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Descriptive Trajectories of How Service Innovation Shapes Customer Exit Intentions in Online Travel Agencies

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Abstract

This study examines the descriptive trajectories through which service innovation is associated with customer exit dynamics after service failures, drawing on a three-wave panel of 532 online travel agency users and employing partial least squares structural equation modeling with predictive assessment. We analyze how innovation is associated with switching intentions via brand hate and brand distrust over time. Results reveal distinct temporal patterns: service innovation is linked to consistent reductions in both hate and distrust, yet only hate emerges as a salient mediator whose marginal association with switching intensifies over time. In contrast, distrust, although mitigated by innovation, remains relatively stable and behaviorally inert. Rather than asserting a causal explanation, we document temporal associations—labelled here as a “dilution effect”—to indicate that innovation coincides with weakening negative emotions but only partial attenuation of their behavioral correlates. By distinguishing between the fading but influential role of hate and the persistent yet inert nature of distrust, this study clarifies differentiated pathways through which negative states coincide with customer exit. For managers, the results highlight the need for staged innovation strategies to dissipate hate, complemented by long-term trust-repair initiatives to address enduring distrust and reduce customer churn.

Keywords: service innovation; switching intentions; brand hate; brand distrust; temporal dynamics



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1. Introduction

Customer switching remains one of the most pressing challenges for service firms, particularly in digital and platform-based industries where alternatives are abundant and switching costs are minimal. Defection not only erodes immediate profitability but also undermines long-term brand equity [1,2]. To counter this risk, research has traditionally emphasized recovery strategies and loyalty mechanisms as means to reduce switching [3,4]. Yet a critical question remains unanswered: beyond recovery, how are service innovations introduced after failures associated with customers' intentions to defect—and how do these associations evolve over time?

Service innovation has largely been examined for its positive contributions, such as enhancing satisfaction, creating value, and strengthening engagement [5–7]. However, in failure contexts, its role remains underexplored, despite dissatisfied customers widely disseminating negative experiences through digital platforms [8,9]. Even when examined, most studies rely on cross-sectional designs that assume static effects [10]. This leaves an

important gap: the temporal dynamics of whether and how innovations can attenuate switching intentions have received little empirical attention [11].

To understand these dynamics, it is necessary to examine the emotional mechanisms that shape switching. Two negative states are particularly salient: brand hate and brand distrust. Although both arise from service failures, they reflect distinct affective and cognitive responses and may follow different trajectories over time [12,13]. Insights from emotion dynamics suggest that negative emotions fluctuate and decay at different rates [14,15], implying that innovation may dilute some emotions more effectively than others [11,16]. Recognizing this distinction is critical: while firms may succeed in mitigating hate, distrust may prove more resistant.

The present study advances the conceptual framing of the “dilution effect,” defined here as a temporal pattern in which service innovation is associated with attenuated negative affective responses and partially reduced behavioral intentions, without implying a uniform or causal diminution of all negative states. Unlike prior theories of emotion decay or service recovery, which emphasize the natural fading of negative reactions or the restorative role of compensatory actions, the dilution effect highlights how innovation coincides with differentiated temporal trajectories of negativity.

In particular, we draw on psychological theory to sharpen the distinction between affective and cognitive responses. Affective reactions such as hate are rapid, visceral, and more malleable in response to new stimuli, consistent with appraisal-based accounts of emotion regulation. Cognitive responses such as distrust, by contrast, involve slower evaluative processes and schema-based judgments, which are more resistant to short-term contextual changes. This theoretical distinction clarifies why innovation is associated with reductions in hate but not in distrust, and it positions the dilution effect as extending beyond descriptive differentiation. By grounding the construct in established frameworks on emotion dynamics and consumer emotion regulation, we provide a theoretically integrated contribution that connects innovation trajectories with the evolving interplay of affect and cognition.

Therefore, this study adopts a three-wave longitudinal design in the online travel agency (OTA) sector, where switching is frequent and innovation is highly visible. By tracking customer responses over twelve months, we examine how perceived service innovation relates to the trajectory of switching intentions and how brand hate and brand distrust play divergent roles across time. Our approach makes two key contributions. First, we extend service innovation and consumer behavior research by documenting what we label the “dilution effect”—a temporal pattern in which innovation coincides with attenuated negative emotions and varying associations with switching. This contribution challenges prior static views by showing that innovation effects are nonlinear and evolving rather than uniform. Second, we enrich brand relationship and emotion dynamics research by distinguishing the divergent roles of hate versus distrust. Hate appears malleable yet behaviorally powerful, whereas distrust, though reduced by innovation, remains persistent but inert in shaping exit behavior. This nuanced understanding clarifies that not all negative states carry equal consequences, offering a more precise descriptive account of customer exit dynamics.

2. Conceptual Foundations: Innovation and the Temporal Attenuation of Negative Emotions

2.1. Service Innovation as a Recovery and Retention Mechanism

Service innovation has long been regarded as a critical driver of value creation, customer satisfaction, and firm performance [5,6]. In service contexts, innovations such as AI-based chatbots, self-service technologies, and platform upgrades are typically intro-

duced to enhance efficiency and improve customer experience [8,17]. While this body of work highlights innovation's potential to generate positive outcomes, far less attention has been devoted to its role in addressing negative states that arise after service failures.

Recent studies suggest that innovation can operate not only as a growth mechanism but also as a recovery tool capable of mitigating customer disappointment and re-engaging disaffected consumers [11,18]. This perspective contrasts with traditional service recovery approaches, which rely heavily on compensation or apology, by emphasizing that novel solutions can alter customer perceptions more profoundly over time. In digital and platform-based settings, where switching costs are low and alternatives abound, the ability of innovation to retain disappointed customers is especially critical.

However, existing research has rarely conceptualized service innovation in terms of its temporal associations with negative emotions—that is, as a pattern in which new offerings coincide with attenuated negativity and lower stated defection tendencies. Most empirical studies adopt cross-sectional designs, implicitly assuming that innovation effects are static [10]. This overlooks the possibility that the impact of innovation may evolve across stages of adoption and over time, particularly among customers who have experienced prior service failures. Thus, to advance theory, it is necessary to frame service innovation not merely as a creator of new value but as a temporal trajectory that may gradually coincide with shifts in negative affect and behavioral intentions.

