Journal of Innovation & Knowledge 10 (2025) 100727

Contents lists available at ScienceDirect

Journal of Innovation & Knowledge

journal homepage: www.elsevier.com/locate/jik

Correcting positioning deviation through platform service innovation: Realisation mechanisms and design principles

Xiao Xuan [a,b], Wenqi Duan [a,*,1], Lijia Kong [c]

[a] School of Business, Taizhou University, Taizhou, Zhejiang, 318000, China
[b] School of Business, Ningbo University, Ningbo, Zhejiang, 315211, China
[c] College of Economics and Management, Zhejiang Normal University, Zhejiang, 321004, China

ARTICLE INFO

JEL classification:
L86
M10
M21
O31
O32

Keywords:
Bilateral platforms
Positioning deviation correction
Service innovation
Realisation mechanisms
Design principles

ABSTRACT

The discrepancy between platform positioning and user needs, termed positioning deviation, is a critical determinant of user churn and potential platform failure. Platform service innovation can be potential remedy to correct positioning deviation. As such, understanding the mechanisms and design principles underlying such platform service innovation for correcting positioning deviation is crucial. Addressing this, this study adopts a systematic problem analysis approach, adhering to the sequence of 'user churn → positioning deviation correction → service innovation.' First, a duopoly competition model is constructed to clarify why platform positioning deviation leads to user churn and platform failure. Next, service innovation is embedded into the user utility function to expand the original model, while the mechanisms for realising positioning deviation correction through platform service innovation is revealed via numerical calculation. Finally, taking the optimal innovative service type under quality demand as an example, simulation analysis is performed on each characteristic parameter's influence. Further, the design principles of platform service innovation for correcting positioning deviation are explored, and subsequently, validated through application cases. The results reveal that platform managers can effectively address positioning deviation by providing personalised and diversified innovative services. The core of service innovation design is based on several parameters, including the demand state when positioning deviation occurs, strength of the cross-side network effect, degree of user heterogeneity, platform development cost required by the unit service, additional value of the platform, buyer utility increased by the unit service, and seller development cost increased by the unit service. Overall, the study offers valuable insights for managers to drive service innovation through adaptive dynamic matching, critical parameter control, utility-cost optimisation, and strategic digital marketing.

Introduction

In the today's rapidly evolving digital landscape, platforms must continuously optimise their business models to align with shifting market dynamics. In particular, realising an appropriate dynamic positioning is crucial to the success of their evolution (Zhao et al., 2020; Sui et al., 2024). However, digital platforms frequently encounter positioning deviations, which arise from the disconnect between the positioning strategies adopted by enterprises and the evaluated positioning formed by users' habitual cognition. This discrepancy makes it challenging to affect substantial adjustments swiftly enough to cater to the rapid shifts in user demands. The resulting inability to adapt promptly results in significant 'user churn' for platforms and creates an urgent challenge for platform managers to be addressed. Further, users' evaluation of existing platforms exhibits cognitive inertia: Consider online shopping platforms in China, Taobao is perceived as a platform which offering affordable prices but with mixed quality. Meanwhile, JD.com is seen as a provider of higher quality at relatively expensive prices. This cognitive inertia leads to segmentation where 'price-oriented' users gravitate towards Taobao, while 'quality-oriented' users favour JD.com. Generally, such perceptions can persist even if the actual conditions on these platforms change. Still, user preferences on the platform change at any time due to time and region (Malgonde et al., 2020; Trabucchi & Buganza, 2020; Shafiloo et al., 2024; Liu et al., 2024). Therefore, when a

* Corresponding author at: School of Business, Taizhou University, Taizhou, Zhejiang, 318000, China.
E-mail address: wenqiduan@vip.126.com (W. Duan).
[1] School of Business, Taizhou University, Taizhou, Zhejiang, 318000, China

https://doi.org/10.1016/j.jik.2025.100727
Received 10 November 2024; Accepted 5 May 2025
Available online 5 September 2025

platform's evaluated positioning is relatively fixed, how should the manager correct the deviation between the platform positioning and user needs, and effectively deal with user churn to enhance firm competitiveness?

The industry is increasingly valuing service innovation's role in solving the positioning deviation correction on bilateral platforms, which are typically digital or physical marketplaces that connect two distinct user groups and create reciprocal network benefits. Alibaba, the world's second-largest Internet platform, noticed the increasing focus on quality in user consumption. Subsequently, it split its independent business-to-consumer (B2C) e-commerce platform to provide authentic and licensed goods, 'Tmall' platform, from Taobao which is known for its cheapness, and avoid a large number of users switching to the competitor platform JD.com, which leads due to high-quality items. Consequently, it currently occupies the first place in the Chinese B2C online retail market. Other bilateral platforms, although not like the 'Tmall' platform, have also performed service innovation to solve the mismatch between the platform positioning and user needs under consumer preference uncertainty. While the literature on platform service innovation is relatively extensive, studies have generally overlooked the idea that user attrition caused by positioning deviation is one of the fundamental reasons for the platform's survival, and that service innovation and its design may be related to the problem of user churn caused by such positioning deviation. Besides, few studies systematically discuss the design of platform service innovation from the perspective of positioning deviation correction.

Here, our research provides a new vision for correcting platform positioning deviation through platform service innovation. First, this study offers a more nuanced understanding of the causes of user churn due to the platform positioning deviation by constructing a duopoly competition model. By contrast, studies adopt the perspectives of pricing structure, network effects, platform quality, transaction costs, etc. (Shi et al., 2018; Akbar & Tracogna, 2022; Sui et al., 2024). Second, this extends the original model of platform service innovation by embedding it into the user utility function. Further, we use numerical calculations to clarify the mechanisms for realising positioning deviation correction through platform service innovation. Third, taking the optimal innovative service type under quality demand as an example, this study distinguishes the influence of characteristic parameters on the optimal innovative service type. Thus, it offers a deeper comprehension of the principles of designing platform service innovation.

