data for convenience while expressing growing concern about surveillance and algorithmic inference. Chinese OTA platforms therefore provide a fertile setting for examining how AIP is appraised in high-involvement tourism environments.

Understanding these mechanisms is valuable for both practitioners and policymakers. For tourism firms, clarifying how personalization simultaneously enhances and constrains continued usage intention (UI) can inform algorithm design strategies that balance efficiency and perceived autonomy. For regulators, insights into privacy-related sensitivities can support governance frameworks that encourage innovation while safeguarding consumer rights. To examine these dynamics, this study adopts the SOR framework [7] and integrates it with PRT [8]. The SOR framework provides the general process structure through which environmental stimuli shape internal psychological states and subsequent behavioral responses. It is particularly relevant because AIP functions not merely as a technological feature but as a service stimulus that triggers internal appraisals before shap-

ing continued usage intention. PRT complements this logic by specifying the defensive pathway triggered by perceived autonomy threat. Compared with broader technology acceptance frameworks, the SOR-PRT combination is better suited to explaining the personalization paradox as a context-contingent appraisal process in which utilitarian support and autonomy-related concern coexist, while privacy concerns function as a boundary condition shaping users' sensitivity to personalization cues.

Accordingly, two main research questions are proposed:

RQ1: How does AIP simultaneously shape utilitarian enhancement and psychological resistance pathways in high-involvement tourism decisions, and how do these competing mechanisms jointly influence continued UI among Generation Y and Z users?

RQ2: Under what conditions do PCs amplify the reactance-related appraisal of AIP, and how does this moderated process influence UI?

This study contributes to the literature in four ways. First, it clarifies the theoretical indeterminacy of the personalization paradox in tourism by explaining how AIP may simultaneously evoke utilitarian support and autonomy-related friction in high-involvement contexts. Second, it develops the TSM as a process-based explanation of how users appraise competing concerns, namely decision uncertainty and autonomy loss. By centering the model on psychological reactance while acknowledging the existence of complementary mechanisms such as trust, transparency, and perceived control, this study offers a focused yet extensible account of how users weigh competing threats in high-involvement tourism decisions. Third, it identifies PC as a boundary condition that sharpens users' sensitivity to personalization quality rather than functioning as a uniform inhibitor of acceptance. Fourth, it suggests that the personalization paradox may take an asymmetrical and context-dependent form in which utilitarian benefits are more prominent while autonomy-related friction persists as a residual constraint. Practically, these findings provide guidance for designing AI systems that balance algorithmic precision with perceived user agency and for calibrating personalization intensity to decision context and user psychology on digital tourism platforms.

2. Literature Review and Related Work

2.1. The Dual-Faceted Nature of AIP as a Stimulus

Research on AI-driven personalization in tourism has expanded in recent years [2,3,10,20]. Existing studies have generated important insights into both the benefits and the risks of personalization, often focusing on outcomes such as satisfaction, trust, engagement, privacy discomfort, and resistance [10,21–23]. However, the literature remains limited in two important respects. First, it has more often documented positive and negative responses as parallel outcomes than explained the cognitive appraisal process through which users interpret and weigh the competing implications of autonomy loss and decision uncertainty. Second, existing studies have more often focused on lower-involvement or general digital service settings and have paid less attention to the role of contextual uncertainty in high-stakes tourism decisions [11,12,24]. As a result, the literature still lacks a process-oriented explanation of when and why utilitarian benefits may outweigh autonomy concerns in such contexts. This theoretical indeterminacy motivates the present study to examine the personalization paradox as a context-contingent appraisal process rather than as a static duality.

Operationalized through performance-oriented attributes including accuracy, relevance, and preference alignment, AIP nonetheless carries dual psychological potential [25,26]. High-precision personalization reduces search costs and enhances decision efficiency [27], thereby signaling competence. At the same time, predictive accuracy implies data monitoring and behavioral inference [22,27], which may activate autonomy-related

concerns consistent with reactance theory [28,29]. Rather than measuring intrusive features directly, this study examines whether competence-based cues alone can elicit reactance. If beneficial personalization signals generate resistance, this would provide stronger evidence for the personalization paradox [15].

In the present study, benefit is defined as the utilitarian dimension of personalization, namely reduced search costs, enhanced decision efficiency, and lower decision uncertainty, whereas threat is defined as the autonomy-related dimension, including perceived loss of freedom, algorithmic prescription, and surveillance concerns. Whether personalization is appraised primarily as a benefit or as a threat depends on the relative salience of these competing concerns. In high-involvement tourism decisions characterized by financial risk and information overload [11,12,24], the risk of decision failure may become more salient than autonomy loss. Under such conditions, accurate and relevant personalization may be reappraised as a coping resource that mitigates uncertainty, thereby attenuating rather than intensifying reactance. By contrast, in lower-uncertainty or lower-stakes contexts, autonomy-related concern may become relatively more salient, making personalization more likely to be perceived as intrusive. This context-contingent appraisal logic is elaborated through the TSM proposed later in the paper. Accordingly, AIP is treated as unidimensional in measurement but dual-potential in theory.