2.2. Temporal Dynamics in Consumer Emotions and Behaviors

Consumer attitudes and intentions are not static; they evolve across time as experiences accumulate and contextual cues shift. Recent research emphasizes that many marketing constructs exhibit temporal dynamics, such that their strength, direction, and mediating roles vary across stages of the customer journey [19,20]. For instance, loyalty intentions, satisfaction, and trust demonstrate nonlinear change patterns when observed longitudinally, challenging the assumption that customer responses can be adequately captured in cross-sectional snapshots [21].

The literature on emotion dynamics further suggests that negative feelings are particularly unstable over time. Emotions such as anger, disappointment, or hate may initially intensify but typically dissipate as individuals reappraise events or encounter new stimuli [14,22]. This perspective implies that the associations between negative brand-related emotions and behavior are likely to fluctuate across time points rather than remain constant. Recent advances demonstrate that temporal trajectories can diverge, with some emotions weakening more rapidly than others in contexts such as the introduction of service innovations [11,23].

Despite these insights, research linking service innovation to temporal patterns in emotion dynamics remains limited. Existing work often treats innovation as a static input associated with satisfaction or loyalty at a single moment in time [10]. However, longitudinal evidence is needed to reveal whether and how innovations are observed to coincide with shifts in negative affect and stated switching intentions over time. Building on emotion dynamics theory, this study frames service innovation as a temporal trajectory whose observed associations with negative emotions and subsequent behaviors unfold in a nonlinear manner rather than as a one-off static association.

2.3. Divergent Roles of Brand Hate and Brand Distrust

Negative consumer responses to brands are heterogeneous, encompassing both affective and cognitive dimensions. Among these, brand hate and brand distrust have emerged as two salient but conceptually distinct constructs. Brand hate is defined as an intense negative emotional state directed at a brand following a painful or unjust experience [12].

It often stems from self-relevant failures or perceived violations of identity, and research shows that hate can drive retaliatory behaviors and strong exit intentions [2,3]. Recent studies suggest, however, that brand hate may not be static; it can diminish or be attenuated over time, particularly when consumers encounter new stimuli such as innovation efforts [24].

By contrast, brand distrust reflects a cognitive judgment that a brand is irresponsible, unreliable, or harmful to consumer interests [13]. Unlike hate, distrust does not necessarily involve emotional intensity but rather a skeptical stance toward the brand's motives. Distrust can persist even in the absence of active negative affect, leading consumers to avoid engagement with the brand regardless of subsequent innovations or recovery efforts [25,26]. Importantly, while distrust may decline slowly if positive signals accumulate, it does not necessarily translate into reduced switching intentions in the same way that hate does.

These distinctions suggest that hate and distrust may play divergent roles in the temporal patterns of switching intentions. Hate appears more likely to fluctuate and decline as service innovations introduce new experiences, thereby coinciding with the attenuation pattern we label the dilution effect. Distrust, however, may be more resistant to change, showing only limited associations with switching intentions even if innovations coincide with lower salience. By explicitly differentiating these constructs, this study provides a descriptive account that extends prior research, which has often treated negative consumer responses as uniform or interchangeable.

2.4. Switching Intentions as a Temporal Construct

Switching intentions capture consumers' willingness to replace their current service provider with an alternative. Traditionally, research has treated switching intentions as a relatively stable predictor of actual churn, closely linked to satisfaction, loyalty, and retention [27,28]. However, recent scholarship emphasizes that switching intentions are temporal constructs that change over time in response to evolving experiences and contextual cues [19,21].

Longitudinal evidence suggests that switching intentions may follow nonlinear patterns, intensifying shortly after service failures but attenuating as customers reappraise their options or encounter recovery and innovation efforts [11,20]. These temporal shifts highlight that intentions are not fixed outcomes but dynamic processes associated with both cognitive and emotional patterns. For example, brand hate may initially amplify exit tendencies but be observed to weaken as innovations coincide with reduced negative affect, whereas distrust may persist without necessarily being associated with immediate switching behavior.

Conceptualizing switching intentions as temporally evolving associations allows researchers to capture a more nuanced picture of customer exit dynamics. This framing not only integrates service innovation into the broader literature on consumer defection but also positions switching as a process observed alongside the attenuation or persistence of negative emotions rather than presuming a causal mechanism. In doing so, it provides the foundation for our hypotheses on how innovation, hate, and distrust are related to exit intentions across time.

2.5. Hypothesis Development

Building on the above conceptual foundations, we frame service innovation as coinciding with attenuation patterns of negative consumer emotions and a potential weakening of switching intentions over time. Consistent with prior research on innovation outcomes and consumer behavior [5,6], we anticipate that perceived service innovation will be associated with lower stated likelihood of customer defection. Moreover, given the temporal nature of

consumer attitudes [19,21], we view this association as evolving dynamically rather than remaining static.

H1. *Perceived service innovation is negatively associated with switching intentions, and this effect evolves over time.*

Service innovations may also shape consumers' affective and cognitive states following service failures. Specifically, innovations are expected to reduce brand hate by offering new value propositions that counterbalance disappointment [2,24]. Similarly, innovations can mitigate brand distrust by signaling responsibility and reliability [13]. We therefore hypothesize:

H2. *Perceived service innovation is negatively associated with brand hate, and this effect evolves over time.*

H3. *Perceived service innovation is negatively associated with brand distrust, and this effect evolves over time.*

Negative emotions and cognitions, in turn, are central predictors of customer exit dynamics. Research shows that brand hate intensifies avoidance and retaliatory behaviors [3,12], whereas distrust undermines engagement and long-term relationships [25]. Building on emotion dynamics theory, affective reactions such as hate are relatively volatile and subject to decay over time, particularly when new stimuli enable cognitive reappraisal [29]. In service contexts, innovation may provide such cues, reducing the salience of hate even as residual levels continue to shape behavior [30]. By contrast, cognitive evaluations such as distrust are schema-based, slower to change, and more resistant to short-term interventions [31]. Trust repair research further suggests that distrust, once formed, is inert and often persists despite compensatory actions [32]. Thus,

H4. *Brand hate is positively associated with switching intentions, but its association attenuates over time as innovation coincides with reduced negative affect.*

H5. *Brand distrust is positively associated with switching intentions and remains relatively stable across time, showing limited attenuation despite innovation.*

Together, these hypotheses outline a framework in which service innovation is positioned as being associated with both direct and indirect patterns in switching intentions across time, rather than asserting a proven causal mechanism. Specifically, the five hypotheses together form the basis of our conceptual model, depicted in Figure 1. As illustrated, perceived service innovation is expected to relate to lower stated switching intentions both directly and indirectly through the attenuation patterns of brand hate and brand distrust. The model further incorporates temporal dynamics by anticipating that the strength of these associations changes across the three measurement waves. This framework integrates prior insights on service innovation, negative emotions, and consumer exit behavior into a unified temporal descriptive perspective that guides the subsequent empirical analysis.