This study makes the following contributions: First, it develops a duopoly competition model to elucidate the impact of platform positioning deviation on user churn and platform failure. By identifying the mechanisms linking positioning deviation to user churn, the study enriches the theoretical frameworks of platform economics, thereby offering novel insights into the dynamics of user retention and churn in two-sided platforms. This deepens our understanding of the critical relationship between platform positioning and user behaviour. Second, we employ the Hotelling model to construct utility functions and utilise MATLAB-based numerical simulations to systematically explore how platform service innovation can mitigate the user churn resulting from positioning deviation. This approach can provide a comprehensive understanding of the intricate interactions among user churn, platform positioning deviation, and service innovation. By integrating these elements, this study illustrates how strategically designed service innovations can effectively rectify positioning deviations, thereby enhancing user retention and ensuring platform sustainability. Finally, the study validates the proposed design principles for platform service innovation through case studies focused on correcting positioning deviations. It systematically analyses the optimal innovative service type under quality demand, examining the influence of key parameters such as seller development cost, buyer utility, user heterogeneity, and the strength of the cross-side network effect. Additionally, a preliminary Sobol global sensitivity analysis is included in the Appendix, reinforcing the robustness and applicability of the framework. These findings offer valuable insights for designing platform service innovation strategies and formulating effective operational approaches, providing practical guidance for platform managers aiming to enhance long-term competitiveness and stability.

The remainder of this article is organised as follows. Section 2 introduces the related literature on user churn and service innovation on bilateral platforms. Section 3 advances the root causes of the user churn on bilateral platforms from a positioning deviation perspective. Section 4 explains the mechanisms for realising positioning deviation correction through platform service innovation. Sections 5 presents the simulation results and managerial implications. Specifically, it analyses the influence of each characteristic parameter, such as the strength of the cross-side network effect, degree of user heterogeneity, platform development cost required by the unit service, additional value of the platform, buyer utility increased by the unit service, and seller development cost increased by the unit service, on the optimal innovative service type according to the simulation results. These insights can guide platform managers to the principles of designing optimal service innovation. 6 presents an application case of Taobao to validate the proposed realisation mechanisms and design principles. Finally, the remaining sections summarise the main findings, and propose the limitations and future research directions.

Literature review

Reasons for user churn on bilateral platforms

The extant research on bilateral platforms mainly focuses on how to achieve user scale to realise network effects (Wu et al., 2023), govern platforms to achieve value co-creation (Latinovic & Chatterjee, 2024; Wang et al., 2024), and supervise platforms to promote healthy development (Luo et al., 2023; Li et al., 2024). Although the industry attaches great importance to the user churn caused by positioning deviation, few scholars have examined it, with only a few studies discussing the causes of the user churn for platform enterprises. Hagiu (2009) discussed the change in user scale caused by the pricing structure of bilateral platforms under consumer demand heterogeneity. Wei et al. (2013) studied the problem of enterprises' service innovation adoption to achieve differentiated competition based on Hotelling improved model, and suggested that the change in user preferences was the main reason for them to leave for the competitive platform. Shi et al. (2018) investigated the evolution of the platform ecosystem, and observed that ignoring platform quality and focusing only on the network effect would lead to a large-scale loss of users and even the platform's collapse. Zheng et al. (2019) examined the factors for the reduction in mobile reading service platform users, highlighting that the direct factors include user transfer costs and platform competition. Urbanink et al. (2022) conducted a large-scale data-driven analysis on how online personal attacks affect user activities on social platforms and believed that uncontrolled personal attacks will lead to user loss. Akbar and Tracogna (2022) analysed transaction costs economics, and proposed that an increase in potential transaction costs could significantly counterbalance the network effect, which would negatively affect the growth of sharing platforms. Conversely, reducing transaction costs can significantly improve the buyers' performance of business-to-business (B2B) platforms. That is, the better the relationship performance between buyers and suppliers, the better the matching between supply and demand, and the larger the scale of buyer users (Zhou et al., 2022). Moreover, Sui et al. (2024) suggested, from a dynamic perspective, that both the user scale and indirect network effects in the initial stage will significantly affect users' willingness to access in the next stage.

Enhancing platform competitiveness through service innovation

As China's service industry continues to expand and evolve, the importance of service innovation has increasingly gained prominence in innovation research. Numerous scholars have extensively examined the imperative of service innovation in the development process of bilateral platforms from multiple perspectives. According to the dynamic capability theory, Zhao et al. (2017) compared the competitive advantages of the platform under two forms of service innovation: incremental and breakthrough innovation. The authors highlighted that the latter was more conducive to the platform enterprises to realise high market performance and high financial performance, especially in a highly uncertain dynamic competitive environment. Based on a consumer' purchase intention perspective, Zhang et al. (2018) contrasted the influence of brand relationship and service innovation. The authors found that the former can improve users' purchase intention not only by fostering defensive emotion but also by promoting positive emotion. Similarly, Yang and Kwon's (2024) argued that both innovation adoption and resistance factors collectively shape actual usage behaviour, which in turn influences continuous purchase intention. Notably, the factors that drive and hinder innovation are not strictly opposed to each other. From the viewpoint of managing users and exchanges, Zhang and Tang (2019) examined the influence of same- and cross-side innovations on platform performance. The authors found that when the platform grows rapidly (slowly), cross-side (same-side) innovations enhance platform performance of the platform. Moreover, for platforms with higher (lower) user acquisition and retention costs, only same-side (cross-side) innovations can enhance platform performance.

From the perspective of open service innovation, Cenamor et al. (2021) examined the performance of different service innovation strategies, and proposed that the proprietary, outbound, inbound, and third-party strategies are better than third-party strategies. Compared with third-party strategies, the advantages enjoyed by the proprietary and outbound strategies decreased over time, while inbound strategies remained be stable. Complementing this, Miremadi et al. (2023) emphasised that greater third-party involvement in innovation strategies significantly enhances the platform's value-creation capacity, thereby better addressing heterogeneous user preferences and driving higher adoption rates.

Regarding value-added service (VAS) quality competition, Gui et al. (2021) distinguished the competitiveness of platform enterprises' investment in VAS under different user attrition conditions. The authors noted that when users are single-homing (i.e., using exclusively one platform for a specific service or product rather than splitting their activities across multiple platforms), investing in high-quality VAS is the dominant strategy for the platform to enhance competitiveness. Similarly, in the case of the multi-homing (where users engage with multiple platforms simultaneously), Sui et al. (2024) emphasised the importance of additional VAS, especially in the second stage of the platform operation, where it is far from enough to rely on basic services, subsidies, or low prices. Building on these foundations, Zhang et al. (2021) developed a game-theoretic framework analysing bilateral VAS-pricing configurations in manufacturing platforms, incorporating cross-network externality effects into strategic decision models. The analysis revealed that service efficiency is positively related to VAS provision intensity but shows non-linear pricing effects. Crucially, cross-network externalities exert differential impacts on pricing-service configurations across user groups.

