

Article

Strategic Interaction of Online Travel Platforms: Cancellation Policies Under Heterogeneous Reputation Sensitivity

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Abstract

The sustainable development of online travel platforms relies on consumer trust and a healthy ecosystem. However, challenging cancellation policies have become a significant issue, threatening the industry's sustainability. Existing research often analyzes cancellation policies from a short-term profit perspective, lacking a dynamic evolutionary analysis. This study employs evolutionary game theory and the Hotelling model, introducing heterogeneity in reputation loss sensitivity to explore how platforms evolve optimal cancellation policies between strict and lenient policies. We find that in markets with low reliance on reputation, platforms tend to adopt differentiated policies, making it difficult for the equilibrium to be unified and lenient. As reputation becomes more important, the market exhibits policy imitation or differentiation, both of which are significantly influenced by user loyalty. In highly competitive environments, reputation becomes central, and even reputation-insensitive platforms may adopt lenient policies to gain market share. Notably, increased user loyalty drives the market toward more lenient cancellation policies. This research provides a theoretical basis for platforms to formulate sustainable policies in dynamic competition.

Keywords: online travel platform; cancellation policy; evolutionary game; reputation heterogeneity; Hotelling model

1. Introduction

Online Travel Agencies (OTAs) serve as an important bridge between hotel suppliers and consumers [1]. The formulation of cancellation policies by these platforms constitutes a critical component of sustainable operations, directly impacting sustainability through consumer rights and platform reputation [2]. In recent years, consumers have shown increasing attention to relevant policies, accompanied by a notable rise in related complaints and disputes. By 2025, issues related to refunds remained the predominant source of consumer complaints in the sector, with hotel cancellation policies—particularly “non-refundable” clauses and restrictive “free cancellation” windows—constituting the primary causes of dissatisfaction. Rigid cancellation policies are ill-suited for modern platform operations, as they fail to foster the long-term user trust required for sustainable development [3]. Given the demonstrated impact of cancellation policies on market fairness and consumer rights, both industry players and regulators must reassess the logic and equity underlying these policies.

In the OTA sector, reputation has become a critical asset, strongly influencing both consumer choices and platform competitiveness [4]. For most users, online reputation plays a crucial role in choosing a hotel, with research indicating it is a primary determinant in their final decision [5]. Reputation can strongly influence consumer behaviour through online



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reviews and social media [6]. Reputation not only attracts customers but also underpins sustained competitive advantage. Favourable reviews boost a hotel's search ranking and visibility on OTAs, resulting in better click-through and booking rates. Currently, pure price competition is unrealistic given market complexities like hotel oversupply and intense pricing pressure. A positive reputation does more than boost user loyalty and repurchases; it also forms the basis for a sustainable competitive edge [7].

The cancellation policies of online travel platforms are closely linked to their reputations, which directly affect their capacity for sustainable development. Generally, unreasonable cancellation policies can spark consumer disputes. This not only harms a platform's reputation but also undermines its image of social responsibility and long-term brand value. Conversely, when cancellation policies are friendly and transparent, they can significantly enhance consumer trust. The trust fuels a cycle of positive reputation, where good experiences lead to favourable reviews, attract new users, and ultimately increase repeat purchases—creating a long-term virtuous circle for the platform. As the role of reputation in market competition becomes increasingly prominent, platforms therefore have a strong incentive to adopt more user-friendly cancellation policies. Reputation has become a key variable that connects cancellation policies, consumer experience, and overall platform performance, forming a pivotal nexus for sustainable growth [8]. The differences in how sensitive platforms are to the impact of reputation will directly affect their choices between lenient and strict cancellation policies.

There is no doubt that reputation is important for sustainable management. However, the significant heterogeneity in platforms' sensitivity to reputational impacts is often overlooked in existing research [9]. This heterogeneity stems from multiple factors, including a platform's market positioning, business model, policy support, stage of development, and strategic orientation. Some platforms regard reputation as a core asset and tend to adopt lenient cancellation policies to enhance consumer trust and loyalty. In contrast, some platforms may prioritize short-term profit maximization, exhibiting a higher tolerance for reputational risks and thus leaning towards stricter cancellation terms. This strategic divergence reflects the differing assessments platforms make of the costs of their reputations. Highly reputation-sensitive platforms perceive negative evaluations as a major threat, whereas those with low reputation sensitivity may view them as an acceptable operational cost. These divergences directly affect platforms' collective choices between lenient and strict cancellation policies, which, in turn, fuel the ongoing strategic interplay across the industry's policy landscape [10].

The cancellation policies of online travel platforms, situated at the intersection of revenue management and consumer relationship management, are increasingly recognized for their impact on managerial sustainability. The existing research provides a basis for understanding the cancellation policies. On one hand, studies have explored fundamental elements such as platform service quality and technology acceptance models. On the other hand, research that focused specifically on cancellation policies has verified their significant influence on hotel financial performance, consumer trust, and purchase intention, with some scholars highlighting the importance of differentiated policies. However, the existing literature still exhibits two primary limitations. Firstly, most studies still regard hotels as the primary decision-makers, which fails to adequately reflect the strategic interactions among platforms. In fact, the platforms are the real decision-makers in an oligopolistic OTA market. Secondly, while the importance of reputation is widely acknowledged, the heterogeneity in reputation sensitivity across platforms and the dynamic impact of this sensitivity on the evolutionary path of cancellation policies lacks in-depth theoretical analysis. This research gap lies precisely at the intersection where sustainable tourism studies call for increased attention to both "platform economy governance" and "consumer rights protection".

This paper addresses these gaps by establishing a game-theoretic model that incorporates hotels, platforms, and users. Using evolutionary game theory, we analyze platforms' cancellation policy choices in an oligopolistic market, treating them as the primary players. Building on an oligopoly competition model, we investigate how platforms' choices regarding cancellation policies are influenced by their varying sensitivities to reputation loss. This research incorporates the impact of reputation as a key entry point to deeply examine user influence on platform decision-making. By taking the platform as the primary decision-maker and considering factors such as platform commissions from hotels and diverse user preferences, our study integrates both hotels and users into the platform's cancellation policy selection model. Through game-theoretic modelling and equilibrium analysis, we analyze the selection of platform cancellation policies under conditions of reputation heterogeneity.

2. Literature Review

In recent years, with the development of online hotel platforms, the sustainable operational mechanisms of OTA platforms have remained a key focus in hotel policy discussions. Kim et al. (2005) [11] compared the web service quality of online travel agencies and online tourism suppliers, identifying significant commonalities in areas such as reputation, security, structure, and ease of use. Park et al. (2007) [12] measured the website quality of OTAs. They examined the impact of perceived website quality on the intention to use OTAs, concluding that ease of use is the most critical dimension influencing usage intention. From the perspective of customer value, Ku et al. (2009) [13] explored the relative importance of nine fundamental tourism products proposed from an internet-based standpoint, finding that privacy, security, and product quality are the three most influential factors affecting customers' online hotel bookings. Kim et al. (2020) [14] investigated the impact of varying degrees of price dispersion on travellers' hotel selection, revealing that travellers prefer hotels with greater price dispersion. Wicaksono et al. (2020) [15] analyzed the influence of perceived usefulness and perceived ease of use on the technology acceptance model for OTAs, demonstrating that both factors significantly affect users' behavioural intentions.

Cancellation policies have always been a focal point in hotel revenue management and are significant for long-term sustainable operations. Riasi et al. (2018) [16] theoretically demonstrated the potential benefits of cancellation policies, confirming their practical value and guiding importance in hotel operations management. Daniel Leung et al. (2022) [17] analyzed how the proactiveness of cancellation policies, the magnitude of policy changes, and the form of refunds affect consumer trust and repurchase intention. From the customer's perspective, Shih-Ping Jeng (2017) [18] found that cancellation policies affect purchase intention, with generous policies enhancing purchase willingness by increasing perceived value. Chih-Chien Chen et al. (2013) [19] examined differentiated cancellation policies in the U.S., highlighting the importance of considering hotel differentiation when formulating such policies. Yukyeong Choi et al. (2024) [20] investigated the signalling effect of hotel cancellation policies. They analyzed the relationship between consumer cancellation rates and hotel quality under different scenarios, showing that these policies convey information about hotel quality. Altin et al. (2023) [21] developed a mathematical model validated with data from over 500 U.S. hotels. Empirical results support the model's prediction that moderate cancellation policies may yield better financial performance compared to stricter or more lenient alternatives. Some scholars have begun linking cancellation policies to long-term hotel revenue, exploring how to adopt optimal policies to maximize profits and reduce risks. For example, Lu Xinyuan et al. (2022) [22] studied hotel cancellation policy choices based on booking cancellation rates, analyzing decision-making in contexts where cancellation rates are a key factor.