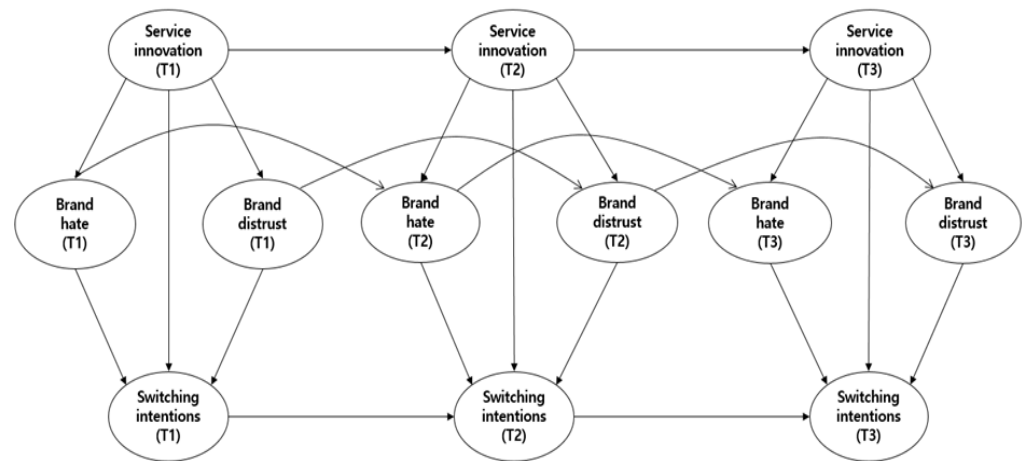


Figure 1. Conceptual model.

3. Methodology

3.1. Data Collection

This study employed a longitudinal study design with three waves of data collected from the same respondents at six-month intervals. Data were collected in November 2023 (T1), May 2024 (T2), and November 2024 (T3). The rationale for the six-month interval was that respondents were likely to use an OTA for personal travel at least once during the entire study period. For example, individuals were more likely to arrange at least one trip during periods such as the Christmas and New Year holidays or the summer vacation season.

Participants were recruited based on the following criteria: (1) those who had experienced a service failure at a specific OTA brand within the last three months; (2) those who had not yet utilized or were hesitant to use the OTA after the adverse experience; and (3) those who had used the OTA for a minimum of two years before the designated service dissatisfaction. Respondents who met all three criteria were included in the study.

To collect data, a series of announcements was posted on prominent Korean traveler communities, blogs, and cafes to promote participation in the study. In early November 2023, a total of 1408 participants responded with personal contact information and provided answers to a series of questions regarding the study's criteria. Of these, 518 were excluded for not meeting the stipulated terms, leaving 890 participants who received the initial survey (T1).

The T1 questionnaire was administered for two weeks in mid-November. A reminder message was sent after one week, yielding 752 responses. After excluding 27 careless responses, 725 usable ones remained. Six months later, the T2 survey was administered to the same participants ($n = 725$) who had completed the T1 survey. The methodology was the same as in T1, resulting in 615 responses. After removing 12 careless responses, 603 usable ones were retained. The final survey (T3) was administered six months later to those ($n = 603$) who had completed T2. The methodology employed was identical to that of T2, resulting in 541 responses. After excluding nine careless responses, a total of 532 remained for hypothesis testing. A modest incentive was provided to respondents who completed the final survey.

Finally, it is important to note that respondents were recruited via a substantial online research panel that regularly books services with various OTAs. Participants were not restricted to a single brand but rather asked to report on their most recent OTA experience in this category. To preserve confidentiality and minimize brand-related bias, brand names were anonymized in the survey and subsequent analyses. This multi-brand sampling

approach enhances the external validity of our findings, allowing them to reflect the OTA sector as a whole rather than any individual brand.

Of the participants, 55.7% were male, and the average age was 34.8 years. Of these, 68.7% had begun using other OTAs after being disappointed with their original one. A significant proportion of the respondents (89.2%) were actively searching for alternative accommodations through the original OTA but did not make bookings via the platform; in this study, such browsing without booking was classified as “searching” rather than “use”. Based on evaluating their attitudes and behaviors, it was concluded that the sample was suitable for the study’s purposes.

To further assess representativeness, we compared the demographic and behavioral profile of our sample with publicly available statistics from the OTA industry. The age distribution (concentrated in the 20s and 30s), gender balance, and high frequency of online travel bookings are consistent with the dominant segments in the Korean OTA market. However, older and less digitally active travelers appear somewhat underrepresented. Therefore, the findings are most applicable to digitally engaged OTA users, who constitute the core customer base. We acknowledge this caveat when interpreting the results.

3.2. Measures

All constructs were measured using items adapted from published studies. As shown in Table 1, perceived service innovation was measured with four items adapted from [33]. As these items emphasized core service innovation and peripheral-core service innovation when measuring perceived service innovation, both were included in this study’s analysis. Because brand hate is a multidimensional construct encompassing three characteristics—anger, sadness, and fear—it was measured using three items adapted from [34]. Although hate is often theorized as multidimensional, we modeled it here as a parsimonious reflective construct. This approach is consistent with prior consumer–brand relationship studies that have operationalized brand hate in a similar manner [35]. The decision is theoretically justified by the shared appraisal structure of anger, sadness, and fear, which collectively represent an oppositional stance toward the brand. At the same time, we acknowledge that alternative specifications, such as a second-order construct, could also capture the multidimensionality of hate. We selected the reflective specification to balance theoretical fidelity with parsimony, in line with recommendations for longitudinal SEM designs. Brand distrust was also measured using three items, which were adapted from [26]. Finally, switching intentions was measured with three items adapted from [36], framed as follows: rate the likelihood that you would switch to a different OTA the next time you travel to that particular location (e.g., your most desired domestic or international city or vacation destination). All items were evaluated using a 7-point Likert scale, with responses ranging from “1 = not at all (or strongly disagree)” to “7 = very much (or strongly agree)”.