2.2. Psychological Reactance in the Digital Context

PRT posits that motivational resistance arises when an external influence is interpreted as an autonomy threat [30]. In AI-mediated tourism environments, such resistance may be triggered by non-transparent or overly prescriptive recommendation algorithms. These algorithms infer user preferences from historical behavior and narrow choice sets without explicit user input [3,12].

While CAT traditionally addresses singular stressors [31], the present study extends this perspective by introducing the Threat-Substitution Mechanism (TSM), a context-specific process grounded in both CAT and PRT. The TSM proposes that users in high-involvement tourism decisions do not appraise autonomy threat in isolation. Instead, they comparatively weigh it against the salient risk of decision failure. When decision uncertainty becomes more salient, accurate AIP can be reappraised as a coping resource rather than a controlling force. This reappraisal attenuates rather than intensifies reactance.

Unlike prior personalization–paradox studies that model positive and negative outcomes as parallel or static dual effects [22,32], the TSM provides a process-oriented explanation. It specifies the boundary condition of high-involvement decisions, under which utilitarian benefits may outweigh autonomy threats. This mechanism is integrated into the unified SOR-PRT framework to move beyond descriptive accounts and clarify when reactance is attenuated.

3. Theoretical Framework and Hypothesis Development

3.1. Theoretical Integration and Research Model

The SOR framework explains how environmental cues shape internal psychological states and subsequent behaviors. It is particularly relevant to the present study because AIP functions not merely as a technological feature but as a service stimulus that triggers internal appraisals before shaping continued usage intention.

PRT complements SOR by specifying the defensive pathway triggered by perceived autonomy threat. The proposed TSM further extends this integration. It frames personalization appraisal as a comparative process between decision uncertainty and autonomy loss. This extension makes the model more sensitive to the contextual dynamics of high-involvement tourism decisions.

PCs are further positioned as a boundary condition that amplifies users' sensitivity to personalization quality signals, shaping whether personalization cues are appraised as supportive or threatening.

3.2. Hypothesis Development

3.2.1. AI Personalization and Usage Intention

AIP functions as a high-quality environmental stimulus within the SOR framework [7], signaling algorithmic competence and decision-support capability. This role is especially important in high-involvement tourism contexts, where travelers often face information overload, financial risk, and complex choice environments [11,24]. Under such conditions, accurate and relevant personalization can enhance UI through several interrelated mechanisms. First, it improves decision efficiency by filtering irrelevant information and presenting options that better match users' preferences and situational needs, thereby reducing cognitive burden. Second, it increases the perceived reliability of the platform by signaling its capacity to deliver useful and accurate recommendations. Third, by offering preference-matched solutions, it enhances the perceived value of the service experience. These effects are especially salient for Generation Y and Z users, who tend to prioritize efficiency, seamless digital experiences, and reliable support in online tourism planning [16,17]. Prior studies likewise show that personalized recommendation systems can improve behavioral intention, perceived usefulness, and user engagement in tourism and digital service settings [10,33]. Taken together, these theoretical and empirical considerations suggest that AIP positively influences continued UI.

H1. *AIP positively affects UI.*

3.2.2. AI Personalization and Psychological Reactance

A theoretical tension exists between the utilitarian benefits and the psychological costs of AIP. Drawing on attitudinal ambivalence [34], personalization may simultaneously activate a cognitive–utilitarian pathway emphasizing efficiency and an affective-defensive pathway reflecting perceived autonomy threat [26,35], thereby explaining the coexistence of convenience and discomfort.

According to Psychological Reactance Theory, resistance arises when personalization is appraised as autonomy-threatening. Integrating CAT, we argue that in high-involvement tourism decisions, users weigh the restriction of autonomy against the risk of decision failure. Under conditions of uncertainty and potential loss, accurate and relevant personalization may be reframed as a coping resource rather than as a controlling force.

Empirical evidence supports this attenuation logic. Goal-congruent recommendations reduce reactance through perceived fit [36]; autonomy-supportive personalization mitigates defensive responses [37]; customization lowers reactance when it is not perceived as manipulative [38]; and in tourism contexts, negative reactions stem primarily from manipulative intent rather than from personalization itself [39]. Thus, although AIP carries dual appraisal potential, in high-involvement tourism settings where decision-failure risk is salient, competence-based personalization is expected to exert a dominant attenuation effect on psychological reactance.