Existing research on cancellation policies is already quite comprehensive, yet several gaps remain. Most studies focus on how hotels choose their cancellation policies and how consumers respond to them, with little attention paid to the relationship between users and platforms. These studies often adopt a hotel-centric perspective, which may overlook the platform's dominant role in shaping cancellation policies and fail to examine how platforms strategically use these policies to maximize their own profits. Moreover, many papers lack characterization of users on the platforms and do not incorporate adequate user feedback mechanisms, which is a place for further study.

3. Problem Description and Formulation

3.1. Problem Description

The OTA platform provides customers with information about hotels, along with services such as matching and screening. Platform profits primarily derive from hotel registration fees and commissions on room bookings. Cancellation policies help the platform manage its revenue effectively. When designing cancellation policies, platforms face a critical trade-off. Overly lenient policies may reduce hotel occupancy rates, leading to higher operational costs due to idle inventory. Conversely, excessively strict policies may harm the platform's reputation, diminish user loyalty, and reduce customer retention.

Following Chen et al., cancellation policies are typically classified into two categories—strict and lenient—based on the cancellation deadline set by the platform. Based on this analysis, we model a two-sided market with two competing online hotel platforms (a duopoly market) using the Hotelling model. In this model, each platform's choice of cancellation policies influences both hotels and users, who in turn provide distinct forms of feedback [23–25]. In practice, hotels can only choose from a limited set of cancellation policies offered by the platform. They cannot design their own terms or adjust them dynamically. Accordingly, and consistent with the focus of this study, hotels are modelled as relatively passive participants in the formulation of cancellation policies. In contrast, users play an active role: they choose platforms not only based on price but also on the leniency of cancellation policies, and they directly shape platform reputation through ratings, reviews, and social sharing. Therefore, platform reputation is treated as the primary factor in cancellation policy decisions. The strategic interaction between the two platforms' cancellation policy choices affects their respective market influence and revenues. The structural relationship between the two competing platforms and the customers is illustrated in Figure 1. After deriving the platforms' revenue functions using the Hotelling model, we further analyze their dynamic revenue outcomes through an evolutionary game-theoretic framework.

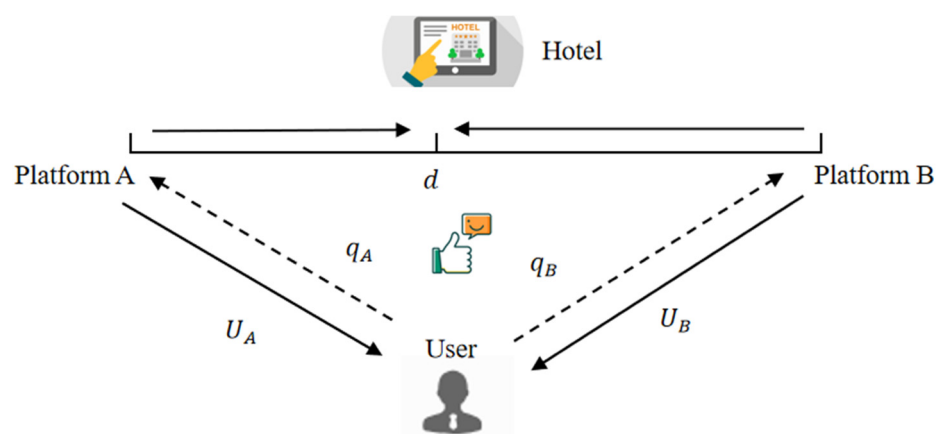


Figure 1. The relationship between the platforms and customers.

3.2. Hypotheses

Based on the above analyses, the following hypotheses are proposed in this paper.

Hypothesis 1. *The market consists of two competing online hotel platforms, denoted as Platform A and Platform B.*

Hypothesis 2. *Platform i ($i = A, B$) has considerable dominance over the cancellation policies of hotels and can determine cancellation policies, which can be categorized into two main types: strict cancellation policy (S) and lenient cancellation policy (L).*

Hypothesis 3. *Platforms A and B offer identical hotel products and are positioned at endpoints of a linear Hotelling market. Platform A is located at the left end of the Hotelling market ($d_1 = 0$) and Platform B is located at the right end of the market ($d_2 = 1$). The two platforms are symmetric in their pricing structures toward both hotels and users. Customers are uniformly distributed over the interval $[0, 1]$ with unit density. In the Hotelling framework, customers incur a generalized “transportation cost” that captures their preference heterogeneity across platforms—stemming from differences in perceived service quality, cost-effectiveness, and usage habits—rather than actual physical travel. The costs for customers located at d to travel to Platform A and Platform B for consumption are td and $t(1 - d)$, respectively [26,27].*

In this model, users are mainly rational, expected-utility-oriented consumers. When making decisions, they consider not only the explicit price but also the implicit risk of potential losses associated with different cancellation policies. The implicit risk includes factors such as refund rates for trip cancellations, procedural complexity, and time costs. In reality, users exhibit significant heterogeneity in their sensitivity to cancellation policies. For example, business travellers usually prioritize trip certainty and are more tolerant of high cancellation costs, whereas leisure travellers generally prefer lenient cancellation terms. Similarly, risk-averse users tend to pay a premium for cancellation protection, while risk-tolerant users may sacrifice flexibility in exchange for lower prices. Some behavioural differences would naturally be reflected in the model through variations in the parameter t or in the distribution of users’ valuations of cancellation losses. Although this paper adopts a representative expected-utility-maximizing user in the baseline model to focus on the core mechanism, user heterogeneity offers a promising direction for future extension.

Hypothesis 4. *Both platforms charge the same commission rate m on hotel transactions. Since this study focuses exclusively on cancellation policies and abstracts from commission competition, we assume that both platforms charge the same commission rate on hotel transactions.*

Hypothesis 5. *When platform i adopts a lenient cancellation policy, a customer who books a hotel through it cancels the reservation with probability β_i . Each cancellation incurs an expected cost of f_i to the platform, capturing both direct operational losses and indirect effects. In contrast, if platform i implements a strict cancellation policy, the cancellation probability decreases to $k\beta_i$, where $0 < k < 1$ captures the extent to which stricter terms deter cancellations.*

Hypothesis 6. *Cancellation policies significantly affect the platform’s reputation by shaping users’ perceptions of fairness and trust. Strict cancellation policies raise users’ cancellation costs, which may be interpreted as unfriendly or a lack of good faith. This can lead to negative reviews, lower ratings, and adverse word of mouth on social media, which, in turn, may reduce user loyalty [28–30]. To focus on the core strategic mechanism, this paper simplifies the per-unit reputational loss caused by strict cancellation policies into a structural parameter q_i . In economic terms, q_i can be interpreted as the present value of expected future demand loss per transaction resulting from the strict cancellation*

policy. Although q_i is treated as a parameter to maintain analytical tractability, it is necessary to acknowledge that reputation is inherently endogenous and dynamically evolving. The value of q_i is actually a concise representation of the complex feedback mechanism under steady or short-term equilibrium. It will vary based on factors such as the platform's past policies, user composition, and the intensity of market competition.

Hypothesis 7. The market demand of both platforms is not 0. The utility customers obtain from purchasing products is defined as V , and V is sufficient to ensure that the market is fully covered.

3.3. Model Formulation

According to the above problem description and hypothesis, the model will ultimately yield four strategic policy combinations: LL, LS, SL, and SS. The profit function of the hotel platform in four cases is shown below.

Strategy LL. Platform A and Platform B both choose the lenient cancellation policies (L), and the unit price of Platform A and Platform B is P_A^{LL} and P_B^{LL} respectively. The net surplus for a user located at point d when consuming the products of these two hotel platforms is, respectively, as follows:

$$U_A^{LL} = V - P_A^{LL} - td \quad (1)$$

$$U_B^{LL} = V - P_B^{LL} - t(1 - d) \quad (2)$$

Assume that $\hat{d}$ is the undifferentiated location that a customer travels to two platforms for consumption. We can obtain the following equation:

$$V - P_A^{LL} - t\hat{d} = V - P_B^{LL} - t(1 - \hat{d}) \quad (3)$$

The demand for the two hotel platforms can be derived as follows:

$$D_A^{LL} = \hat{d} = \frac{P_B^{LL} - P_A^{LL} + t}{2t} \quad (4)$$

$$D_B^{LL} = 1 - \hat{d} = \frac{P_A^{LL} - P_B^{LL} + t}{2t} \quad (5)$$

Assuming the cost of the platform's product is zero, the profit function for platform i when choosing a lenient policy (L) is as follows:

$$\pi_i^L = m(P_i^L - \beta_i f_i) D_i^L \quad (6)$$

The condition of profit maximization for both platforms requires taking the first-order derivatives of their respective profit functions with respect to P_A^{LL*} and P_B^{LL*} , setting them equal to zero. Solving these equations yields the optimal prices for Platform A and Platform B as follows:

$$P_A^{LL*} = t + \frac{2\beta_A f_A + \beta_B f_B}{3} \quad (7)$$

$$P_B^{LL*} = t + \frac{\beta_A f_A + 2\beta_B f_B}{3} \quad (8)$$

The maximum profits for the two platforms under the LL policy combination can be derived by substituting P_A^{LL*} and P_B^{LL*} into their respective profit functions:

$$\pi_A^{LL*} = \frac{m(3t + \beta_B f_B - \beta_A f_A)^2}{18t} \quad (9)$$

$$\pi_B^{LL*} = \frac{m(3t + \beta_A f_A - \beta_B f_B)^2}{18t} \quad (10)$$

Strategy LS. Platform A adopts the strict cancellation policy (S), while Platform B chooses the lenient cancellation policy (L). The prices of a unit product on Platform A and Platform B are denoted as P_A^{SL} and P_B^{SL} , respectively. The net surplus for a user located at point d when consuming the products of these two hotel platforms is, respectively, as follows:

$$U_A^{SL} = V - P_A^{SL} - td \quad (11)$$

$$U_B^{SL} = V - P_B^{SL} - t(1-d) \quad (12)$$

Under the strict cancellation policy, the platform's profit function is given by:

$$\pi_i^S = m(P_i^S - k\beta_i f_i - q_i)D_i^L \quad (13)$$

The condition of profit maximization for both platforms requires taking the first-order derivatives of their respective profit functions with respect to P_A^{SL*} and P_B^{SL*} , setting them equal to zero. Solving these equations yields the optimal prices for Platform A and Platform B as follows:

$$P_A^{SL*} = t + \frac{2(k\beta_A f_A + q_A) + \beta_B f_B}{3} \quad (14)$$

$$P_B^{SL*} = t + \frac{(k\beta_A f_A + q_A) + 2\beta_B f_B}{3} \quad (15)$$

The maximum profits for the two platforms under the SL policy combination can be derived by substituting P_A^{SL*} and P_B^{SL*} into their respective profit functions:

$$\pi_A^{LL*} = \frac{m(3t + \beta_B f_B - k\beta_A f_A - q_A)^2}{18t} \quad (16)$$

$$\pi_B^{LL*} = \frac{m(3t + k\beta_A f_A - \beta_B f_B + q_A)^2}{18t} \quad (17)$$

Strategy SL. Platform A adopts the lenient cancellation policy (L), while Platform B chooses the strict cancellation policy (S). The prices of a unit product on Platform A and Platform B are denoted as P_A^{LS} and P_B^{LS} , respectively. The net surplus for a user located at point d when consuming the products of these two hotel platforms is, respectively, as follows:

$$U_A^{LS} = V - P_A^{LS} - td \quad (18)$$

$$U_B^{LS} = V - P_B^{LS} - t(1-d) \quad (19)$$

The maximum profits for the two platforms under the LS policy combination are as follows:

$$\pi_A^{LS*} = \frac{m(3t + k\beta_B f_B - \beta_A f_A + q_B)^2}{18t} \quad (20)$$

$$\pi_B^{LS*} = \frac{m(3t + \beta_A f_A - k\beta_B f_B - q_B)^2}{18t} \quad (21)$$

Strategy SS. Platform A and Platform B both choose the strict cancellation policy (S), and the unit price of Platform A and Platform B is P_A^{SS} and P_B^{SS} respectively. The net surplus for a user located at point d when consuming the products of these two hotel platforms is, respectively, as follows:

$$U_A^{SS} = V - P_A^{SS} - td \quad (22)$$

$$U_B^{SS} = V - P_B^{SS} - t(1-d) \quad (23)$$

The maximum profits for the two platforms under the SS policy combination are as follows:

$$\pi_A^{SS*} = \frac{m(3t - k\beta_A f_A + k\beta_B f_B - q_A + q_B)^2}{18t} \quad (24)$$

$$\pi_B^{SS*} = \frac{m(3t - k\beta_B f_B + k\beta_A f_A + q_A - q_B)^2}{18t} \quad (25)$$

4. Model Solution and Equilibrium Analysis

4.1. Model Solution

After calculating the optimal income of the platform, this paper analyzes the stable profits of the two platforms under long-term competition using an evolutionary game.

To simplify the expression and facilitate subsequent analysis, let $q_A = q$ and $q_B = eq$, where q denotes the reputation loss incurred by a platform due to implementing the strict cancellation policy, and e ($0 < e < 1$) represents the degree of variation in reputation decline when platforms adopt strict policies, reflecting heterogeneity across platforms. This study primarily investigates how changes in hotel room supply rates across platforms and user-perceived costs influence platform cancellation policies. Accordingly, we define the following variables: $\beta_A = \beta_B = \beta$, $f_A = f_B = f$ and $H = \beta f - k\beta f$, where $0 < k < 1$. H can be interpreted as the additional loss bincurred by adopting the lenient cancellation policy relative to the strict cancellation policy, quantified as the higher cancellation rate under the lenient cancellation policy. Table 1 presents the simplified profit matrix, highlighting the payoff structure for both platforms under the four strategy combinations.

Table 1. The simplified profit matrix.

		Platform B			
The Policy		L		S	
Platform A	L	$\frac{9mt^2}{18t}$	$\frac{9mt^2}{18t}$	$\frac{m(3t - H + eq)^2}{18t}$	$\frac{m(3t + H - eq)^2}{18t}$
	S	$\frac{m(3t + H - q)^2}{18t}$	$\frac{m(3t - H + q)^2}{18t}$	$\frac{m(3t - q + eq)^2}{18t}$	$\frac{m(3t + q - eq)^2}{18t}$

The probability of Platform A and Platform B choosing a strict refund policy is noted as x and y , $0 \leq x, y \leq 1$. The expected earnings of Platforms A and B choosing the lenient refund policy are U_A^L and U_B^L . The expected earnings of Platforms A and B choosing the strict refund policy are U_A^S and U_B^S . The average earnings are $\bar{U}_A$ and $\bar{U}_B$, respectively. Their expressions are as follows.

$$\begin{cases} U_A^L = y\pi_A^{LL*} + (1-y)\pi_A^{LS*} \\ U_A^S = y\pi_A^{SL*} + (1-y)\pi_A^{SS*} \\ \bar{U}_A = xU_A^L + (1-x)U_A^S \end{cases} \quad (26)$$

$$\begin{cases} U_B^L = x\pi_B^{LL*} + (1-x)\pi_B^{SL*} \\ U_B^S = x\pi_B^{LS*} + (1-x)\pi_B^{SS*} \\ \bar{U}_B = yU_B^L + (1-y)U_B^S \end{cases} \quad (27)$$

The replication dynamic equations of Platform A and Platform B were established as follows:

$$F_A(x) = \partial_x / \partial_T = x(1-x) \left[y(\pi_A^{LL*} - \pi_A^{LS*} - \pi_A^{SL*} + \pi_A^{SS*}) + \pi_A^{LS*} - \pi_A^{SS*} \right] \quad (28)$$

$$F_B(x) = \partial_x / \partial_T = y(1-y) \left[x(\pi_B^{LL*} - \pi_B^{SL*} - \pi_B^{LS*} + \pi_B^{SS*}) + \pi_B^{SL*} - \pi_B^{SS*} \right] \quad (29)$$

Based on the equilibrium conditions derived above, we conducted numerical simulations using MATLAB R2020a to visualize the results. Let $F_A(x) = F_B(y) = 0$ and calculate for the system's equilibrium point by MATLAB.

When $x = 0, y = 0$ or 1 , we can obtain equilibrium point $O(0, 0), A(0, 1)$;

When $x = 1, y = 0$ or 1 , we can obtain equilibrium point $B(1, 0)$ and $C(1, 1)$;

When $x \neq 0$ or 1 and $y \neq 0$ or 1 , the equations are as follows:

$$\begin{cases} y(\pi_A^{LL*} - \pi_A^{LS*} - \pi_A^{SL*} + \pi_A^{SS*}) + \pi_A^{LS*} + \pi_A^{SS*} = 0 \\ x(\pi_B^{LL*} - \pi_B^{SL*} - \pi_B^{LS*} + \pi_B^{SS*}) + \pi_B^{SL*} + \pi_B^{SS*} = 0 \end{cases} \quad (30)$$

The equilibrium point: $D\left(\frac{-\pi_B^{SL*} - \pi_B^{SS*}}{\pi_B^{LL*} - \pi_B^{SL*} - \pi_B^{LS*} + \pi_B^{SS*}}, \frac{-\pi_A^{LS*} - \pi_A^{SS*}}{\pi_A^{LL*} - \pi_A^{LS*} - \pi_A^{SL*} + \pi_A^{SS*}}\right)$.

MATLAB is used to obtain the optimal point $D(x^*, y^*)$.

We list the Jacobian matrix of the system and analyze which equilibrium points are evolutionarily stable strategies (ESSs).

The Jacobian matrix of the system is $J = \begin{bmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} \end{bmatrix}$.