While the theoretical framework characterizes brand hate as comprising anger, sadness, and fear, our operationalization follows prior multidimensional brand-hate studies that distilled these affective reactions into core evaluative and avoidance responses [37]. The items “revulsion” and “displeasure” capture the anger/disgust–sadness dimension, whereas the item “threatened” reflects the anticipatory/avoidance aspect of fear that motivates protective or exit behavior. These three-item measures have been validated in analogous service contexts and offer a parsimonious yet theoretically grounded representation of brand hate. Accordingly, we modeled brand hate as a single reflective construct to capture its overall temporal intensity rather than its individual sub-facets.

Table 1. Measures.

Construct	Outer Loading			AVE		
	T1	T2	T3	T1	T2	T3
Perceived service innovation (T1: CR = 0.83, α = 0.81; T2: CR = 0.95, α = 0.95; T3: CR = 0.84, α = 0.83)				0.63	0.88	0.67
AAA continuously introduces new, technology-based service products/offerings.	0.85	0.94	0.82			
AAA introduces technologies for excellent user experience (UX).	0.78	0.93	0.82			
AAA continuously brings new features to its content solutions.	0.81	0.94	0.81			
AAA introduces new services.	0.74	0.94	0.81			
Brand hate (T1: CR = 0.74, α = 0.73; T2: CR = 0.94, α = 0.94; T3: CR = 0.80, α = 0.76)				0.64	0.89	0.67
I have a feeling of revulsion toward this AAA.	0.85	0.95	0.86			
I feel displeased when I think about this AAA.	0.80	0.94	0.85			
I feel threatened when I think about this AAA.	0.76	0.95	0.74			
Brand distrust (T1: CR = 0.75, α = 0.75; T2: CR = 0.94, α = 0.94; T3: CR = 0.84, α = 0.81)				0.67	0.89	0.71
AAA looks suspicious and distrustful.	0.81	0.95	0.87			
The way AAA operates its business is irresponsible and unreliable.	0.80	0.94	0.89			
AAA engages in damaging and harmful behavior to customers to pursue its own interests.	0.84	0.94	0.79			
Switching intentions (T1: CR = 0.78, α = 0.77; T2: CR = 0.93, α = 0.93; T3: CR = 0.79, α = 0.78)				0.67	0.87	0.69
Improbably...Probably	0.81	0.93	0.81			
Unlikely...Likely	0.79	0.94	0.84			
No change...Certain	0.87	0.93	0.84			

Note: AVE = Average variance extracted; CR = Composite reliability.

In particular, because the original measurement items were developed in English, we employed a rigorous translation–back-translation process to ensure semantic and conceptual equivalence. Two marketing professors with expertise in service research and one professional linguist independently translated the items into Korean and then back into English; discrepancies were discussed and resolved to achieve accuracy. To further assess clarity and cultural appropriateness, we conducted a pretest with 21 undergraduate students from the target population. The pretest indicated that all items were easily understood and culturally appropriate, providing clear evidence of face validity for the Korean version of the measures.

3.3. Measurement Invariance

Given the three-wave longitudinal design, it was necessary to ensure that the measurement model operated equivalently across T1, T2, and T3. Following the MICOM procedure, we conducted tests of configural, compositional, and scalar invariance. First, configural invariance was satisfied, as all constructs were measured with the same indicators, scale anchors, and data treatment procedures across waves. Second, compositional invariance was established for all constructs, as permutation tests (5000 resamples) revealed correlations between original and permuted composite scores close to 1.0, with nonsignificant differences (all $p > 0.05$). Finally, equality of means and variances was examined. The results indicated that differences in construct means and variances across time points were nonsignificant at the 5% level for perceived service innovation, brand distrust, and switching intentions; brand hate showed a small but statistically significant decline over time,

consistent with our theoretical expectation. Taken together, these results support partial measurement invariance across time waves, which is sufficient for meaningful comparisons of structural relationships in longitudinal partial least squares structural equation modeling (PLS-SEM) analysis [38].

3.4. Common Method Bias

To address potential common method bias, we conducted common method analysis by incorporating a single factor into a confirmatory factor analysis model, assessing measure variations across two models, and subsequently determining that the smaller the variation, the lower the common method bias problem [39]. In our case, the results indicated that the difference in the magnitude of change in the measurements from the two models was 0.09, which fell below the recommended threshold of 0.2. Following Kock [40], we also assessed full collinearity variance inflation factors (VIFs) of all constructs to test for collinearity and common-method bias. All VIF values ranged from 1.10 to 2.35, well below the conservative threshold of 3.3. This indicates that there are no serious concerns regarding multicollinearity or common-method bias.

To further minimize the potential for common method bias, several procedural remedies were implemented during the survey design and administration. First, respondents were assured of anonymity and confidentiality to reduce their apprehension regarding the evaluation. Second, the measurement items were drawn from validated multi-item scales, randomized within the questionnaire, and used different scale anchors to reduce response patterning. Third, the predictor and criterion variables were psychologically separated by presenting them in different sections of the survey. The findings of this study, when considered in conjunction with the results of the statistical test, suggest that common method bias is unlikely to compromise the validity of the results.

3.5. Attrition Analysis

We conducted an attrition analysis outside the SEM framework by comparing baseline demographics and key constructs at T1 between respondents who completed all three waves ($n = 532$) and those who dropped out ($n = 193$), using independent-sample t -tests and χ^2 tests. No significant differences emerged (all $ps > 0.10$), indicating that attrition did not introduce systematic bias into the results.