H2. *AIP negatively affects PR.*

3.2.3. Psychological Reactance and Usage Intention

Within the SOR framework, psychological reactance represents a defensive organismic state that constrains subsequent behavioral responses [7,30]. Consistent with PRT, perceived threats to autonomy evoke motivational arousal aimed at restoring freedom, typically

expressed through resistance, avoidance, or disengagement [8,39]. Empirical studies consistently show that reactance reduces technology usage. Serravalle et al. [40] identify a significant negative effect of reactance on AI platform UI, while Wang et al. [41] demonstrate that privacy risk heightens reactance and leads to disengagement. Snyder et al. [38] further show that reducing threat-to-freedom perceptions lowers reactance, and Niu et al. [42] document tourism-related resistance toward AI-designed travel plans, consistent with reactance dynamics.

Although H3 is not a direct expression of the TSM itself, it is theoretically important within the present model because it specifies the downstream behavioral consequence of reactance once this defensive state has been activated through personalization appraisal. In this sense, while the TSM explains when AIP is more or less likely to attenuate reactance under competing concerns, H3 explains why any residual reactance still matters for continued UI. This path clarifies that the personalization paradox is not resolved by eliminating resistance entirely, but rather by ensuring that the positive utilitarian pathway remains stronger than the constraining influence of reactance in high-involvement tourism contexts. Accordingly, psychological reactance is expected to negatively affect UI.

H3. *PR negatively affects UI.*

3.2.4. The Mediating Role of Psychological Reactance

AIP produces both enabling and constraining effects. Although its utilitarian attributes can enhance UI, personalization may also elicit defensive responses under certain appraisal conditions [32]. Accordingly, the effect of AIP on UI may be partially offset by affective resistance.

Within the SOR framework, psychological reactance functions as a frictional organismic mechanism that transmits part of AIP's influence on UI [43]. When personalization is appraised as autonomy-supportive, reactance remains low; when it is perceived as autonomy-threatening, motivational resistance counteracts efficiency gains. Empirical evidence corroborates this mediation logic. Higher AI autonomy increases threat-to-freedom perceptions and reactance, thereby reducing favorable responses [44]. Mismatched recommendation characteristics activate reactance and lower satisfaction [36]. Likewise, perceived privacy risk elevates reactance and strengthens discontinuance intentions [41]. Collectively, these findings suggest that reactance serves as a transmission mechanism linking personalization cues to downstream behavioral outcomes.

H4. *PR mediates the relationship between AIP and UI.*

3.2.5. The Moderating Role of Privacy Concerns

PCs heighten vigilance toward data collection and algorithmic intervention [45], thereby increasing sensitivity to personalization cues. When privacy risks are salient, users engage in stricter appraisal of data use and algorithmic inference, which in turn shapes how personalization is interpreted.

Empirical evidence supports this moderating role. Personalization can elicit both trust and psychological reactance, with PC influencing which pathway becomes dominant [46]. Intrusive personalization may backfire when PCs are high, and perceived surveillance intensifies autonomy-related discomfort in tourism contexts [12]. Thus, PCs operate as a sensitivity amplifier rather than as a uniformly inhibiting force.

Drawing on this logic, we propose a gain–loss asymmetry mechanism. Users with higher PCs are expected to respond more strongly to personalization quality: poorly calibrated cues heighten reactance, whereas accurate and preference-aligned personalization more effectively attenuates it. This does not imply higher baseline trust among privacy-

sensitive individuals. Prior studies in AI-mediated service contexts indicate that such users often exhibit heightened skepticism and defensive evaluations toward data-driven systems [21,22]. Rather, PCs amplify responsiveness to personalization quality signals.

H5. *PCs moderate the relationship between AIP and PR, such that the negative relationship is stronger when PCs are higher.*

Although the broader AIP and digital consumer behavior literature discusses a rich set of complementary constructs, including perceived control, trust in algorithms, perceived transparency, and algorithmic fairness [37,38,47,48], the present study deliberately adopts a parsimonious model centered on psychological reactance as the focal organismic mechanism within the SOR-PRT-TSM framework. This choice is theoretically motivated rather than a limitation of scope. The primary objective is to isolate and rigorously test one central mechanism underlying the personalization paradox: whether, and under what contextual conditions, AIP is appraised as a threat to autonomy or as a resource for reducing decision uncertainty. Psychological reactance is particularly well suited to this purpose because it directly captures the motivational arousal and defensive response triggered by perceived autonomy threat [8,30,39], while AIP, as reflected in accuracy, relevance, and preference alignment, operationalizes the utilitarian cues that may attenuate such threat via the proposed TSM.