The determinant of the Jacobian matrix:

$$Det(J) = \frac{\partial F(x)}{\partial x} \times \frac{\partial F(y)}{\partial y} - \frac{\partial F(x)}{\partial y} \times \frac{\partial F(y)}{\partial x} \quad (31)$$

Trace of the Jacobian matrix:

$$Tr(J) = \frac{\partial F(x)}{\partial x} + \frac{\partial F(y)}{\partial y} \quad (32)$$

The determinant and trace of the Jacobian matrix for each equilibrium point are calculated and summarized in Table 2. According to evolutionary game theory, when $Det(J) > 0$ and $Tr(J) < 0$, the equilibrium point of the system evolves into a stable point. When the value is $Det(J) > 0$ and $Tr(J) > 0$, the equilibrium point of the system is unstable. If the value is $Det(J) < 0$, the system equilibrium point is the target.

Table 2. The determinant and traces of each equilibrium point.

	$Det(J)$	$Tr(J)$
$(0, 0)$	$(\pi_A^{LS*} - \pi_A^{SS*})(\pi_B^{SL*} - \pi_B^{SS*})$	$(\pi_A^{LS*} - \pi_A^{SS*}) + (\pi_B^{SL*} - \pi_B^{SS*})$
$(1, 1)$	$(\pi_A^{LL*} - \pi_A^{SL*})(\pi_B^{LL*} - \pi_B^{LS*})$	$-(\pi_A^{LL*} - \pi_A^{SL*}) - (\pi_B^{LL*} - \pi_B^{LS*})$
$(0, 1)$	$-(\pi_A^{LL*} - \pi_A^{SL*})(\pi_B^{LS*} - \pi_B^{SS*})$	$(\pi_A^{LL*} - \pi_A^{SL*}) - (\pi_B^{LS*} - \pi_B^{SS*})$
$(1, 0)$	$-(\pi_A^{LS*} - \pi_A^{SS*})(\pi_B^{LL*} - \pi_B^{LS*})$	$-(\pi_A^{LS*} - \pi_A^{SS*}) + (\pi_B^{LL*} - \pi_B^{LS*})$

Note: The superscript * denotes the optimal values at the equilibrium state.

The results can be obtained as follows.

The complex threshold expressions in Table 3 delineate how the strategic landscape is shaped by the interplay between potential reputation loss (q) and platform differentiation (t). In our model, q represents the present value of expected future demand loss per transaction resulting from adopting a strict cancellation policy. Practically, a high q indicates a market where consumers are highly sensitive to policy strictness (e.g., mature markets with high expectations), meaning a strict policy would incur severe long-term reputational damage. Conversely, a low q suggests that the reputational penalty for strict policies is negligible.

In the Hotelling framework of this paper, t represents the unit “transportation cost”, which practically corresponds to the degree of platform differentiation or user stickiness. A high t implies that users perceive significant differences across platforms (e.g., due to

interfaces, ecosystems, or habits) and are less sensitive to policy variations. Conversely, a low t indicates a homogeneous market in which users view platforms as near-perfect substitutes and switch easily for better terms.

Table 3. The equilibrium point.

Situation	The Condition	Equilibrium Point
$q < H$	$0 < t < \frac{H-2q+eq}{6}$ and $e > \frac{H-2q}{q}$;	(0, 1) and (1, 0)
	$\frac{H-2q+eq}{6} < t < \frac{H+q-2eq}{6}$;	(1, 0)
	$t > \frac{H+q-2eq}{6}$;	(0, 0)
$H < q < \frac{H}{e}$	$\frac{(H-q)^2+(H-eq)^2}{6(q+eq-2H)} < t < \frac{q-H}{6}$ and $q > \frac{2H}{e+1}$;	(0, 0) and (1, 1)
	$0 < t < \frac{H+q-2eq}{6}$;	(0, 0)
	$t > \frac{H+q-2eq}{6}$;	(1, 0)
$q > \frac{H}{e}$	$\frac{1}{3} < e < 1$, $0 < H < \frac{q(3e-1)}{2}$ and $\max\left(0, \frac{H-2eq+q}{6}\right) < t < \frac{eq-H}{6}$;	(0, 1) and (1, 0)
	$0 < t < \frac{q-H}{6}$;	(0, 1)
	$t > \frac{q-H}{6}$;	(1, 1)

The conceptual map of equilibrium strategies across different market stages can be seen in Figure 2.

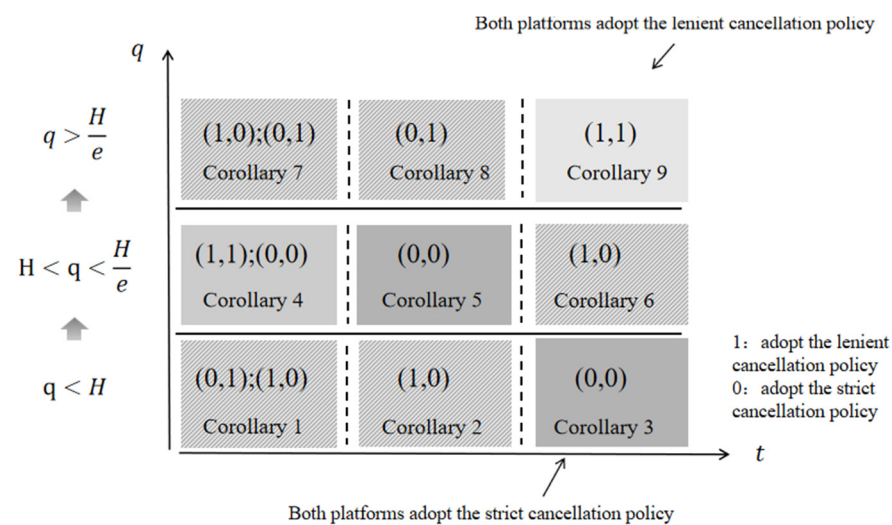


Figure 2. Conceptual map of equilibrium strategies across different market stages.

In the Low-Reputation-Loss Region (Situation 1: $q < H$), the potential future demand loss (q) from a strict policy is smaller than the immediate cost of cancellations (H) incurred under a lenient policy. When platforms are highly substitutable (Corollary 1 and 2), fierce competition prevents a “both strict” outcome. Instead, the market settles into asymmetric equilibria (0,1) or (1,0). One platform adopts a lenient policy to capture sensitive users, while the other maintains a strict policy to minimize costs. This differentiation avoids a destructive price war. As t exceeds the threshold $\frac{H+q-2eq}{6}$ (Corollary 3), user lock-in becomes strong enough to insulate platforms from competitive pressure. Both platforms can safely coordinate on strict policies, maximizing immediate profits since the reputational risk (q) is negligible.

In the Transitional Region (Situation 2: $H < q < \frac{H}{e}$), the reputation loss (q) begins to outweigh the cancellation cost (H), creating a complex tension between cost-saving and reputation protection. This region reveals a counterintuitive “reputation-competition paradox”

where market structure dictates strategy more than reputation risk itself. Paradoxically, low differentiation (low t) often forces a “Competition Trap” of dual strictness $(0, 0)$: despite moderate reputation risks ($H < q < \frac{H}{e}$), fierce competition squeezes margins tightly, such that platforms prioritize immediate cost survival over long-term reputation. Conversely, high differentiation (high t) triggers a “Free-Rider Asymmetry”: secure in their locked-in bases, one platform leverages monopoly power to stay strict, while the competitor adopts leniency to differentiate. Thus, in this zone, increased loyalty sustains strategic imbalance rather than consumer-friendly coordination.

In the High-Reputation-Loss Region (Situation 3: $q > \frac{H}{e}$), the market is forced towards lenient outcomes regardless of differentiation levels. In highly competitive markets (low t), the threat of massive demand loss compels at least one, if not both, platforms to adopt lenient policies, creating an “involuntary leniency” where the cost of strictness exceeds any competitive advantage. As differentiation increases (high t), the system stabilizes into a coordinated lenient equilibrium $(1, 1)$, with reputational risk becoming catastrophic, such that even the most loyal user base cannot ignore it. Here, high q overrides the “free-rider” incentive, making leniency the only viable survival strategy for all actors.

4.2. Parameter Interpretation and Numerical Illustration

This paper presents purely hypothetical numerical scenarios constructed to illustrate the theoretical mechanisms and equilibrium properties derived in the previous sections. No empirical data calibration, statistical estimation, or validation against observed market data was performed. The parameter values selected below are not derived from proprietary datasets, nor do they represent specific observed realities. Instead, they are chosen to satisfy the model’s theoretical conditions while reflecting plausible magnitudes found in the general hotel industry context. This approach ensures that the analytical results remain general and applicable to any parameter set satisfying the stated inequalities, while providing readers with an intuitive understanding of the model’s behaviour.

To better analyze and interpret the numerical findings of the model, this section presents the underlying parameter assumptions. The key parameters used in the model and their corresponding interpretations are summarized in Table 4. Moreover, to enhance interpretability, a simple numerical illustration is employed to simulate the scenarios under consideration. The aforementioned conclusions are further exemplified and clarified by examining the dynamic variation in reputational losses.