4. Results

4.1. Analytical Methods

We employed PLS-SEM for its suitability in estimating and testing the hypothesized relationships among multiple latent variables in our three-wave longitudinal model. PLS-SEM is ideal for complex, theory-developing contexts and enhances predictive assessment and validity [38,41]. Given that our model integrates several latent constructs and temporal paths and emphasizes prediction rather than covariance fit, PLS-SEM offers clear advantages over covariance-based SEM. Furthermore, PLS-SEM is robust to moderate non-normality and unequal sample sizes, which is beneficial in longitudinal designs subject to attrition [42,43]. To address potential attrition bias, we compared respondents who completed all three waves ($n = 532$) with those who dropped out and found no significant differences on key variables (all $p > 0.05$), suggesting that attrition is unlikely to compromise the validity of our findings [42]. In line with these observations, SmartPLS software 4.1.1.4 was utilized to analyze our hypothesized path model.

4.2. Measurement Model

Internal consistency was first checked to verify the measurement model's validity and reliability. As an indicator of internal consistency, Cronbach's alpha values ranged from 0.73 to 0.95, exceeding the recommended threshold of 0.7 (see Table 1), indicating adequate consistency. Next, convergent validity was tested using composite reliability (CR), outer loadings, and average variance extracted (AVE) values. The CR values ranged from 0.74 to 0.95, and the outer loading values ranged from 0.74 to 0.95, all above the recommended value of 0.7. The AVE values ranged from 0.63 to 0.89, surpassing the recommended value of 0.5 [42]. It is noteworthy that several T2 loadings were unusually high (approximately 0.93–0.95). However, additional diagnostic checks did not reveal substantial bias. Therefore, it was concluded that convergent validity had been established.

Finally, discriminant validity was evaluated to ensure that each latent factor was conceptually distinct from the other factors. Following the recommendations of prior research, we applied the heterotrait-monotrait (HTMT) ratio criterion of correlations, derived from SmartPLS, as the test of discriminant validity [44]. Notably, from a conservative perspective, HTMT ratios below 0.85 indicate that discriminant validity has been achieved. As shown in Table 2, the HTMT values for each construct ranged from 0.02 to 0.49, with their 95% confidence intervals entirely below the 0.85 threshold [44], thereby confirming discriminant validity across constructs and time waves. In addition, as noted earlier, measurement invariance across time waves was confirmed, ensuring comparability of constructs across T1–T3.

Table 2. HTMT results.

	1	2	3	4	5	6	7	8	9	10	11	12
1. Perceived service innovation (T1)												
2. Brand hate (T1)	0.43											
3. Brand distrust (T1)	0.39	0.45										
4. Switching intentions (T1)	0.28	0.38	0.37									
5. Perceived service innovation (T2)	0.03	0.04	0.05	0.08								
6. Brand hate (T2)	0.04	0.10	0.06	0.06	0.35							
7. Brand distrust (T2)	0.04	0.09	0.06	0.07	0.34	0.49						
8. Switching intentions (T2)	0.03	0.05	0.02	0.06	0.37	0.32	0.30					
9. Perceived service innovation (T3)	0.09	0.08	0.06	0.07	0.02	0.03	0.03	0.04				
10. Brand hate (T3)	0.05	0.04	0.08	0.04	0.06	0.04	0.05	0.10	0.29			
11. Brand distrust (T3)	0.03	0.49	0.08	0.06	0.05	0.03	0.03	0.08	0.37	0.49		
12. Switching intentions (T3)	0.05	0.07	0.04	0.07	0.06	0.03	0.04	0.11	0.30	0.44	0.41	

4.3. Structural Model

To evaluate predictive validity, we first conducted the cross-validated predictive ability test (CVPAT). As shown in Table 3, most latent variables exhibited significantly negative average loss differences, indicating that the exogenous variables demonstrated substantial predictive validity for the endogenous constructs [45]. At the same time, several T2 differences were positive. This pattern aligns with our interpretation that predictive relevance is strongest at T1 and T3, and weaker at T2.

Given our emphasis on prediction, we further assessed the model's predictive relevance using Q^2_{predict} and PLSpredict in SmartPLS 4 [46]. All endogenous constructs yielded positive Q^2_{predict} values ranging from 0.05 to 0.19, indicating small to moderate predictive relevance beyond the sample. In addition, the PLS model consistently produced lower root mean square error and mean absolute error values than the linear benchmark model in PLSpredict, confirming that the model offers superior out-of-sample predictive power for switching intentions and brand hate.

Table 3. CVPAT results.

Time Wave	Construct	Average Loss Difference	t-Value
T1:	Brand hate	−0.154	3.164 **
	Brand distrust	−0.129	2.959 **
	Switching intentions	−0.086	2.027 *
T2:	Perceived service innovation	0.010	3.086 **
	Brand hate	0.006	1.059
	Brand distrust	0.004	1.294
	Switching intentions	0.002	1.255
T3:	Perceived service innovation	−0.182	3.326 **
	Brand hate	−0.013	2.283 *
	Brand distrust	0.000	0.364
	Switching intentions	−0.032	3.178 **
Overall model	2.238	−0.052	3.373 **

Note: *, $p < 0.05$; **, $p < 0.01$. Negative values of average loss difference indicate that the PLS model produces lower prediction error (better predictive performance) than the benchmark model, whereas positive values indicate higher prediction error relative to the benchmark.

The model demonstrated moderate to substantial explanatory power across all time points. Specifically, the R^2 values were 0.33, 0.31, and 0.26 for brand hate at T1–T3; 0.30, 0.37, and 0.32 for brand distrust; and 0.41, 0.52, and 0.44 for switching intentions. These values exceed the benchmark of 0.25 for moderate explanatory power [47], indicating that the model consistently accounts for a meaningful proportion of the variance in the key outcomes over time.

Table 4 and Figure 2 summarize the structural path estimates. Regarding H1, perceived service innovation had a consistently negative effect on switching intentions across all three waves (T1: $\beta = -0.130$, $p < 0.01$; T2: $\beta = -0.284$, $p < 0.01$; T3: $\beta = -0.158$, $p < 0.01$). The magnitude of this effect increased between T1 and T2 but weakened at T3, reflecting a nonlinear trajectory. Thus, H1 was partially supported.