By focusing on this core pathway, the model achieves greater theoretical precision and avoids construct proliferation that could obscure the unique contribution of the TSM. Complementary constructs such as algorithmic transparency and perceived control, while theoretically important, tend to function as antecedents to or parallel mechanisms alongside reactance in prior work. Incorporating them into the current framework would shift the research focus from process-based threat appraisal toward a broader omnibus model, which is beyond the scope of the present inquiry. Future research is therefore encouraged to integrate these constructs as additional mediators, moderators, or competing pathways in order to develop a more comprehensive nomological network.

The proposed research model is presented in Figure 1.

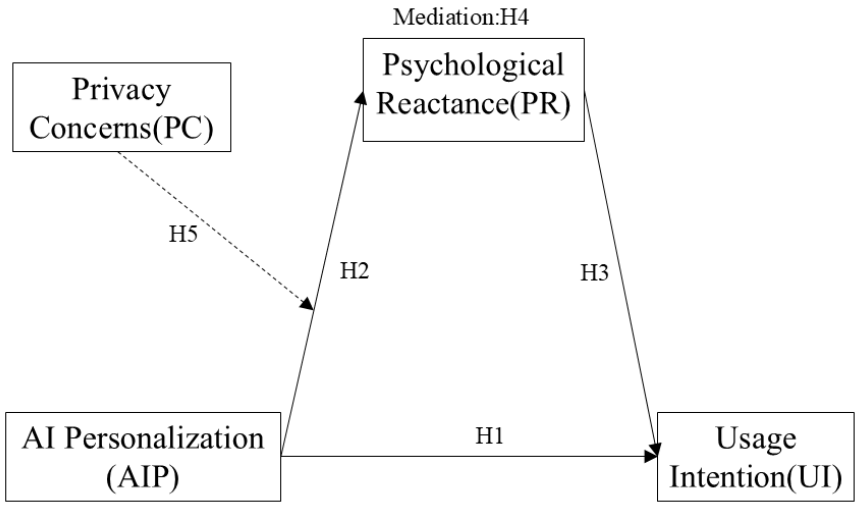

Figure 1. Research model.

4. Methodology

4.1. Sample and Procedure

This study employed a non-probability purposive sampling approach via the Credamo platform (https://www.credamo.com (accessed on 20 May 2025)), a professional academic

survey platform widely used in management and tourism research [49]. Before entering the main questionnaire, respondents were screened based on their prior experience. Only those who had adopted personalized travel recommendations and had successfully purchased tourism-related products more than three times in the past year were allowed to proceed, in order to ensure credible self-reports of post-adoption perceptions rather than to capture high-frequency usage patterns. Credamo incorporates multiple built-in quality controls, including respondent screening, embedded attention checks, response-time monitoring, IP validation, duplicate prevention, and the exclusion of invalid submissions. These features help improve data reliability and make the platform suitable for collecting self-reported post-adoption perceptions from active users of online travel platforms. Those who did not meet this criterion or failed attention checks were excluded. The target audience consists of the Z generation and the Y generation. Generation Y (born between 1981 and 1996, aged 29 to 44) came of age during the rise of the Internet. Generation Z (born 1997–2012) was born into the digital era. As all respondents were required to be aged 18 or above, the participating Generation Z members ranged from 18 to 28 years of age at the time of data collection.

An initial total of 543 responses were collected. After data cleaning, 488 valid responses were retained for analysis. Ethical approval was obtained from the Institutional Review Board (IRB), and all participants provided informed consent electronically and anonymously. Upon completion, each respondent received a reward of RMB 1.

To ensure sufficient statistical power, a priori power analysis was conducted using G*Power software version 3.1.9.7. With an expected medium effect size ($f^2 = 0.15$), four predictors, an alpha level of 0.05, and power set at 0.80, the minimum required sample size was determined to be 85. However, the G*Power estimate represents a minimum threshold under ideal assumptions, and a larger initial sample was intentionally collected to accommodate screening exclusions, failed attention checks, and invalid responses, as well as to improve the stability of parameter estimates in the mediation and moderation tests. The actual sample size of 488 substantially exceeded this threshold, ensuring robust statistical power.

PLS-SEM (Partial Least Squares Structural Equation Modeling) was employed for data analysis due to its suitability for exploratory research and its advantages in handling complex models with small to medium sample sizes [50].

4.2. Measurement Instruments

All constructs were measured using a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). Measurement items were adapted from established scales in prior research, but their adaptation was not a simple linguistic substitution. Instead, we conducted a process of contextual revalidation, ensuring that each construct reflected the unique characteristics of AI-powered personalization in high-involvement tourism decisions.