Table 4. Parameter Interpretation.

Parameter	Interpretation
q	The variable q can be interpreted as the present value of expected future demand loss per transaction resulting from the strict cancellation policy.
H	The parameter H can be interpreted as the additional loss incurred by adopting the lenient cancellation policy relative to the strict cancellation policy, quantified by the higher cancellation rate under the lenient policy.
e	The parameter e ($0 < e < 1$) can be interpreted as the difference in reputation loss between platforms when platforms adopt strict cancellation policies. A smaller value of e indicates a larger disparity in reputation impact between the two platforms.
m	The parameter m represents the average commission rate that the platform charges hotels per transaction.
t	The parameter t denotes users’ preference for different platforms. This preference heterogeneity stems from variations in users’ valuations of service quality, cost-effectiveness, and other attributes, as well as differences in usage habits.
x	The variable x ($0 < x < 1$) denotes the probability that Platform A adopts a lenient cancellation policy.
y	The variable y ($0 < y < 1$) denotes the probability that Platform B adopts a lenient cancellation policy.

The analytical results show that, as q varies across different ranges, platforms' optimal choices regarding cancellation policies also differ accordingly. To illustrate the above mathematical findings more clearly, we here assume the following parameter values: $H = 48$, $e = 0.8$, $m = 0.2$, and $t = 35$. We set the variable q to 40, 50, and 60, respectively. Under the steady state, the equilibrium solutions for the cancellation policies of both platforms are as presented in the Table 5.

Table 5. The cancellation policies of platforms.

The Variable q	(x,y)	Platform A	Platform B
40	(0,0)	Strict cancellation policy	Strict cancellation policy
50	(1,0)	Lenient cancellation policy	Strict cancellation policy
60	(1,1)	Lenient cancellation policy	Lenient cancellation policy

In this numerical example, as reputation loss increases, the equilibrium combination of cancellation policies adopted by Platform A and Platform B gradually shifts. The equilibrium evolves from both platforms initially adopting strict cancellation policies to only Platform A switching to a lenient policy, and ultimately to both platforms adopting lenient cancellation policies. When $q = 40$, both platforms opt for the strict cancellation policy, as the associated reputational loss is small and the operational benefits—such as higher room turnover—outweigh the negative impact. When q increases to 50, only Platform A switches to a lenient cancellation policy, while Platform B continues to maintain a strict policy. When q rises to 60, only Platform A adopts a lenient cancellation policy, while Platform B retains its strict policy. This difference occurs because Platform A is more sensitive to reputation. For example, its users place greater importance on service experience. In contrast, Platform B is less affected by reputation effects. Its users tend to prioritize price over service quality. As a result, Platform B can better tolerate the reputational risks associated with a strict cancellation policy. When q further increases to 60, both platforms switch to the lenient cancellation policies. In this situation, even Platform B, which is less sensitive to reputational concerns, can no longer ignore the user attrition and negative feedback triggered by strict cancellation rules.

In short, the greater the reputational pressure, the more inclined platforms are to take lenient cancellation policies. However, the timing of this strategic shift depends on each platform's sensitivity to reputational losses. Platforms with higher reputation sensitivity adjust their policies first, while those with lower sensitivity follow only when the pressure becomes sufficiently strong.

4.3. Equilibrium Analysis

To better align the numerical findings with real-world contexts, we map the three values of q identified in the numerical analysis to three distinct market types. It is important to clarify methodologically that, while our model treats reputation sensitivity (q) as an exogenous parameter for comparative static analysis, we conceptualize these static snapshots as distinct stages in a hypothetical reputation development trajectory. Specifically, Situations 1, 2, and 3 correspond to markets with low, divergent, and high reputation sensitivity, respectively.

This conceptual framing illustrates how the strategic equilibrium shifts as a platform's reputation matures: from a peripheral constraint (Situation 1) to a lever for differentiation (Situation 2), and ultimately to a core strategic element in platform competition (Situation 3). While the model does not endogenously simulate the time-dependent evolution of q , this comparative static approach effectively captures the structural differences in equilibrium

strategies across these developmental stages. Based on these analytical solutions, the following section integrates the equilibrium characteristics of each stage to provide a detailed discussion of their corresponding real-world contexts.

- **Market with Low Reputation Sensitivity**

When $q < H$, the impact of user reputation on the platform is relatively limited. In this scenario, the benefits of implementing the strict cancellation policy largely offset the associated reputational losses. From the perspective of platform decision-makers, factors such as booking turnover carry greater weight than reputation in strategic considerations.

Proposition 1. *A solution exists at the point (0,1) if and only if it satisfies the conditions that $0 < t < \frac{H-2q+eq}{6}$ and $0 < t < \frac{2(H-q)^2-q^2(1-e)^2}{6q(1-e)}$ simultaneously. Given that $\frac{H-2q+eq}{6} < \frac{2(H-q)^2-q^2(1-e)^2}{6q(1-e)}$, the binding condition is $0 < t < \frac{H-2q+eq}{6}$; a solution exists at the point (1,0) if and only if it satisfies the conditions that $0 < t < \frac{H+q-2eq}{6}$ and $t > \frac{2H^2+4Heq+q^2(1-e^2-2e)}{6q(1-e)}$ simultaneously. Given that $\frac{2H^2+4Heq+q^2(1-e^2-2e)}{6q(1-e)} < 0$ at this time, the binding condition is $0 < t < \frac{H-2q+eq}{6}$.*

Corollary 1. *For the parameter range $0 < e < 1$, the condition for the existence of solutions at both (0,1) and (1,0) is given by the intersection of their respective intervals, which is $0 < t < \frac{H-2q+eq}{6}$. When the parameters satisfy $0 < t < \frac{H-2q+eq}{6}$ and $e > \frac{H-2q}{q}$, the dynamical system possesses stable equilibrium points at (0,1) and (1,0).*

In this situation, users are largely indifferent to differences in platform service quality and exhibit no strong preference. Concurrently, the impact of user reputation varies minimally across different platforms. Given the limited influence of user reputation and the comparable levels of reputation sensitivity and user stickiness across the two competing platforms, both tend to adopt differentiated cancellation policies. By implementing policies distinct from those of its rivals, each platform aims to avoid direct competition. In this context, adopting a strict cancellation policy can enhance hotel turnover rates, and the financial gains are sufficient to offset potential reputation-related risks. Therefore, platforms have an incentive to adapt to enforce strict cancellation policies under these conditions.

Corollary 2. *When the parameters satisfy $\frac{H-2q+eq}{6} < t < \frac{H+q-2eq}{6}$, the dynamical system possesses stable equilibrium points at (1,0).*

In contrast to Corollary 1, users become more sensitive to platform differentiation, thereby amplifying the role of preference heterogeneity in their choice behaviour. Nevertheless, the impact of reputation remains limited. Under these conditions, Platform B—which is less sensitive to reputational feedback—tends to adopt a strict cancellation policy. This policy aligns with its lower reputation sensitivity and helps it gain a competitive advantage over its rival. In contrast, platforms more vulnerable to reputation loss are inclined to adopt lenient cancellation policies as user sensitivity rises. Although the direct benefits of a strict policy might still offset reputation losses, adopting such a policy would place these platforms at a competitive disadvantage, preventing them from maximizing gains.

Proposition 2. *A solution exists at the point (1,0) if and only if it satisfies the conditions that $0 < t < \frac{H-2q+eq}{6}$ or $t > \frac{H+q-2eq}{6}$, and $t > \frac{-2H^2+2qH(e+1)+q^2(e^2-4e+1)}{6[q(1+e)-2H]}$. The intersection of these conditions yields the effective range: $t > \frac{H+q-2eq}{6}$.*

Corollary 3. When the parameters satisfy $t > \frac{H+q-2eq}{6}$, the dynamical system possesses stable equilibrium points at $(0,0)$.

When users are highly sensitive to factors like price and pay less attention to cancellation terms (meaning the policy itself has minimal influence on the users' choice), both platforms have a strong incentive to adopt strict cancellation policies. If a platform unilaterally adopts a lenient policy, it attracts few additional users but incurs higher operational costs and greater revenue volatility due to increased cancellations. Consequently, in the absence of effective external constraints, convergence toward the strict policy for platforms emerges as a seemingly stable equilibrium.

In the low reputation-dependent market, when considering the point $(1,1)$, the condition that $Tr(J) \geq 0$ is satisfied for all $q < H$. Therefore, when $q < H$, there is no equilibrium point at $(1,1)$, which means that a state where both platforms adopt lenient cancellation policies in the low-reputation-dependent market is unsustainable.

This outcome can be attributed to the market characteristics, such as information asymmetry and weak consumer awareness of their rights. In a low-reputation-dependent market, strict cancellation policies do not result in significant reputational damage or user attrition. Consequently, platforms implementing strict policies not only benefit from cost savings and stable revenue but also avoid substantial customer attrition due to reputation concerns. In contrast, adopting a lenient policy leads to higher operational costs and greater income uncertainty without attracting sufficient additional market share among consumers who are largely indifferent to cancellation policies. Therefore, a scenario in which both platforms maintain lenient cancellation policies is difficult to sustain in the long term in a low-reputation-dependent market.