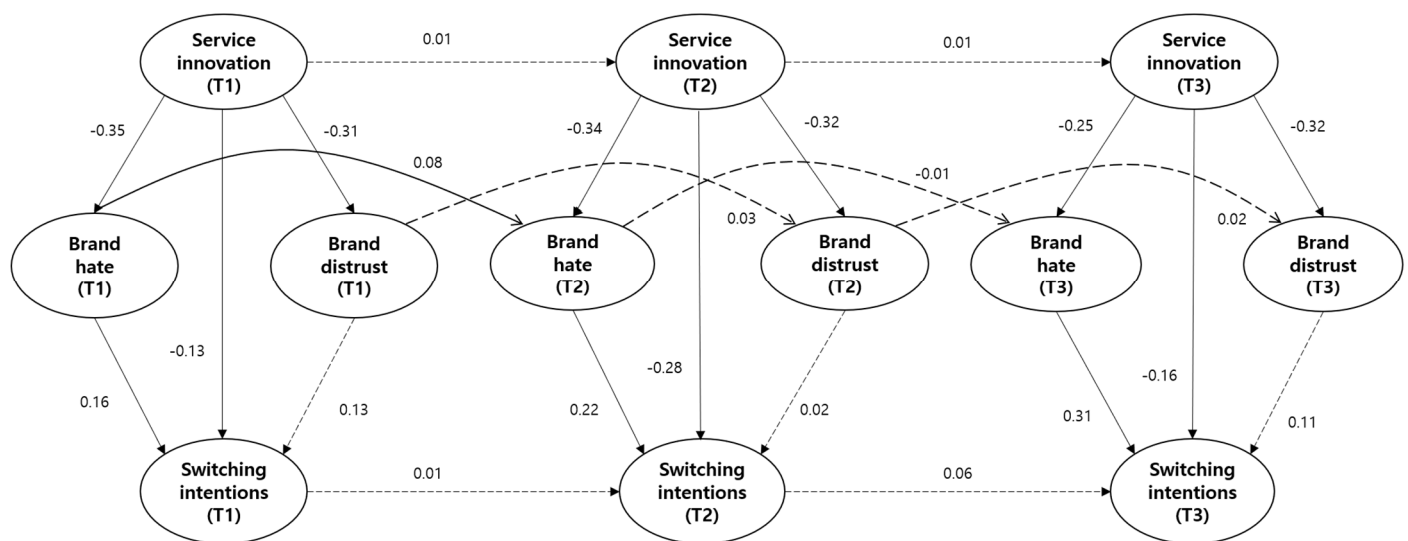
**Figure 2.** Path estimates.

Table 4. Estimates of the structural model using PLS.

Time Wave	Paths	Coefficient	95% CI (2.5–97.5%)
T1	Perceived service innovation → switching intentions	−0.130 **	[−0.230, −0.033]
	Perceived service innovation → brand hate	−0.347 **	[−0.437, −0.261]
	Perceived service innovation → brand distrust	−0.315 **	[−0.401, −0.232]
	Brand hate → switching intentions	0.164 *	[0.016, 0.302]
	Brand distrust → switching intentions	0.128 (ns)	[−0.005, 0.260]
T2	Perceived service innovation → switching intentions	−0.284 **	[−0.383, −0.184]
	Perceived service innovation → brand hate	−0.336 **	[−0.423, −0.245]
	Perceived service innovation → brand distrust	−0.323 **	[−0.409, −0.230]
	Brand hate → switching intentions	0.223 *	[0.025, 0.462]
	Brand distrust → switching intentions	0.021 (ns)	[−0.264, 0.225]
T3	Perceived service innovation → switching intentions	−0.158 **	[−0.291, −0.032]
	Perceived service innovation → brand hate	−0.246 **	[−0.377, −0.122]
	Perceived service innovation → brand distrust	−0.320 **	[−0.444, −0.208]
	Brand hate → switching intentions	0.314 **	[0.046, 0.634]
	Brand distrust → switching intentions	0.113 (ns)	[−0.115, 0.293]
	Carryover effects		
	Brand hate (T1) → Brand hate (T2)	0.076 *	

Note: *, $p < 0.05$; **, $p < 0.01$. Aside from the carry-over effect shown in the table, none of the results were statistically significant and were therefore omitted. ns = not significant.

For H2, perceived service innovation significantly reduced brand hate at each wave (T1: $\beta = -0.347$, $p < 0.01$; T2: $\beta = -0.336$, $p < 0.01$; T3: $\beta = -0.246$, $p < 0.01$). The results suggest that innovation attenuates hate most strongly in the early stages, with diminishing intensity over time. Accordingly, H2 was partially supported. H3 predicted a negative effect of service innovation on brand distrust. This relationship was consistently significant (T1: $\beta = -0.315$, $p < 0.01$; T2: $\beta = -0.323$, $p < 0.01$; T3: $\beta = -0.320$, $p < 0.01$), indicating that innovation steadily reduces distrust throughout the observation period. Hence, H3 was partially supported.

H4 proposed that brand hate would be positively associated with switching intentions but that this effect would weaken over time. Results confirmed a significant positive effect at all three stages (T1: $\beta = 0.164$, $p < 0.05$; T2: $\beta = 0.223$, $p < 0.05$; T3: $\beta = 0.314$, $p < 0.01$); however, contrary to the hypothesis, the strength of the relationship increased over time. Thus, H4 was not supported. Notably, H5 was also not supported: brand distrust did not show a significant association with switching intentions at any wave, even though its observed association with innovation was consistently negative. This suggests that distrust may be diluted by innovation but does not translate into reduced switching intentions.

We assessed between-wave differences in path coefficients using the bootstrapped parameter difference test in SmartPLS 4, as described by Hair et al. [47]. This procedure calculates the difference ($\Delta\beta$) and its bootstrapped t-value between coefficients. Table 5 presents a synthesis of these results, highlighting three main insights: (1) the effect of service innovation on switching intentions follows a nonlinear trajectory, strengthening in the mid-stage before weakening; (2) brand hate is strongly mitigated early, but, contrary to our expectation, its marginal impact on switching intensifies over time, whereas brand distrust steadily decreases yet remains behaviorally inert; and (3) negative emotions are not equivalent in their associations with exit dynamics. These results provide longitudinal evidence describing the temporal patterns that we label as the dilution effect of innovation.

Table 5. Changes in path coefficients.