AIP was measured as users' perceptions of personalization accuracy, contextual relevance, and preference alignment. The items were adapted from Tam and Ho [33] and Bleier and Eisenbeiss [32], which have been widely applied in recent AI-driven service contexts [10]. PR was measured using items adapted from Dillard and Shen [39] and van Esch et al. [21], capturing perceived threat to freedom and motivational resistance in digital contexts. UI was measured using established technology adoption scales from Venkatesh et al. [51]. PCs were measured using items adapted from Malhotra et al. [52], Son and Kim [45], and Chen et al. [46], which reflect users' apprehensions regarding data collection and AI-driven data utilization. The comprehensive list of measurement items and their respective sources is detailed in Table 1.

Table 1. Construct reliability and validity.

Measurement Items	Factor Loading
AIP and α = 0.751, CR = 0.755, AVE = 0.572	
AIP1: The AI recommendation system provides suggestions that match my travel preferences.	0.783
AIP2: The recommendations generated by the system are relevant to my travel needs.	0.787
AIP3: The system accurately understands my interests and travel intentions.	0.711
AIP4: The AI recommendations effectively reduce my effort in searching for suitable travel options.	0.742
PC and = 0.918, CR = 0.922, AVE = 0.859	
PC1: I am concerned about how online travel platforms collect my personal information.	0.911
PC2: I worry that AI systems may use my personal data in ways I am not fully aware of.	0.945
PC3: I feel uneasy about the extent to which travel platforms track my online behavior.	0.925
PR and α = 0.824, CR = 0.826, AVE = 0.654	
PR1: The AI recommendations sometimes make me feel that my freedom of choice is being restricted.	0.795
PR2: I feel resistant when the system strongly pushes certain travel options.	0.796
PR3: The recommendations make me feel pressured to choose specific options.	0.825
PR4: When I see highly tailored recommendations, I sometimes want to make my own decision independently.	0.818
UI and α = 0.862, CR = 0.862, AVE = 0.707	
UI1: I intend to continue using AI-based recommendation services on travel platforms.	0.835
UI2: I will frequently rely on AI recommendations when planning future trips.	0.847
UI3: I would choose a travel platform that provides AIP over one that does not.	0.839
UI4: I am likely to use AI-generated travel suggestions in my future decisions.	0.843

To ensure contextual validity, the scale adaptation process was conducted in several steps. First, all measurement items were initially selected from established and widely used scales in prior studies, for the present research, based on their conceptual relevance to AIP, PR, UI, and PC [33,39,50]. Second, the wording of these items was carefully adapted to fit the context of AI-driven personalization in high-involvement tourism decisions, while preserving the original theoretical meaning of each construct. Third, a standard back-translation procedure was conducted to ensure semantic equivalence between the original and translated versions. Fourth, the translated items were reviewed by academic experts familiar with tourism technology and consumer behavior research in order to assess content clarity, conceptual consistency, and contextual appropriateness. Fifth, a pilot test was conducted with tourism platform users to identify ambiguous wording, comprehension difficulties, or context-specific mismatches, and minor wording refinements were made based on the combined feedback from the expert review and pilot test prior to final data collection.

5. Results

5.1. Common Method Variance

This study used self-reported survey data, which may raise concerns about common method variance (CMV). To reduce this risk, several procedural remedies recommended by Podsakoff et al. [53] were adopted, including anonymity assurance, honest response instructions, and careful item arrangement. In addition, Harman's single-factor test was conducted as a supplementary statistical check. The first unrotated factor explained 38.3% of the total variance, below the 50% threshold [53].

5.2. Respondent Profiles

A total of 488 valid responses were collected from 31 provinces in China. The sample comprised 68.2% females and 31.8% males. In terms of age, 49.0% were 25–34 years, 29.1%

were 35–44 years, and 21.9% were 18–24 years. Most respondents held a bachelor's degree (69.1%), followed by a master's degree or above (21.7%), while 9.2% had an associate degree or lower. Regarding prior use of personalized travel recommendations, 42.6% reported at least five purchases in the past year, 30.5% at least three, 16.2% at least seven, and 10.7% more than ten. The most frequently used platforms were Ctrip (30.5%), Tongcheng (20.0%), Qunar (18.8%), and Fliggy (15.9%). Monthly income was concentrated in the RMB 6001–15,000 range (50.5%), with only 1.4% earning above RMB 30,000.

5.3. Measurement Model Analysis

The measurement model demonstrates satisfactory reliability and convergent validity. As reported in Table 1, Cronbach's alpha values range from 0.751 to 0.918, while composite reliability values range from 0.755 to 0.922, exceeding the recommended threshold of 0.70 [54]. Additionally, AVE values are above 0.50 for all constructs, confirming convergent validity. All factor loadings exceed 0.70, indicating strong indicator reliability. As shown in Table 2, discriminant validity was further assessed using the HTMT ratio and Fornell–Larcker criterion. All HTMT values were below 0.90, and the square roots of AVEs (UI = 0.841; PC = 0.927; AIP = 0.756; PR = 0.809) exceeded inter-construct correlations, confirming satisfactory discriminant validity [23].