- Market with Divergent Reputation Effects

As the market matures, the influence of reputation has increased, further raising q value. When $H < q < \frac{H}{e}$, the impact of reputation has now stabilized at a level slightly above the tolerance threshold for one platform but remains within the acceptable range for the other. For the platform more susceptible to reputational risk, adopting a strict cancellation policy no longer yields sufficient direct benefits to compensate for the risks of potential reputational damage. In contrast, because of its operational policy, the competing platform can still achieve higher direct benefits by maintaining a strict cancellation policy. At this stage, the influence of reputation is objectively present but not yet a decisive factor; its impact differs across platforms due to their heterogeneous sensitivity to reputation.

Proposition 3. A solution exists at the point $(0,0)$ if and only if it satisfies the condition that $\frac{H-2q+eq}{6} < t < \frac{H+q-2eq}{6}$. Since $\frac{H-2q+eq}{6} < 0$ under the given parameter constraints and $t > 0$, the valid range reduces to $0 < t < \frac{H+q-2eq}{6}$; a solution exists at the point $(1,0)$ if and only if it satisfies the conditions that $\frac{(H-q)^2+(H-eq)^2}{6(q+eq-2H)} < t < \frac{q-H}{6}$ and $H < \frac{q+eq}{2}$.

Corollary 4. By comparing the upper bounds of the two intervals, we find that $\frac{q-H}{6} < \frac{H+q-2eq}{6}$. When the parameters satisfy $\frac{(H-q)^2+(H-eq)^2}{6(q+eq-2H)} < t < \frac{q-H}{6}$ and $q > \frac{2H}{e+1}$, the dynamical system possesses stable equilibrium points at $(0,0)$ and $(1,1)$.

When users exhibit low loyalty to a specific platform and market reputation exerts a relatively strong influence on user decisions, online travel platforms tend to converge in formulating cancellation policies. In a market environment characterized by low user loyalty, consumers are more likely to switch platforms due to differences in service experiences, such as the flexibility of cancellation policies. In such contexts, any negative feedback

arising from stringent cancellation rules can be rapidly amplified, directly impacting platform bookings. To avoid falling into a competitive disadvantage due to unfavourable cancellation policies, platforms are strongly motivated to mimic each other. The platforms strive to offer more reasonable or lenient cancellation terms to safeguard their reputation and retain customers. The outcome of this dynamic interaction is that the cancellation rules of major platforms gradually converge toward a relatively consistent industry standard.

Corollary 5. *When the parameters satisfy $0 < t < \frac{H+q-2eq}{6}$, the dynamical system possesses stable equilibrium points at $(0,0)$.*

In the market with divergent reputation effects, the platform that is less reliant on reputation and more resilient to reputational risks has an inherent incentive to persistently adopt a strict cancellation policy. This policy aims to maximize short-term revenue by restricting cancellations. Correspondingly, although the other platform, which is more sensitive to reputation, is often regarded as preferring a lenient policy, it is compelled to mimic the strict policy in this situation. This mimicry is to avoid falling into a disadvantage in the dynamic competition. The ultimate outcome of this dynamic interaction is not necessarily an optimal market equilibrium for the platforms and users. Instead, it may lead to a Nash equilibrium in which both sides compromise, with both platforms maintaining strict policies. This results in an overall reduction in consumer welfare and may inhibit the healthy, long-term development of the market.

Proposition 4. *A solution exists at the point $(1,0)$ if and only if it satisfies the conditions that $t > \frac{H+q-2eq}{6}$ and $t > \frac{(H-eq)^2 + (q-H)(-H-q+2eq)}{6q(1-e)}$.*

Corollary 6. *Since the parameters satisfy $H < q < \frac{H}{e}$, the inequality $\frac{(H-eq)^2 + (q-H)(-H-q+2eq)}{6q(1-e)} < \frac{H+q-2eq}{6}$ holds. When the parameters satisfy $t > \frac{H+q-2eq}{6}$, the dynamical system possesses stable equilibrium points at $(1,0)$.*

When users exhibit high platform loyalty, the market reputation effect becomes significantly polarized. This divergence allows different platforms to formulate differentiated cancellation policies based on their unique risk tolerance regarding reputation. Platforms that are less reliant on reputation and more resilient to reputational risks—such as some e-commerce platforms targeting price-sensitive users—tend to maintain or even strengthen strict cancellation policies. This approach aims to control operational costs and maximize short-term revenue. Conversely, competitors with greater sensitivity to reputation—such as premium platforms that emphasize service guarantees and brand credibility—may adopt more lenient cancellation policies. They leverage user-friendly cancellation experiences as a differentiated competitive advantage to attract and solidify trust among users. This strategic divergence is sustainable in an oligopolistic market because it aligns with the core demands of distinct user segments. One group of users prioritizes the lowest possible prices and accepts corresponding service limitations, while the other is willing to pay a premium for assurance and service reliability.

- **Market with High Reputation Sensitivity**

As the market approaches saturation, competition for users intensifies significantly. In this situation, the importance of reputation becomes markedly more pronounced. The widespread adoption of the internet and advancements in network technology, particularly the rise of social media platforms, have dramatically lowered the barriers to reputation entering the picture. This has amplified the influence of reputation exponentially. Under the condition where $q > \frac{H}{e}$, platforms with low sensitivity to reputation also need to

incorporate the potential impact of reputation into their decision-making for critical service policies, such as cancellation rules. This is essential to avoid competitive disadvantage in the battle to retain the limited pool of existing users.

Proposition 5. *A solution exists at the point (0,1) if and only if it satisfies the conditions that $0 < t < \frac{q-H}{6}$ and $0 < t < \frac{2(q-H)^2 - q^2(1-e)^2}{6q(1-e)}$. When $q > \frac{H}{e}$, the inequality $\frac{q-H}{6} < \frac{2(q-H)^2 - q^2(1-e)^2}{6q(1-e)}$ holds. Thus, the valid range for t reduces to $0 < t < \frac{q-H}{6}$; a solution exists at the point (1,0) if and only if it satisfies the conditions that $\max\left(0, \frac{H-2eq+q}{6}\right) < t < \frac{eq-H}{6}$ with the parameter constraints $\frac{1}{3} < e < 1$ and $0 < H < \frac{q(3e-1)}{2}$. Under these constraints, $\frac{q-H}{6} > \frac{eq-H}{6}$, indicating that the feasible range for (1,0) lies entirely within the feasible range for (0,1).*

Corollary 7. *When the parameters satisfy $\frac{1}{3} < e < 1$, $0 < H < \frac{q(3e-1)}{2}$ and $\max\left(0, \frac{H-2eq+q}{6}\right) < t < \frac{eq-H}{6}$, the dynamical system possesses stable equilibrium points at (0,1) and (1,0).*

In this situation, the heterogeneity in platforms' sensitivity to reputation is relatively small, their overall operational policies are similar, and users generally exhibit low platform loyalty. Under the above conditions, platforms often adopt differentiated cancellation policies. This differentiation helps them establish unique competitive advantages.

For such strategic divergence to be sustainable, the market must be able to accommodate diverse segmented needs. If platforms can accurately target their respective user bases and effectively demonstrate the value of their policies, both strict and lenient policies can find their place in the market. This leads to a dynamic equilibrium in their strategic interactions.

Corollary 8. *When the parameters satisfy $0 < t < \frac{q-H}{6}$, the dynamical system possesses stable equilibrium points at (0,1).*

In the market with high reputation sensitivity, platforms that are less reliant on user reputation may proactively adopt lenient cancellation policies when users generally exhibit low platform loyalty. The cost of switching between platforms for users is low, and users' platform preferences are not obvious. In this situation, a lenient cancellation policy can significantly reduce purchase hesitation among users, helping platforms quickly attract price-sensitive or service-cautious users. At the same time, lenient cancellation policies help platforms that are less reliant on user reputation gain an advantage and put platforms highly dependent on reputation in a difficult position. If platforms that are highly dependent on reputation follow lenient cancellation policies, they will be easily replaced, and their original advantages will be eroded. However, if they take strict cancellation policies, they risk losing users to competitors. Ultimately, low-reputation-dependence platforms can pressure high-reputation-dependence platforms to adopt strict cancellation policies. This dynamic can shape a competitive equilibrium more favourable to the low-reputation-dependence platforms.

This mechanism also applies to other service-intensive markets, such as e-commerce and local services. For instance, some emerging platforms might implement very friendly policies at first to attract users. Although this may increase short-term after-sales costs, it effectively carves out market share. This forces traditional platforms with reputational sensitivity to make concessions on price or terms and to adjust their market positioning.