Thus, the platform's attractiveness is based on the services it provides (Alaimo et al., 2020), and in reducing the cost of providing products and services for other types of users through the common functions contained in the platform architecture (Brunswicker et al., 2019; Mao et al., 2024). Therefore, to prevent user churn, dynamic positioning is crucial. Platform enterprises should continue to expand the boundary of platform service system (Leong et al., 2019; Daradkeh, 2023) and promote platform business model innovation through service innovation (Jiang et al., 2024; Tian & Xu, 2020) to enhance overall competitiveness.

Some studies note that the user churn caused by platform positioning deviation is the root cause of platform failure. Although the research on service innovation can help in understanding the important role of service innovation in platform competition, few studies explore the mechanisms and design methods of platform service innovation from the perspective of platform positioning deviation correction, especially following the logic of 'positioning deviation leading to user loss, which in turn leads to platform failure'. Based on these considerations, this study follows the management problem analysis logic of 'user churn → positioning deviation correction → service innovation' and constructs the Hotelling duopoly competition model. First, it analyses the reasons for the failure of bilateral platforms and explains the importance of solving the positioning deviation correction problem for them. Second, it extends the original utility model and platform profit function based on service innovation, and clarifies the underlying mechanisms for realising positioning deviation correction through platform service innovation via numerical calculations using MATLAB. Third, it distinguishes the simulation results of the influence of each characteristic parameter on the optimal innovative service type, proposes the management implications of achieving positioning deviation correction through platform service innovation, and therefore, provides a reference for platform managers to design service innovation on bilateral platforms.

Analysing the causes of the user churn caused by positioning deviation on bilateral platforms

Model assumptions

The scale of platform users is the key metric in platform competition. Thus, user churn can reduce platform performance. To design service innovation in a targeted manner, and retain and expand the user base, platform managers need to clarify the root causes of user attrition. Based on the Hotelling game framework (Hotelling, 1990), this study extends Guo's (2006) analysis method on unilateral users in the bilateral platform market and constructs a duopoly competition model. Then, we discuss the causes of the user churn for bilateral platforms, providing a theoretical basis for service innovation design. Before performing the modelling, we outline our assumptions below.

Assumption 1. The duopoly market consists of two differentiated platforms recorded as A and B, respectively. The platform's bilateral users include buyers b and sellers s, and both belong to single-homing. Assuming that all utilities required by the bilateral users can be obtained from Platforms A and B, and the market of bilateral users can also be fully covered. The scale of buyers and sellers is denoted by N_i and M_i, where $N_A + N_B = 1$, $M_A + M_B = 1$. The registration fee charged by the platform for bilateral users is $p_i^I (p_A < p_B)$. Since users on different platforms have different price sensitivity, λ_i denotes the price sensitivity of bilateral users ($i \in \{A, B\}$).

Assumption 2. The user's platform evaluation based on their experience and word-of-mouth is E_i, and evenly distributed in a straight line of Hotelling where Platform A is located at point E_A and Platform B is located at E_B: that is, $E_A = 0$ and $E_B = 1$. Selecting the price and quality desired by users as the classification criteria, the evaluated positioning of Platform A is low price coupled with uneven quality, and Platform B is relatively expensive and of good quality. Generally, the evaluated positioning based on both platform positioning and user evaluation remains unchanged for a certain period. However, user needs are dynamically updated. Therefore, under different demand states, the degree of matching of the same platform is different, resulting in platform positioning deviation.

Assumption 3. Only changes in consumer demand status are considered. It is assumed that the future demand state will only switch between price and quality demands. Under the price demand, buyers prefer low price products and prefer price Platform A. Conversely, under the quality demand, buyers prefer high-quality products, and consequently, favour Platform B.

Assumption 4. User preferences are evenly distributed in the interval [0,1]. When the platform positioning deviates from the user preferences, the utility obtained by users will decrease. The quantum of this decrease is a function of the distance between user preferences and platform positioning (Guo, 2006).

Model construction

(1) Buyer utility model

Assuming that the initial utility obtained by the buyers joining the platform is X_i ($i \in \{A,B\}$). Further, the marginal utility obtained by their interaction with sellers; that is, the strength of the cross-side network effect is β. Then, the total buyer utility through trading activities is βM_i. Buyers' platform preferences are the result of various factors, including interests and hobbies, economic conditions, educational background, age and gender, and word-of-mouth, and is not influenced by the future demand state. Assuming that buyers' preferences are described by α ($0 \le \alpha \le 1$) and the degree of heterogeneity is represented by φ ($|a - E_i|\varphi$), the buyer utility reduced by the platform positioning deviation is $|a - E_i|\varphi$. When buyers join a platform that matches their demand state, they can gain additional value ν; that is, under the price demand, buyers can gain additional value by joining the price platform. The same holds under the quality demand.

The utilities obtained by the buyers joining Platforms A and B under the price demand are characterised by the following function:

$$\begin{cases} U_A^b = X_A + \beta M_A - |a - E_A|\varphi + \nu - \lambda_A p_A^b = X_A + \beta M_A - a\varphi + \nu - \lambda_A p_A^b \\ U_B^b = X_B + \beta M_B - |a - E_B|\varphi - \lambda_B p_B^b = X_B + \beta M_B - (1-a)\varphi - \lambda_B p_B^b \end{cases} \tag{1}$$

Moreover, under the quality demand, the buyer utility of joining Platforms A and B are as follows:

$$\begin{cases} U_A^b = X_A + \beta M_A - |a - E_A|\varphi - \lambda_A p_A^b = X_A + \beta M_A - a\varphi - \lambda_A p_A^b \\ U_B^b = X_B + \beta M_B - |a - E_B|\varphi + \nu - \lambda_B p_B^b = X_B + \beta M_B - (1-a)\varphi + \nu - \lambda_B p_B^b \end{cases} \tag{2}$$