Table 2. Discriminant validity.

HTMT				
	UI	PC	AIP	PR
UI				
PC	0.506			
AIP	0.888	0.392		
PR	0.505	0.65	0.542	
Fornell–Larcker criterion				
UI	0.841			
PC	−0.45	0.927		
AIP	0.717	−0.331	0.756	
PR	−0.428	0.569	−0.432	0.809

5.4. Structural Model Analysis

As shown in Table 3, AIP has a significant positive effect on UI ($\beta = 0.654$, $p < 0.001$) and a significant negative effect on psychological reactance ($\beta = -0.249$, $p < 0.001$). PR also negatively influences UI ($\beta = -0.146$, $p = 0.001$). The model explains 53.1% of the variance in UI and 39.7% of psychological reactance. The VIF values ranged from 1.208 to 1.23, which are substantially below the conservative threshold of 3.30, suggesting that multicollinearity does not threaten the stability of the structural model estimates. The effect size (f^2) indicates that AIP has a substantial impact on UI ($f^2 = 0.741$), while the other effects are small. Moreover, Q^2 values exceed zero, confirming the model's predictive relevance.

As shown in Table 4, AIP has a significant total effect on UI ($\beta = 0.69$, $p < 0.001$). The indirect effect through PR is significant ($\beta = 0.036$, $p = 0.004$), while the direct effect remains significant ($\beta = 0.654$, $p < 0.001$), indicating partial mediation. Furthermore, PCs significantly moderate the relationship between AIP and PR ($\beta = -0.087$, $p = 0.044$), suggesting that the negative impact of AIP on PR is stronger when PC are higher.

Table 3. Structural model path coefficients and hypothesis testing.

Hy.no	Path	β	Std. Dev	f^2	VIF	R^2	Q^2	95%CI	t-V	*p*-V
H1	AIP -> UI	0.654	0.031	0.741	1.23	0.531	0.531	(0.592, 0.715)	20.797	0
H2	AIP -> PR	−0.249	0.041	0.085	1.208	0.397	0.397	(−0.332, −0.171)	6.086	0
H3	PR -> UI	−0.146	0.044	0.037	1.23	0.531	0.531	(−0.231, −0.058)	3.333	0.001

Note(s): Std. Dev = Standard deviation, β = Coefficient, t-V = T-Value, *p*-V = *p*-Value, 95%CI = Bootstrap 95%CI.

Table 4. Mediating effect and moderating effect.

	Path		β	Std. Dev	95%CI	t-V	*p*-V
Mediating effect	Total effects	AIP -> UI	0.69	0.026	(0.639, 0.740)	26.72	0
	Specific indirect effects	AIP -> PR -> UI	0.036	0.012	(0.014, 0.062)	2.911	0.004
	Direct effects	AIP -> UI	0.654	0.031	(0.592, 0.715)	20.8	0
Moderating effect	AIP -> PR		−0.249	0.041	(−0.332, −0.171)	6.086	0
	PC -> PR		0.48	0.038	(0.404, 0.551)	12.68	0
	PC × AIP -> PR		−0.087	0.043	(−0.171, −0.001)	2.012	0.044

Note(s): Std. Dev = Standard deviation, β = Coefficient, t-V = T-Value, *p*-V = *p*-Value, 95%CI = Bootstrap 95%CI.

6. Discussion

The present study examines the dual psychological mechanisms through which AIP influences continued UI among Generation Y and Z travelers in high-involvement tourism contexts [10]. Based on data from 488 users of major Chinese online travel agencies and analyzed using PLS-SEM, the findings support all proposed hypotheses and explain 53.1% of the variance in UI and 39.7% of the variance in psychological reactance.

6.1. Direct Effects of AI Personalization

AIP demonstrated a substantial positive effect on UI (H1: β = 0.654, $p < 0.001$), representing the dominant pathway in the model. This finding confirms the direction established by prior empirical work while extending its scope. Gao et al. [55] reported a positive personalization–engagement effect (β = 0.41) on Chinese travel platforms, and Tam and Ho [33] demonstrated increased behavioral compliance in general e-commerce settings. One plausible explanation for the larger effect observed in the present study is the high-involvement nature of the tourism context. In high-involvement tourism contexts, the utility value of accurate personalization may become especially important [11,12,24].

At the same time, AIP exhibited a significant negative effect on psychological reactance (H2: β = −0.249, $p < 0.001$). This finding is not fully consistent with earlier reactance research, which has often reported a positive association between personalization and resistance [28,29]. Studies in lower-involvement digital advertising contexts likewise suggest that higher personalization intensity may elevate reactance [14,21]. By contrast, the present results suggest that, in high-involvement tourism decisions, accurate and contextually relevant personalization may be interpreted as a coping resource that attenuates autonomy threat rather than amplifying it [31,36,37]. In this respect, the present study extends Fitzsimons and Lehmann [28] and White et al. [29] by suggesting that the relationship between personalization and reactance is context-contingent and may depend on the relative salience of decision-failure risk versus autonomy-loss concern.