Path Coefficient	T1 Coefficient	$\Delta T1 - T2$	$\Delta T2 - T3$	Significant Change?
Perceived service innovation → Switching intentions	−0.130	−0.154	0.126	Yes (both)
Perceived service innovation → brand hate	−0.347	0.011	0.090	No/Yes
Perceived service innovation → brand distrust	−0.315	−0.008	0.003	No
Brand hate → switching intentions	0.164	0.059	0.091	Yes (both)
Brand distrust → switching intentions	0.128	−0.107	0.092	Yes (T2–T3)

Note: “Significant change?” flags indicate whether the difference between coefficients across waves is significant ($p < 0.05$) based on the bootstrapped parameter difference test in SmartPLS 4. Changes were flagged as significant at $p < 0.05$.

We also estimated a contemporaneous-plus-carryover model, in which constructs at each wave predict subsequent values and outcomes at the same time. Although cross-lagged and latent-growth models capture richer dynamics, they require more waves and larger samples to yield stable estimates [48]. Our three-wave panel of 532 respondents does not provide sufficient degrees of freedom for reliable full cross-lagged or latent growth specifications. Furthermore, our theoretical framework focuses on how service innovation is associated with the temporal trajectory of negative emotions and switching intentions, rather than on reciprocal feedback loops. For these reasons, the contemporaneous-plus-carry-over specification maximizes parsimony and predictive validity while avoiding over-parameterization.

Finally, additional analyses of variance were conducted to test systematic changes in construct means over time [21]. No significant differences were observed for perceived service innovation, brand distrust, or switching intentions. Only brand hate showed a significant decline (T1: 3.105; T2: 2.914; T3: 2.728; $F = 5.429$, $p < 0.001$), consistent with the structural results showing that hate diminishes as innovation unfolds.

Taken together, Figures 3 and 4 indicate that while service innovation is associated with consistent reductions in both brand hate and distrust, only hate displays a growing association with switching intentions over time, whereas distrust remains relatively stable and behaviorally inert. This highlights their divergent trajectories and indicates what we label a partial but incomplete dilution pattern. This joint evidence clarifies that emotions such as hate, even when attenuated, retain strong behavioral correlates, whereas cognitions such as distrust, though persistent, may not directly translate into exit behavior.

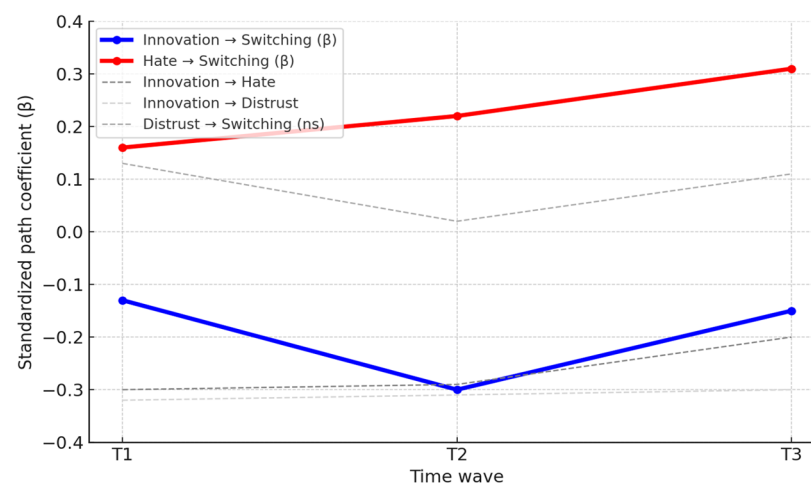


Figure 3. Simplified temporal trajectories of key path coefficients over three waves. Note: Standardized path coefficients (β) were estimated using SmartPLS 4 with 5,000 bootstraps. The blue and red lines represent the only paths showing significant changes between T1–T2 and T2–T3, whereas the gray dashed lines indicate the other modeled relationships.

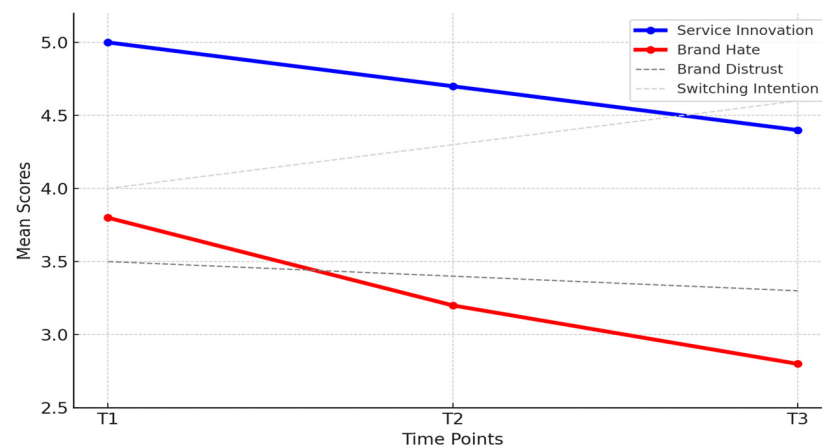


Figure 4. Simplified mean trajectories of key constructs over three waves (T1–T3). Note: Mean scores for each construct across T1–T3. The blue and red lines (service innovation and brand hate) represent significant mean declines over time ($p < 0.05$), whereas the gray dashed lines (brand distrust and switching intentions) indicate relatively stable trends.

5. Discussion

The present study examined the associations of service innovation with the temporal evolution of switching intentions among disappointed customers, using a three-wave longitudinal design. The findings indicate a nonlinear trajectory, whereby innovation is observed to coincide with reductions in switching intentions, with the strongest association in the mid-stage phase, but does not uniformly weaken the associations between negative emotions and exit across time. Brand hate emerged as the primary indicator of this dilution pattern; however, contrary to our expectation, its marginal association with switching intentions intensified over time even as its mean level declined. In contrast, brand distrust, although observed to decline alongside innovation, showed no significant behavioral association. Thus, these results provide longitudinal evidence that switching intentions are dynamic rather than static, and that service innovation is mainly associated with a reduction in the prevalence of brand hate, even as its behavioral association among remaining high-hate customers may intensify.

Two mechanisms may help explain this divergence. First, selective attrition may have played a role. Respondents with lower levels of hate were more likely to disengage from later survey waves. This left a sample that was disproportionately composed of individuals with higher levels of hate. Second, entrenched negative affect offers a theoretical explanation. Previous studies have shown that intense moral emotions, such as hate, can endure and intensify over time, fueling motives of revenge and resistance to reconciliation based on identity [3,37]. Accordingly, although mean levels of hate decreased, high-hate consumers became more predictive of exit intentions. This pattern shows that, while innovation may reduce average levels of hate, entrenched hate continues to disproportionately influence behavior over time.