(2) Seller utility model

Assuming that the initial utility obtained by the sellers joining the platform is Y_i ($i \in \{A,B\}$), and affected by the cross-side network effect, the net seller utility from transactions with consumer with installation base N_i is denoted as γN_i, wherein γ represents the marginal net income obtained by merchants from consumers. Sellers' platform preferences are comprehensively affected by the consumer's installation foundation, buyer user quality, platform registration fees and other characteristic parameters, and is unrelated to the future demand state. Suppose that the preferred evaluation position of the sellers is described by $h(0 \le h \le 1)$ and the degree of heterogeneity is represented by ϕ. Assuming that the future demand state does not affect the seller utility; that is, the seller utility functions under the two demands are equal:

$$\begin{cases} U_A^s = Y_A + \gamma N_A - |h - E_A|\phi - \lambda_A p_A^s = Y_A + \gamma N_A - h\phi - \lambda_A p_A^s \\ U_B^s = Y_B + \gamma N_B - |h - E_B|\phi - \lambda_B p_B^s = Y_B + \gamma N_B - (1-h)\phi - \lambda_B p_B^s \end{cases} \tag{3}$$

(3) Platform profit function

The platform provides space, infrastructure, and services for the interaction of bilateral users, and makes profits by charging registration fees to them. The platform's profit s related to the scale of the user base, registration fees, and platform costs. It is assumed that the platform cost only includes the construction cost; further, the better the platform evaluated positioning, the higher the construction cost. For the convenience of analysis, it is assumed that the construction cost of the price platform is 0 and that of the quality platform is 1.

Then, under the price and quality demands, the profit function of the platform is defined as:

$$\begin{cases} \pi_A = p_A^b N_A + p_A^s M_A \\ \pi_B = p_B^b N_B + p_B^s M_B - 1 \end{cases} \tag{4}$$

Analysing the causes

Buyers' decision to join the platform is dynamically adjusted with the change in the future demand state. Intuitively, this change should affect the scale of the user base. Meanwhile, due to the cross-side network effect, the scale of sellers will also change. To reveal the quantitative impact of future demand state changes on bilateral user scale and reveal the causes of user churn, we focus on the price of Platform A as an example to solve for the equilibrium condition of user scale and platform profit under price and quality demands.

(1) Equilibrium solution under the price demand

When buyers' utility from joining Platforms A and B does not differ, the utility model reaches equilibrium, represented by the following equation:

$$U_A^b = U_B^b = X_A + \beta M_A - a\varphi + \nu - \lambda_A p_A^b = X_B + \beta M_B - (1-a)\varphi - \lambda_B p_B^b$$

According to the solution, the scale of buyer users on Platforms A and B are as follows:

$$\begin{cases} \underline{N_{A1}} = \underline{a^*} = \dfrac{1}{2} + \dfrac{X_A - X_B + \beta(M_A - M_B) + \nu + \lambda_B p_B^b - \lambda_A p_A^b}{2\varphi} \\ \underline{N_{B1}} = 1 - \underline{a^*} = \dfrac{1}{2} - \dfrac{X_A - X_B + \beta(M_A - M_B) + \nu + \lambda_B p_B^b - \lambda_A p_A^b}{2\varphi} \end{cases} \tag{5}$$

Similarly, the scale of seller users on Platforms A and B is as follows:

$$\begin{cases} \underline{M_{A1}} = \underline{h^*} = \dfrac{1}{2} + \dfrac{Y_A - Y_B + \gamma(N_A - N_B) + \lambda_B p_B^s - \lambda_A p_A^s}{2\phi} \\ \underline{M_{B1}} = 1 - \underline{h^*} = \dfrac{1}{2} - \dfrac{Y_A - Y_B + \gamma(N_A - N_B) + \lambda_B p_B^s - \lambda_A p_A^s}{2\phi} \end{cases} \tag{6}$$

Based on Eqs. (5) and (6), under the price demand, the equilibrium scale of bilateral users joining Platform A is calculated as follows:

$$\begin{cases} \underline{N_{A1}} = \dfrac{\phi(X_A - X_B) + \beta(Y_A - Y_B) + \phi\left(\lambda_B p_B^b - \lambda_A p_A^b\right) + \beta\left(\lambda_B p_B^s - \lambda_A p_A^s\right) + \phi\varphi + \nu\phi - \beta\gamma}{2(\phi\varphi - \beta\gamma)} \\ \underline{M_{A1}} = \dfrac{\varphi(Y_A - Y_B) + \gamma(X_A - X_B) + \varphi\left(\lambda_B p_B^s - \lambda_A p_A^s\right) + \gamma\left(\lambda_B p_B^b - \lambda_A p_A^b\right) + \phi\varphi + \nu\gamma - \beta\gamma}{2(\phi\varphi - \beta\gamma)} \end{cases} \tag{7}$$

Meanwhile, the equilibrium scale of bilateral users joining Platform B is:

$$\begin{cases} \underline{N_{B1}} = \dfrac{\phi(X_B - X_A) + \beta(Y_B - Y_A) + \phi\left(\lambda_A p_A^b - \lambda_B p_B^b\right) + \beta\left(\lambda_A p_A^s - \lambda_B p_B^s\right) + \phi\varphi - \nu\phi - \beta\gamma}{2(\phi\varphi - \beta\gamma)} \\ \underline{M_{B1}} = \dfrac{\varphi(Y_B - Y_A) + \gamma(X_B - X_A) + \varphi\left(\lambda_A p_A^s - \lambda_B p_B^s\right) + \gamma\left(\lambda_A p_A^b - \lambda_B p_B^b\right) + \phi\varphi - \nu\gamma - \beta\gamma}{2(\phi\varphi - \beta\gamma)} \end{cases} \tag{8}$$

Finally, the equilibrium profit of Platform A is as follows:

$$\underline{\pi_{A1}} = \frac{\left(\beta p_A^b + \varphi p_A^s\right)\left(Y_A - Y_B + \lambda_B p_B^s - \lambda_A p_A^s\right) + \left(\phi p_A^b + \gamma p_A^s\right)\left(X_A - X_B + \lambda_B p_B^b - \lambda_A p_A^b\right)}{2(\phi\varphi - \beta\gamma)} + \frac{\left(p_A^b + p_A^s\right)(\phi\varphi - \beta\gamma) + \left(\nu\phi p_A^b + \nu\gamma p_A^s\right)}{2(\phi\varphi - \beta\gamma)} \tag{9}$$