6.2. The Mediating Role of Psychological Reactance Interpreting the Partial Mediating Effect of Psychological Reactance

PR negatively influenced UI (H3: β = −0.146, $p = 0.001$) and partially mediated the relationship between AIP and UI (H4: indirect effect β = 0.036, $p = 0.004$).

The negative effect of reactance on UI is consistent with prior research showing that perceived autonomy threat reduces engagement with AI systems and personalized digital services [40,41]. The smaller magnitude observed here, compared with some earlier studies, may be theoretically meaningful. In this setting, the dominant utilitarian pathway from

AIP to UI appears to outweigh the reactance-mediated friction, suggesting that reactance may function as a secondary constraint rather than a primary inhibitor in this context. This pattern extends prior work by indicating that the behavioral weight of reactance may vary across settings and levels of decision involvement [12].

The partial mediation pattern further extends rather than contradicts earlier findings. While Zhang et al. [44] reported full mediation of reactance in AI autonomy contexts, the present results indicate that reactance transmits only a modest portion of the total effect. The residual direct pathway suggests that utilitarian benefits are strong enough to offset much of the autonomy-related friction in high-stakes settings, although not all of it. This residual indirect effect supports a more process-based understanding of the personalization paradox, in which positive and negative responses coexist but exert unequal influence [15,21].

6.3. The Moderating Role of Privacy ConcernsInterpreting the Moderating Effect of Privacy Concerns

PCs amplified the negative relationship between AIP and psychological reactance (H5: $\beta = -0.087$, $p = 0.044$). This finding is not fully consistent with conventional privacy-calculus interpretations, which typically position PCs primarily as a uniform inhibitor of technology acceptance [21,22]. Under that view, higher PCs would be expected to produce generalized resistance regardless of personalization quality. By contrast, the present results reveal a gain–loss asymmetry, suggesting that PCs do not uniformly elevate reactance but instead amplify users' sensitivity to personalization quality. Users with higher PCs exhibit stronger reductions in reactance when personalization is accurate and relevant [46,56].

It is also worth noting that PCs exhibit a significant positive direct effect on psychological reactance ($\beta = 0.48$, $p < 0.001$), indicating that privacy-sensitive users tend to experience greater reactance overall, consistent with prior research [21,22,41]. However, the present study extends these accounts by showing that this heightened baseline reactance coexists with a stronger reactance-attenuating response to high-quality personalization. Unlike prior work that treats PCs as a uniform inhibitor [21,22], and extending Chen et al. [46] beyond pathway selection to the asymmetric magnitude of reactance reduction, privacy-sensitive users do not respond uniformly: their reactance is reduced more substantially when personalization is accurate and relevant, producing the amplification pattern observed in H5.

This pattern extends Chen et al. [46] by specifying the mechanism as heightened cue sensitivity rather than a simple pathway switch. It also complements Kim and Han [46] by suggesting symmetric implications: poorly calibrated personalization may be judged more critically, whereas well-calibrated personalization may be valued more strongly. The modest effect size suggests that PC operate as a bounded sensitivity amplifier rather than a transformative driver of behavioral intention. In other words, privacy concern appears to refine the appraisal process rather than fundamentally reverse it [21,22,46].

6.4. Synthesis: Resolving the Personalization Paradox

Taken together, the findings provide a process-oriented interpretation of the personalization paradox through the Threat-Substitution Mechanism (TSM). The results show an asymmetrical and context-dependent pattern: utilitarian benefits through enhanced decision efficiency represent the dominant pathway, while autonomy-related friction persists only as a residual constraint. This friction is particularly attenuated in high-involvement tourism decisions and among users with higher privacy concerns.

This pattern extends prior dual-effects models [10,22] by demonstrating that the relationship between AIP and psychological reactance is not uniformly positive or negative. Instead, it depends on users' comparative appraisal of competing threats. When decision uncertainty is salient, supportive cues from accurate personalization become more promi-

nent than autonomy concerns. Seemingly inconsistent findings across the literature can therefore be reconciled from this perspective.

Furthermore, the modest mediating role of reactance indicates that psychological friction is not fully eliminated but functions as a secondary rather than primary inhibitor in this setting. The personalization paradox should therefore be understood not as a fixed property of AI systems, but as a context-dependent appraisal outcome shaped by the interaction among personalization quality, user sensitivity, and decision context.