Proposition 6. *A solution exists at the point (1,1) when it satisfies the conditions that $t > \frac{q-H}{6}$ or $0 < t < \frac{eq-H}{6}$. And to ensure $\text{Tr}(J) < 0$, the condition that $t > \frac{(H-q)^2 + (H-eq)^2}{6(q+eq-2H)}$ should be satisfied.*

Corollary 9. Since $\frac{q-H}{6} > \frac{(H-q)^2 + (H-eq)^2}{6(q+eq-2H)} > \frac{eq-H}{6}$ at this time, the valid range for t is $t > \frac{q-H}{6}$. When the parameters satisfy $t > \frac{q-H}{6}$, the dynamical system possesses stable equilibrium points at $(1,1)$.

When users develop strong loyalty to a platform, and its reputation significantly influences the market, the platform tends to evolve toward a stable equilibrium characterized by lenient cancellation policies. Highly loyal users place greater emphasis on long-term service experience and brand identity rather than merely comparing prices for individual transactions. By adopting lenient cancellation policies, platforms can further strengthen trust among existing users and attract new customers with similar service preferences by building a positive reputation.

At the same time, the amplifying effect of user reviews in the media continuously reinforces the competitive advantage of lenient policies. Social media and online evaluations have made cancellation experiences a critical factor influencing brand perception, as negative feedback can significantly impact potential users' booking decisions.

In summary, the three market scenarios identified in this paper jointly delineate a trajectory of competitive evolution driven by reputation mechanisms. In the initial stage, the reputation effect is weak and exerts limited influence on platform strategies. As the market matures, reputation begins to exert heterogeneous effects, emerging as an actionable variable through which platforms pursue differentiated competition. By the mature stage, reputational constraints are universally reinforced, becoming an unavoidable strategic prerequisite. This dynamic evolutionary process provides a theoretical framework for understanding the phased adjustment of platform governance mechanisms, such as cancellation rules.

5. Evolutionary Simulation Analysis

To ground these illustrative scenarios in a conceptually realistic context, we loosely reference broad market characteristics reported in recent industry surveys (e.g., the Guangdong Hotel Market Report, 2024 [31]) solely to ensure our parameter magnitudes are order-of-magnitude consistent with typical market conditions. For instance, industry reports indicate four primary types of cancellation policies: free cancellation, time-limited cancellation, tiered-fee cancellation, and strict non-refundable policies. Reflecting this diversity, our model classifies the first three as “lenient” and the latter as “strict” to explore the strategic trade-offs between them.

Parameter Setting:

- **Market Scale and Price:** Currently, the common hotel commission rate in the market typically ranges from 10% and 20%. The commission rate is set to 20% in hypothetical numerical scenarios. According to official data from the Chinese Market Supervision Administration [32], the average price of five-star hotels in Guangdong Province was CNY 886 per transaction in that period.
- **Cancellation Behaviour (f):** The paper assumes that under the strict cancellation policy, per-room cancellation loss: $f = \text{hotel price} - \text{cancellation fee} \times 29.5\%$.
- **Reputation and Sensitivity (q, β):** According to study of Lu et al. [22], the paper assumes that $q_i = \text{hotel price} \times 13\%$. According to a study of Xiong et al. [33], approximately 29.5% of guests cancel their bookings on the day of scheduled arrival. The cancellation rate is set as 0.3.

Combined with the above hypothetical numerical scenarios, the initial values of variable parameters are assumed as follows: $m = 0.2$, $e = 0.8$, $k = 0.9$, $\beta = 0.3$, $q = 115$, $f = 620$, and $t = 35$.

Initial State:

The initial state of the system is: $x_0 = 0.5$, $y_0 = 0.5$. It can be understood that the tendency to adopt a lenient cancellation policy on the platform is 0.5, or that half of the hotels on the platform adopt lenient cancellation policies. In the initial state, H is solved as 46.2. By comparison, q is greater than $\frac{H}{e}$, and the whole market can be regarded as the market with high reputation sensitivity in this scenario.

It should be noted that readers should interpret these results as qualitative demonstrations of the theoretical propositions rather than quantitative predictions of specific market outcomes.

- Figure 3 describes the influence of the change in cancellation rate on the cancellation policy when the other parameters are consistent. When the cancellation rate of users is 0.8 under the strict cancellation policy, both sides of the platform are more inclined to adopt a lenient cancellation policy. When the cancellation rate drops to 0.6 under the strict cancellation policy, the platform will obviously slow the implementation of the lenient policy. This change reflects the platform's attitude towards its strict cancellation policy becoming more friendly and inclusive, with fewer constraints on user cancellations. On the contrary, when the strict cancellation policy cannot significantly reduce users' cancellation rates on the original basis, the platform will be more inclined to adopt a lenient cancellation policy.

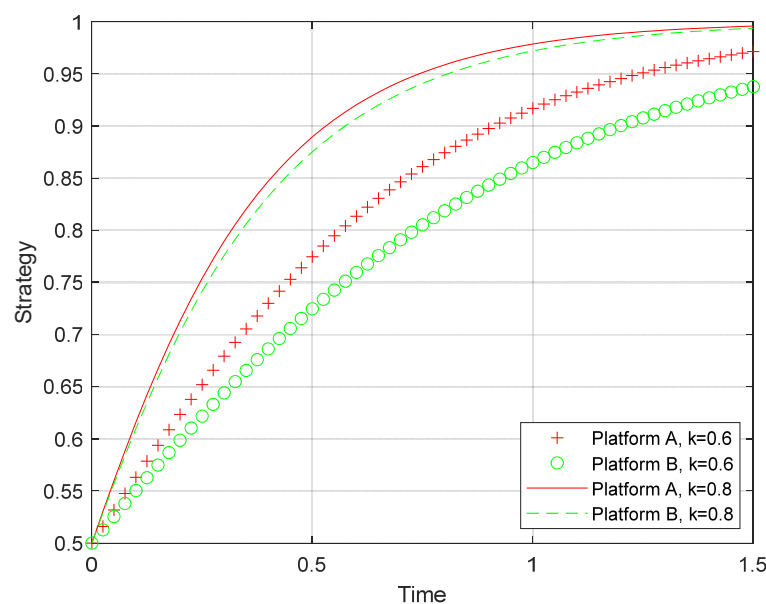


Figure 3. Impact of Cancellation Rate on Platform Cancellation Policies.

Due to the differences in the strategies and positioning, Platform B faces less reputation loss than Platform A (when $0 < e < 1$). The trend of Platform B adopting the cancellation policy is slower than that of Platform A. This observation confirms the finding that reputation-sensitive platforms tend to prefer lenient cancellation policies. It also shows that as strict policies become more effective, platforms with lower reputational sensitivity may have a higher proportion of hotels adopting them.

- Figure 4 describes the influence of the change in reputational loss on the cancellation policy when the other parameters are consistent. As reputational losses decrease, platforms converge more slowly toward lenient cancellation policies. With the reputational damage caused by the strict cancellation policy, the platform will be more inclined toward a lenient policy. This is also consistent with the real situation. When users express greater dissatisfaction or complaints about strict cancellation rules, the

platform tends to be more cautious in implementing them. As a whole, higher reputational losses dampen both the speed and extent of platforms' shift toward strict cancellation policies.

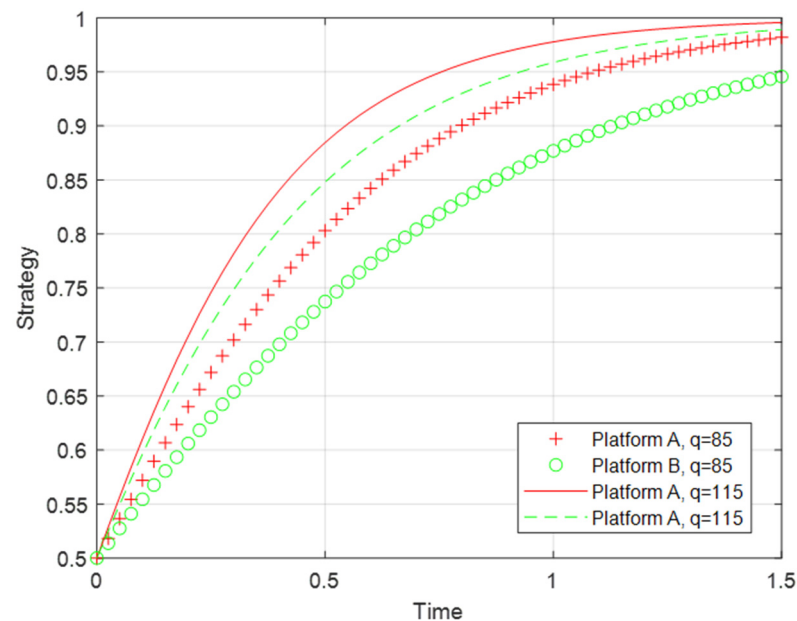


Figure 4. Effect of Reputational Loss on Platform Cancellation Policies.