(2) Equilibrium solution under the quality demand

Under the quality demand, the equilibrium scale of bilateral users joining Platform A can be calculated as:

$$\begin{cases} \overline{N_{A2}} = \dfrac{\phi(X_A - X_B) + \beta(Y_A - Y_B) + \phi\left(\lambda_B p_B^b - \lambda_A p_A^b\right) + \beta\left(\lambda_B p_B^s - \lambda_A p_A^s\right) + \phi\varphi - \nu\phi - \beta\gamma}{2(\phi\varphi - \beta\gamma)} \\ \overline{M_{A2}} = \dfrac{\varphi(Y_A - Y_B) + \gamma(X_A - X_B) + \varphi\left(\lambda_B p_B^s - \lambda_A p_A^s\right) + \gamma\left(\lambda_B p_B^b - \lambda_A p_A^b\right) + \phi\varphi - \nu\gamma - \beta\gamma}{2(\phi\varphi - \beta\gamma)} \end{cases} \tag{10}$$

The equilibrium scale of bilateral users joining Platform B is:

$$\begin{cases} \overline{N_{B2}} = \dfrac{\phi(X_B - X_A) + \beta(Y_B - Y_A) + \phi\left(\lambda_A p_A^b - \lambda_B p_B^b\right) + \beta\left(\lambda_A p_A^s - \lambda_B p_B^s\right) + \phi\varphi + \nu\phi - \beta\gamma}{2(\phi\varphi - \beta\gamma)} \\ \overline{M_{B2}} = \dfrac{\varphi(Y_B - Y_A) + \gamma(X_B - X_A) + \varphi\left(\lambda_A p_A^s - \lambda_B p_B^s\right) + \gamma\left(\lambda_A p_A^b - \lambda_B p_B^b\right) + \phi\varphi + \nu\gamma - \beta\gamma}{2(\phi\varphi - \beta\gamma)} \end{cases} \tag{11}$$

The equilibrium profit of Platform A is:

$$\overline{\pi_{A2}} = \frac{\left(\beta p_A^b + \varphi p_A^s\right)\left(Y_A - Y_B + \lambda_B p_B^s - \lambda_A p_A^s\right) + \left(\phi p_A^b + \gamma p_A^s\right)\left(X_A - X_B + \lambda_B p_B^b - \lambda_A p_A^b\right)}{2(\phi\varphi - \beta\gamma)} + \frac{\left(p_A^b + p_A^s\right)(\phi\varphi - \beta\gamma) - \left(\nu\phi p_A^b + \nu\gamma p_A^s\right)}{2(\phi\varphi - \beta\gamma)} \tag{12}$$

(3) Analysis of the user churn caused by platform positioning deviation

To explore the impact of the demand state change on the scale of bilateral users, subtract Eq. (7) from Eqs. (10), (8) from (11), and (9) from (12), yielding:

$$\begin{aligned} \overline{N_{A2}} - \underline{N_{A1}} &= \frac{\nu\phi}{\beta\gamma - \phi\varphi} \\ \overline{M_{A2}} - \underline{M_{A1}} &= \frac{\nu\gamma}{\beta\gamma - \phi\varphi} \\ \overline{\pi_{A2}} - \underline{\pi_{A1}} &= \frac{\nu\phi p_A^b + \nu\gamma p_A^s}{\beta\gamma - \phi\varphi} \end{aligned} \tag{13}$$

When the platform pricing remains unchanged and buyer demand shifts from price to quality, the user scale on Platform A changes. Specifically, the scale of buyers changes as $\frac{\nu\phi}{\beta\gamma-\phi\varphi}$, scale of sellers changes as $\frac{\nu\gamma}{\beta\gamma-\phi\varphi}$, and profit of bilateral platforms changes as $\frac{\nu\phi p_A^b+\nu\gamma p_A^s}{\beta\gamma-\phi\varphi}$.

These changes caused by changing demand state are due to the positioning deviation of bilateral platforms. When user preferences change, the platform does not innovate products or services in time to update its evaluated positioning, resulting in a low degree of matching between the two. Then, users migrate to the platform with the highest matching. Specifically, under the price demand, Platform A is more competitive due to its low price. However, when buyer demand changes—that is, they start demanding high-quality products—their preferences deviate from the evaluated positioning of Platform A because it is still positioned as a low-price platform coupled with uneven quality. In contrast, Platform B is more competitive. At this time, the buyer users on platform A will flee to platform B. Further, coupled with the cross-side network effect between bilateral users, the scale of seller users can also suddenly decrease, which will affect the bilateral platforms' total profit. Therefore, the condition for user churn caused by platform positioning deviation is:$\beta\gamma < \phi\varphi$.

Realisation mechanisms analysis

Industry practice demonstrates that bilateral platforms adopting both personalised and diversified service innovations can more effectively meet users' needs. Specifically, personalised services—tailored to individual preferences—ensure precise demand fulfilment, whereas diversified services—offering a variety of categories to cater to heterogeneous user groups—provide broad market coverage. However, the impact of platform service innovation on merchant effectiveness is mixed. Such innovation has different degrees and directions of effects on the utility of bilateral users, which affects the platform's profit by affecting users' platform adoption decisions. Therefore, considering the impact of service innovation on the user utility and platform profit, a quantitative analysis combined with mathematical models is needed. Here, we elaborate on the user utility model and platform profit function to explore the mechanisms whether service innovation can realise the positioning deviation correction of bilateral platforms.

Expanding the utility model based on service innovation

Service innovation is reflected both in the quantity of innovative services introduced and quality of the functions offered by these services. Importantly, the types of innovative services can not only represent the quantity of innovative services in terms of diversity, but also represent the quality of innovative services through functionality. Therefore, in this study, the types of innovative services are represented by a digital variable, which quantifies both the diversity and functionality of the services using numerical values, instead of directly using service innovation itself. To simplify the analysis, consider the innovative services provided by Platform A for users related to the price and quality.