7. Conclusions

7.1. Theoretical Contributions

The first contribution of this study lies in extending AIP research within tourism technology adoption by foregrounding psychological ambivalence in high-involvement tourism decisions. Rather than treating personalization effects as either predominantly positive or as parallel positive and negative responses, the present study suggests that the same stimulus may activate both utilitarian enhancement and defensive resistance, with their relative prominence shaped by contextual threat salience. By integrating the SOR framework with PRT, the study offers a process-based account of the conditions under which competence-based AIP may enhance UI while attenuating reactance, thereby clarifying when the personalization paradox may emerge.

Second, it develops the TSM as a process-based extension of CAT and PRT. By specifying the comparative appraisal process between decision uncertainty and autonomy loss, TSM offers a process-based mechanism-level explanation that helps interpret previously inconsistent findings in prior personalization-paradox research, which often treated positive and negative effects as parallel rather than dynamically substitutable. With indirect empirical support from the negative AIP–reactance path, partial mediation through reactance, and the moderating effect of privacy concerns, TSM provides a more dynamic alternative to static dual-effects accounts by demonstrating how utilitarian benefits can dynamically outweigh autonomy threats under specific high-involvement conditions.

The third contribution concerns the role of PC in algorithmic service evaluation. In contrast to privacy-calculus perspectives that treat privacy concern as a uniform inhibitor, the present findings suggest that privacy-sensitive users may respond more strongly to personalization quality, showing greater reductions in reactance when personalization is accurate and relevant. This finding offers a more nuanced account of how privacy psychology intersects with algorithmic service evaluation, suggesting that vigilance and responsiveness may coexist and that privacy concern may intensify evaluative discrimination rather than generate blanket resistance.

Fourth, this study suggests that the personalization paradox need not manifest as an equal balance of positive and negative effects. Rather, it may take an asymmetrical and context-dependent form in which utilitarian benefits are more prominent while autonomy-related friction persists as a residual constraint. By linking this pattern to high-involvement tourism decisions and privacy-related appraisal sensitivity, the study extends static dual-effects perspectives and offers a more process-oriented explanation of how the personalization paradox may take shape under different conditions.

7.2. Managerial Implications

The findings suggest that tourism platforms should prioritize the substantive quality of AIP, particularly in high-involvement tourism contexts. Accurate, relevant, and preference-aligned recommendations appear more valuable than merely increasing personalization intensity.

At the same time, the mediating role of psychological reactance indicates that effective personalization should not be designed solely for efficiency. Even when overall effects are positive, residual autonomy-related friction may still weaken user acceptance. Platforms may therefore benefit from presenting AI recommendations as decision-support tools rather than directive interventions, while incorporating transparency features that help users retain a sense of control.

Finally, the moderating role of PC suggests that privacy-sensitive users are not uniformly resistant to personalization, but are more responsive to its quality. This implies that firms may benefit from adopting more differentiated personalization practices for users with stronger PC. Clear consent procedures, appropriate privacy controls, and high-quality recommendation delivery may help reduce defensive responses while maintaining trust in AI-enabled tourism platforms.

7.3. Limitations and Future Research

This study has several limitations. First, the use of cross-sectional data precludes causal inference; future research could employ longitudinal or experimental designs to examine how reactance evolves across repeated platform interactions. Second, the sample is limited to Chinese OTA users, which constrains cross-cultural generalizability; future work could examine whether the TSM operates similarly across individualistic and collectivistic contexts. Third, consistent with its focused theoretical objective, the present study adopts a deliberately parsimonious model that isolates psychological reactance as the primary organismic mechanism transmitting the dual effects of AIP. While this design enhances conceptual clarity and theoretical focus in testing the TSM, it does not exhaustively capture all psychological pathways discussed in the broader AIP literature, such as perceived control, algorithmic transparency, trust in algorithms, or algorithmic fairness. These constructs represent promising avenues for future research to examine as parallel mediators, additional moderators, or boundary conditions, thereby building a more holistic understanding of user responses to AI-driven personalization. Such extensions would be particularly valuable in multi-stage or longitudinal designs that can disentangle the temporal dynamics among these interrelated mechanisms. Fourth, AIP was measured through user perceptions rather than objective system features. Future studies could combine behavioral trace data with self-reports to distinguish more clearly between actual personalization accuracy and perceived relevance. Finally, because the study focuses on high-involvement tourism decisions, future research could further examine the boundary conditions of the proposed mechanism in lower-involvement service settings, where autonomy concerns may become more salient.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AIP	AI Personalization
OTA	Online Travel Agency
PC	Privacy Concerns
PLS-SEM	Partial Least Squares Structural Equation Modeling
PR	Psychological Reactance
PRT	Psychological Reactance Theory
SOR	Stimulus–Organism–Response
UI	Usage Intention

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