5.1. Theoretical Implications

This study contributes to the literature in two primary ways. First, while prior studies on service innovation have primarily emphasized its role in generating positive outcomes such as satisfaction, value creation, and loyalty (e.g., [5,6]), they have seldom examined its associations with negative consumer responses. The present study introduces the concept of a dilution effect, describing how service innovation is observed not only as a value-creation mechanism but also as a temporal pattern associated with weaker negative emotions and lower stated switching intentions. This theoretical framing builds upon extant work by

conceptualizing innovation as a dynamic recovery-related pattern rather than a static correlate of performance. Unlike general theories of emotional decay, which assume uniform attenuation, the dilution effect highlights the uneven weakening of negative states, thereby extending theories of consumer emotion regulation and service recovery trajectories.

Second, the study makes a significant contribution to the literature on brand relationships and consumer emotion dynamics by disentangling the roles of brand hate and brand distrust. While prior research has frequently treated negative emotions and cognitions as interchangeable predictors of customer defection [3,13], our longitudinal evidence shows that these states follow divergent temporal trajectories. Specifically, hate substantially declines alongside innovation yet remains closely associated with stronger switching intentions over time, whereas distrust, although mitigated, persists as a relatively stable state exerting no significant behavioral association. This distinction can be grounded in appraisal-based perspectives. Affective states, such as hate, are more malleable and dynamic. In contrast, cognitive judgments, such as distrust, are schema-driven and more resistant to change. Such a perspective enriches theoretical understanding of how different forms of negativity evolve and clarifies that not all negative states coincide equally with exit behavior.

5.2. Managerial Implications

This study also offers practical guidance for managers in service industries where customer defection is frequent and innovations are continuously introduced. First, the results demonstrate that service innovation operates as a mechanism for diluting brand hate but not brand distrust. Managers should therefore closely monitor and manage the intensity of hate among disappointed customers, as this emotion is malleable yet highly influential in driving exit behavior. Our findings show that while average levels of hate decline with innovation, its predictive association with switching actually intensifies among the remaining high-hate segment. This means that staged, visible innovations must directly address the concerns of these customers if firms are to reduce actual churn. Targeted innovations that directly address customer frustrations—such as improved complaint-handling systems, personalized recovery interfaces, or transparent information features—can effectively reduce hate and, consequently, switching intentions. By contrast, distrust is more persistent and resistant to short-term fixes, requiring complementary long-term trust-building strategies such as consistent service reliability, transparent governance, and reputation management that extend beyond innovation alone.

Second, the temporal nature of the findings highlights that the impact of innovation on switching intentions is not constant but strongest in the mid-stage of adoption. Managers should thus recognize that innovation-driven retention benefits may fade over time if not reinforced. This temporal insight suggests that staged innovation strategies—rolling out improvements in visible phases—are essential to sustain reductions in hate and to prevent a resurgence of exit tendencies. A useful example can be found in Chinese hotels' adoption of delivery robots, which resolve complaints about service delays, hygiene concerns, and privacy—effectively diluting negative emotions and sustaining customer engagement in the short term. To align with these patterns, firms may consider staged innovation strategies that introduce visible improvements in waves to match the temporal dynamics of customer emotions. By doing so, managers can capitalize on the observed attenuation of hate while simultaneously implementing broader initiatives to address the more persistent barrier of distrust—thereby supporting re-engagement and reducing the likelihood of churn.

Although our analysis is firmly rooted in the OTA context, the mechanisms we identify are observable in other service-intensive industries. For example, in the 2023–2024 period, several prominent airlines unveiled AI-driven self-service and dynamic compensation mechanisms to address flight disruptions. These innovations coincided with reductions in customer complaints and attrition, paralleling the dilution pattern identified in OTAs. Similarly, hotels and digital platforms that implement incremental yet perceptible innovations (e.g., personalized booking engines, loyalty program enhancements) can mitigate negative emotions and reduce switching intentions, aligning with our findings. The recent case evidence supports the generalizability of the results and provides managers with a concrete illustration of how innovation strategies can mitigate customer exit beyond the OTA sector.

5.3. Limitations and Future Research Directions

The present study is not without its limitations, which also open avenues for further inquiry. First, data were collected from OTA users in a single country. While this setting provides an ideal context for examining temporal dynamics in switching behavior, it is important to consider the potential associations of cultural and industry-specific factors with the findings. Future studies could extend this framework to other service sectors—such as airlines, restaurants, and hospitality—or to cross-cultural samples to test the generalizability of the dilution pattern across different contexts.

Second, this study focused on two negative states—brand hate and brand distrust—as pathways through which service innovation is associated with switching intentions. While these constructs are critical to the study of customer emotions, they do not fully capture the spectrum of customer emotions. Subsequent research endeavors may explore how other affective states, including anger, disappointment, or even re-established trust and attachment, evolve over time in response to innovation. Integrating a broader range of emotional dynamics would deepen theoretical understanding of how service innovations reshape customer–brand relationships over time.

Third, the analysis relied exclusively on self-reported switching intentions rather than on actual behavioral data, such as booking or cancellation records. Stated intentions may not always align with actual behaviors. Future studies could address this limitation by incorporating transactional or digital trace data to verify whether innovations truly reduce churn. Additionally, the study used a single survey-based method, raising the potential for common-method bias despite diagnostic checks. Mixed-methods approaches, such as combining surveys with behavioral experiments or qualitative interviews, could mitigate this risk and provide richer insights.

Finally, although partial measurement invariance was established, several T2 loadings were unusually high (approximately 0.93–0.95). While additional checks revealed no substantial bias, we acknowledge that minor response-shift effects or methodological artifacts may have contributed to the elevated coefficients at T2. Future studies could explicitly model response shift or differential item functioning across waves to better capture potential changes in measurement properties over time. Therefore, these unusually high T2 loadings should be considered as a caveat when interpreting temporal comparisons.

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Informed Consent Statement: All respondents were informed about the voluntary and anonymous nature of the survey and provided their consent before participation.

Data Availability Statement: Data presented in this study are available upon request from the corresponding author due to restrictions on the external exposure of data.

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