The development of innovative services on Platform A can enhance the effectiveness of buyers; the richer the types, the better the user experience. Assuming that the buyer utility is positively correlated with the types of innovative services η, and the buyer utility increased by the unit service is θ, the added value of buyer utility is denoted as $U(\eta) = \theta\eta$. Therefore, the utility obtained by the buyers joining Platforms A and B under the price demand are as follows:

$$\begin{cases} U_A^b = X_A + \beta M_A - a\varphi + \nu - \lambda_A p_A^b + \theta\eta \\ U_B^b = X_B + \beta M_B - (1-a)\varphi - \lambda_B p_B^b \end{cases} \tag{14}$$

Similarly, the buyer utility of adding to Platforms A and B under the quality demand are as follows:

$$\begin{cases} U_A^b = X_A + \beta M_A - a\varphi - \lambda_A p_A^b + \theta\eta \\ U_B^b = X_B + \beta M_B - (1-a)\varphi + \nu - \lambda_B p_B^b \end{cases} \tag{15}$$

Moreover, assume that the Platform A's innovative services can enhance the development cost for merchants, with the seller development cost increasing by the unit service ω. Then, the increase in the seller development cost due to service innovation is $k(\eta) = \omega\eta$, while the reduction in seller utility brought about by the increase in seller development cost is $\omega\eta$. Then, the seller utility on Platforms A and B under two demand states are as follows:

$$\begin{cases} U_A^s = Y_A + \gamma N_A - h\phi - \lambda_A p_A^s - \omega\eta \\ U_B^s = Y_B + \gamma N_B - (1-h)\phi - \lambda_B p_B^s \end{cases} \tag{16}$$

Finally, assume that the increased cost for Platform A to design and develop innovative services $C(\eta)$ is positively correlated with the type of innovative services. Further, the platform development cost required by the unit service is f. Then, the profit of Platform A after service innovation is:

$$\pi_A = p_A^b N_A + p_A^s M_A - f\eta \tag{17}$$

Extended model solution and realisation mechanisms analysis

Service innovation affects the scale of bilateral users by changing their utility. Based on the solution principle outlined in the previous section, we can obtain the equilibrium of user scale and platform profit on Platform A after service innovation in the two demand states.

Under the price demand, the equilibrium scale of bilateral users joining Platforms A and B can also be calculated as follows:

$$\begin{cases} \underline{N_{A3}} = \dfrac{\phi(X_A - X_B) + \beta(Y_A - Y_B) + \phi\left(\lambda_B p_B^b - \lambda_A p_A^b\right) + \beta\left(\lambda_B p_B^s - \lambda_A p_A^s\right) + \phi\varphi + \nu\phi - \beta\gamma + \theta\eta\phi - \omega\eta\beta}{2(\phi\varphi - \beta\gamma)} \\ \qquad = \underline{N_{A1}} + \dfrac{\theta\eta\phi - \omega\eta\beta}{2(\phi\varphi - \beta\gamma)} \\ \underline{M_{A3}} = \dfrac{\varphi(Y_A - Y_B) + \gamma(X_A - X_B) + \varphi\left(\lambda_B p_B^s - \lambda_A p_A^s\right) + \gamma\left(\lambda_B p_B^b - \lambda_A p_A^b\right) + \phi\varphi + \nu\gamma - \beta\gamma + \gamma\theta\eta - \omega\eta\varphi}{2(\phi\varphi - \beta\gamma)} \\ \qquad = \underline{M_{A1}} + \dfrac{\gamma\theta\eta - \omega\eta\varphi}{2(\phi\varphi - \beta\gamma)} \end{cases} \tag{18}$$

$$\begin{cases} \underline{N_{B3}} = \dfrac{\phi(X_B - X_A) + \beta(Y_B - Y_A) + \phi\left(\lambda_A p_A^b - \lambda_B p_B^b\right) + \beta\left(\lambda_A p_A^s - \lambda_B p_B^s\right) + \phi\varphi - \nu\phi - \beta\gamma - \theta\eta\phi + \omega\eta\beta}{2(\phi\varphi - \beta\gamma)} \\ \qquad = \underline{N_{B1}} - \dfrac{\theta\eta\phi - \omega\eta\beta}{2(\phi\varphi - \beta\gamma)} \\ \underline{M_{B3}} = \dfrac{\varphi(Y_B - Y_A) + \gamma(X_B - X_A) + \varphi\left(\lambda_A p_A^s - \lambda_B p_B^s\right) + \gamma\left(\lambda_A p_A^b - \lambda_B p_B^b\right) + \phi\varphi - \nu\gamma - \beta\gamma - \gamma\theta\eta + \omega\eta\varphi}{2(\phi\varphi - \beta\gamma)} \\ \qquad = \underline{M_{B1}} - \dfrac{\gamma\theta\eta - \omega\eta\varphi}{2(\phi\varphi - \beta\gamma)} \end{cases} \tag{19}$$

The equilibrium profit of Platform A is defined as follows:

$$\underline{\pi_{A3}} = p_A^b \underline{N_{A3}} + p_A^s \underline{M_{A3}} - f\eta = \underline{\pi_{A1}} + \frac{p_A^b(\theta\eta\phi - \omega\eta\beta) + p_A^s(\gamma\eta\theta - \omega\eta\varphi)}{2(\phi\varphi - \beta\gamma)} - f\eta \tag{20}$$

Meanwhile, under the state of quality demand, the equilibrium scale of bilateral users joining Platforms A and B are, respectively, as follows:

$$\begin{cases} \overline{N_{A4}} = \dfrac{\phi(X_A - X_B) + \beta(Y_A - Y_B) + \phi\left(\lambda_B p_B^b - \lambda_A p_A^b\right) + \beta\left(\lambda_B p_B^s - \lambda_A p_A^s\right) + \phi\varphi - \nu\phi - \beta\gamma + \theta\eta\phi - \omega\eta\beta}{2(\phi\varphi - \beta\gamma)} \\ \qquad = \overline{N_{A2}} + \dfrac{\theta\eta\phi - \omega\eta\beta}{2(\phi\varphi - \beta\gamma)} \\ \overline{M_{A4}} = \dfrac{\varphi(Y_A - Y_B) + \gamma(X_A - X_B) + \varphi\left(\lambda_B p_B^s - \lambda_A p_A^s\right) + \gamma\left(\lambda_B p_B^b - \lambda_A p_A^b\right) + \phi\varphi - \nu\gamma - \beta\gamma + \gamma\theta\eta - \omega\eta\varphi}{2(\phi\varphi - \beta\gamma)} \\ \qquad = \overline{M_{A2}} + \dfrac{\gamma\theta\eta - \omega\eta\varphi}{2(\phi\varphi - \beta\gamma)} \end{cases} \tag{21}$$