3. Figure 5 describes the influence of the change in platforms' sensitivity to reputational loss on the cancellation policy when the other parameters are consistent. When e decreases to 0.3, it indicates there is high heterogeneity among platforms in their sensitivity to reputational loss. When implementing strict cancellation policies, Platform A (the reputation-sensitive platform) suffers greater reputational losses, whereas Platform B (the platform less dependent on reputation) incurs smaller losses. As a result, Platform B deviates from the previous equilibrium—where both platforms adopted lenient policies—and proactively shifts toward a strict cancellation policy.

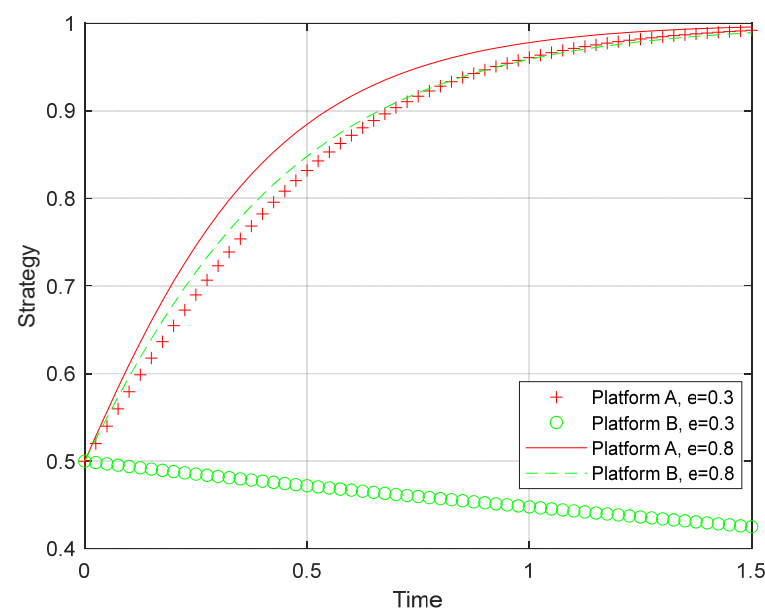


Figure 5. Impact of Differences in Platform Sensitivity to Reputational Loss on Cancellation Policy Choices.

When $e = 0.3$, the condition that $H < q < \frac{H}{e}$ holds. In this situation, the whole market can be regarded as the market with divergent reputation effects. The process that e changes from 0.8 to 0.3 represents a dynamic transition corresponding to the shift from Proposition 9 to Proposition 6. Due to increasing heterogeneity in how platforms respond to reputational loss, the market evolves from one with high reputation sensitivity to one with divergent reputation effects. Platforms that rely less on reputation are more inclined to adopt strict cancellation policies to build a long-term competitive advantage.

Notably, this strategic divergence not only influences market competition but also has profound implications for the sustainability of the digital service ecosystem. Lenient cancellation policies can usually reduce users' cancellation costs and enhance consumer autonomy. This fosters a fairer and more transparent digital marketplace, which aligns with the "Responsible Consumption and Production" and the principles of inclusive digital governance in Sustainable Development Goals (SDGs). When Platform B adopts strict cancellation policies under certain conditions, it may achieve higher short-term benefits. However, without institutional safeguards for user rights, this approach can form vicious competition and erode user trust. Such outcomes may ultimately undermine the long-term health and resilience of the platform ecosystem.

6. Conclusions, Implications, and Limitations

6.1. Conclusions

The relationship between reputation and platform cancellation policy choices varies significantly across different market types. When the impact on reputation is less significant, the benefits of maintaining a strict cancellation policy can effectively offset the associated risks. In such cases, platforms have little incentive to avoid implementing strict policies. At this stage, if users are largely indifferent to platform heterogeneity and reputation carries little weight, platforms tend to adopt policies that differ from those of their competitors. This helps them carve out a distinct market position. It is important to note that an equilibrium where both platforms adopt lenient policies does not exist in the market with low reputation sensitivity.

In a market with divergent reputation effects, user loyalty is important for the platform's strategic decision-making. Under conditions of low user loyalty, platforms tend to mimic one another, leading to convergence in cancellation policies. Conversely, when user loyalty is high, platforms with varying sensitivities to reputation will sustain differentiated policies. While the influence of reputation exists objectively at this time, it is not the only decisive factor. The impact intensity of reputation still varies significantly across platform types.

In highly competitive market environments, reputation has become a core competitive factor. When user loyalty is low, platforms that are less reliant on reputation may proactively adopt lenient policies to rapidly capture market share, thereby establishing an advantage. When user loyalty is high, the entire market tends to evolve toward lenient cancellation policies. This shift results in a stable state where the industry collectively adopts more lenient policies.

These findings highlight the interactive effect between reputation sensitivity and user loyalty on platform policy selection. The interplay significantly influences how platforms choose their competitive policies. It is noteworthy that the increasing importance of reputation does not necessarily lead to universally lenient policies; instead, it can act as a catalyst for some platforms to reinforce stricter policies at some point. In the market with divergent reputation effects, when the reputational pressure reaches a critical range—within the tolerance threshold of platforms less reliant on reputation but exceeding the acceptance limit of those highly sensitive to it—a unique strategic divergence emerges. Platforms less reliant on reputation may not follow the trend toward leniency but could

proactively adopt or maintain stricter cancellation policies. This policy persists until the marginal losses from deteriorating reputation eventually surpass the originally tolerated limit, forcing a reassessment of the strategic balance. This finding explains why, in markets, even amid calls for enhanced consumer protection and industry guidelines, some platforms continue to uphold strict cancellation policies for some specific products.

6.2. Managerial Implications

Based on the conclusions, several managerial implications can be drawn.

- (1) In markets where user-driven reputational constraints are weak, platforms often treat cancellation policies primarily as cost-control instruments. Our results show that without intervention, fierce competition can lead to asymmetric equilibria $((0, 1)$ or $(1, 0))$, while high differentiation may trap the market in a dual-strict equilibrium $(0, 0)$. To avoid the inefficiency of homogeneous strictness, platforms should proactively pursue strategic differentiation. One platform might maintain strict terms for cost efficiency, while the other introduces partial leniency to capture niche segments.

While the asymmetric outcome $((0, 1))$ offers some users better protection, the dual-strict equilibrium $(0, 0)$ represents a welfare loss for consumers, as all users bear higher cancellation risks without compensating price reductions. Regulators should monitor such markets to prevent tacit collusion that results in strict terms that unnecessarily burden consumers.

- (2) When some platforms in the market are significantly affected by reputation while others are not, reputation becomes a strategically exploitable lever for differentiation. This regime reveals a counterintuitive dynamic in which market structure dictates welfare more than reputation risk itself. We identify a “Competition Trap” in which low differentiation forces both platforms to adopt strict policies to survive margin pressure, despite moderate reputational risks. Conversely, high differentiation can lead to a “Free-Rider Asymmetry” $(1, 0)$, where one platform exploits user lock-in to remain strict. In this situation, platforms must avoid blind imitation. High-reputation-sensitivity brands should leverage leniency as a trust signal, while cost-oriented platforms must carefully calibrate strictness to avoid regulatory backlash.

The “Competition Trap” $(0, 0)$ is particularly detrimental to social welfare, as intense competition paradoxically forces platforms to cut service quality (strict policies) rather than improve it. Meanwhile, the asymmetric outcome $(1, 0)$ creates welfare inequality: loyal users of the strict platform suffer disproportionate losses compared to those on the lenient platform. Policies that reduce switching costs could help break the strict equilibrium and improve overall user protection.

- (3) In highly mature markets where social media amplifies service failures, reputation loss becomes catastrophic. Our model shows that the market naturally converges towards lenient equilibria $((0, 1)$ or $(1, 1))$, regardless of differentiation levels. Strict policies are no longer viable. In this situation, platforms should view reasonably lenient policies not as a competitive tactic but as a baseline service commitment. Leading platforms can spearhead industry-wide upgrades to cancellation standards, erecting barriers to entry for competitors who cannot afford the reputational risk of strict terms.

This convergence towards leniency $((1, 1))$ marks the highest potential consumer welfare state in our model, as users are broadly protected from cancellation losses. However, if the operational costs of such leniency force platforms to raise prices significantly, a trade-off emerges. Therefore, the optimal welfare outcome involves maintaining lenient policies while ensuring operational efficiencies to keep prices stable.

6.3. Limitations and Future Research Directions

This study focuses only on the evolutionary choice between strict and lenient cancellation policies. In practice, however, cancellation policies can be more complex—for example, tiered cancellation policies or cancellation insurance. Although strict and lenient policies may serve as broad categories in real-world settings, finer distinctions are often necessary within each category. As a result, it can produce dynamic, adjustable outcomes that fall somewhere between strict and lenient policies. Future research could extend the current evolutionary game framework by incorporating these composite strategies—such as tiered cancellation rules and cancellation insurance—to better capture the richness and dynamism of the cancellation policies.

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