$$\begin{cases} \overline{N_{B4}} = \dfrac{\phi(X_B - X_A) + \beta(Y_B - Y_A) + \phi\left(\lambda_A p_A^b - \lambda_B p_B^b\right) + \beta\left(\lambda_A p_A^s - \lambda_B p_B^s\right) + \phi\varphi + \nu\phi - \beta\gamma - \theta\eta\phi + \omega\eta\beta}{2(\phi\varphi - \beta\gamma)} \\ \qquad = \overline{N_{B2}} - \dfrac{\theta\eta\phi - \omega\eta\beta}{2(\phi\varphi - \beta\gamma)} \\ \overline{M_{B4}} = \dfrac{\varphi(Y_B - Y_A) + \gamma(X_B - X_A) + \varphi\left(\lambda_A p_A^s - \lambda_B p_B^s\right) + \gamma\left(\lambda_A p_A^b - \lambda_B p_B^b\right) + \phi\varphi + \nu\gamma - \beta\gamma - \gamma\theta\eta + \omega\eta\varphi}{2(\phi\varphi - \beta\gamma)} \\ \qquad = \overline{M_{B2}} - \dfrac{\gamma\theta\eta - \omega\eta\varphi}{2(\phi\varphi - \beta\gamma)} \end{cases} \tag{22}$$

Similarly, the function of equilibrium profit on Platform A is:

$$\overline{\pi_{A4}} = p_A^b\overline{N_{A4}} + p_A^s\overline{M_{A4}} - f\eta = \overline{\pi_{A2}} + \frac{p_A^b(\theta\eta\phi - \omega\eta\beta) + p_A^s(\gamma\theta\eta - \omega\eta\varphi)}{2(\phi\varphi - \beta\gamma)} - f\eta \tag{23}$$

Thus, when the demand state and platform pricing remain unchanged, the scale of bilateral users on Platform A will increase through service innovation. Among them, the scale of buyer users increases by $\frac{\theta\eta\phi-\omega\eta\beta}{2(\phi\varphi-\beta\gamma)}(\beta\gamma < \phi\varphi;\ \theta\phi > \omega\beta)$; scale of seller users increases by $\frac{\gamma\theta\eta-\omega\eta\varphi}{2(\phi\varphi-\beta\gamma)}(\beta\gamma < \phi\varphi;\ \gamma\theta > \omega\varphi)$; and the change in the profit of the bilateral platforms is $\frac{p_A^b(\theta\phi-\omega\beta)+p_A^s(\gamma\theta-\omega\varphi)}{2(\phi\varphi-\beta\gamma)} > f$. Thus, the increase or decrease in profit is determined by the characteristic parameters and development costs. Specifically, when $\frac{p_A^b(\theta\phi-\omega\beta)+p_A^s(\gamma\theta-\omega\varphi)}{2(\phi\varphi-\beta\gamma)} > f$ holds, the profit of Platform A increases; otherwise, it decreases.

Conversely, when the demand of buyers changes, the scale of buyer and seller users on Platform A decreases by $\frac{\nu\phi}{\phi\varphi-\beta\gamma}$ and $\frac{\nu\gamma}{\phi\varphi-\beta\gamma}$, respectively. Then, after undertaking service innovation, their scale on Platform A increases by $\frac{\theta\eta\phi-\omega\eta\beta}{2(\phi\varphi-\beta\gamma)}$ and $\frac{\theta\eta\gamma-\omega\eta\varphi}{2(\phi\varphi-\beta\gamma)}$, respectively. In general, whether the scale of buyer and seller users on Platform A will increase or not mainly depends on the direction of the scale changes. When $\eta > \frac{2\nu\phi}{\theta\phi-\omega\beta}$and $\eta > \frac{2\nu\gamma}{\theta\gamma-\omega\varphi}$ hold, both buyer and seller users increase. Meanwhile, when $\eta = \frac{2(\nu\gamma+\nu\phi)}{\theta\phi-\omega\beta+\theta\gamma-\omega\varphi}$, the total scale on Platform A remains unchanged.

In summary, service innovation corrects the positioning deviation of bilateral platforms when $\eta > \frac{2(\nu\gamma+\nu\phi)}{\theta\phi-\omega\beta+\theta\gamma-\omega\varphi}$. That is, the price platform can effectively prevent large-scale loss of users caused by platform positioning deviation when demand state changes through service innovation. Meanwhile, the price platform can update users' evaluated positioning of the platform through service innovation to improve the matching degree between user preferences and platform evaluated positioning. From this perspective, although the development of innovative services on the price platform can increase the costs for merchants and the platform, it can effectively the user attrition by the platform positioning deviation. Further, when the development cost of unit service fulfils the condition $\frac{p_A^b(\theta\phi-\omega\beta)+p_A^s(\gamma\theta-\omega\varphi)}{2(\phi\varphi-\beta\gamma)} > f$, service innovation can effectively improve and maximise the profit of bilateral platforms.

Simulation results and managerial implications

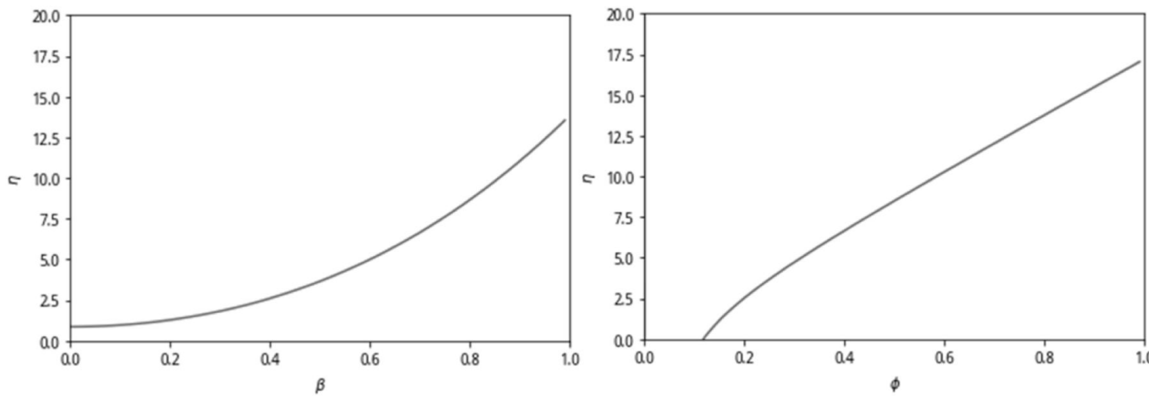
As mentioned previously, the design of platform service innovation should not only effectively avoid the massive user churn caused by platform positioning deviation when the demand changes, but also comprehensively consider the principle of cost-benefit matching to ensure platform profitability. That is, it should develop innovative services to retain and attract users under the premise of maximising profits. Here, we design service innovation based on the profit function and select the innovative service types of the Platform A under the quality demand for simulation analysis. Then, we elucidate how the characteristic parameters influence the innovative service types and propose principal implications for formulating the optimal service innovation to realise positioning deviation correction.

Simulation results and analysis

(1) The optimal innovative service type under the quality demand

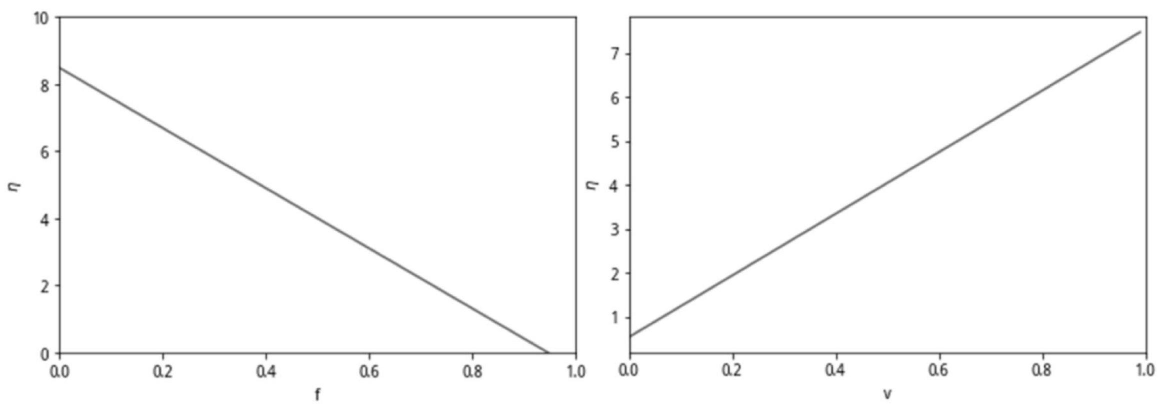
By solving Eqs. (21) and (23), we find the first-order partial derivative of Eq. (23) with respect top_A^b, p_A^s, and η. Specifically, let the first derivative be equal to 0, and we solve forp_A^{b*}, p_A^{s*}, and η^* under profit maximisation. Then, the second derivatives are calculated to obtain $\frac{\partial^2\pi_A}{\partial^2 p_A^b} \le 0$, $\frac{\partial^2\pi_A}{\partial^2 p_A^s} \le 0$, and $\frac{\partial^2\pi_A}{\partial^2\eta} = 0$, satisfying the conditions for the optimal solution. The specific formula is as follows:

$$\begin{aligned} \eta^* = {} & \frac{\lambda_A f\left(2(\beta+\gamma)^2 - 8\phi\varphi\right) + (\beta+\gamma)\left(-\gamma\theta - \lambda_B p_B^b\omega + \nu\omega\right) + (X_A - X_B)(-\omega\beta - \omega\gamma + 2\phi\theta)}{2\left(\beta\theta\omega + \gamma\theta\omega - \phi\theta^2 - \varphi\omega^2\right)} \\ & + \frac{\beta\omega(\beta+\gamma-\varphi) + \omega\varphi(\gamma - 2\phi) + (Y_A - Y_B)(\theta\beta + \theta\gamma - 2\omega\varphi) + \phi\theta(2\varphi - 2\nu + \gamma - \beta)}{2\left(\beta\theta\omega + \gamma\theta\omega - \phi\theta^2 - \varphi\omega^2\right)} \\ & + \frac{\lambda_B\left(2\phi p_B^b\theta + \beta p_B^s\theta - 2\varphi p_B^s\omega\right)}{2\left(\beta\theta\omega + \gamma\theta\omega - \phi\theta^2 - \varphi\omega^2\right)} \end{aligned} \tag{24}$$



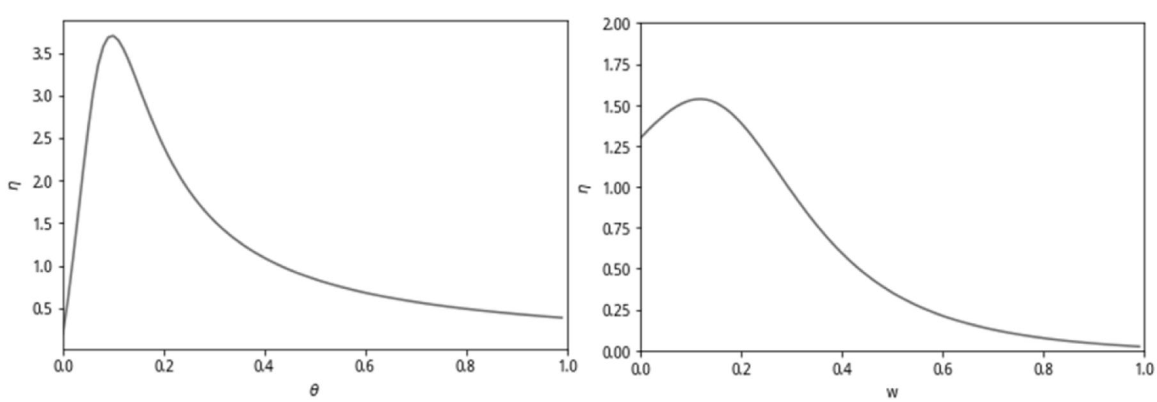
(a) Strength of cross-side network effect (b) Degree of user heterogeneity

Fig. 1. Relationship between characteristic parameters cross-side network effect and user heterogeneity, respectively, and the optimal innovative service type.



(a) Platform development cost required by the unit service (b) Additional value of the platform

Fig. 2. Relationship between characteristic parameters development cost and additional value of the platform, respectively, and the optimal innovative service type.



(a) Buyer utility increased by the unit service (b) Seller development cost increased by the unit service cost

Fig. 3. Relationship between characteristic parameters buyer utility and seller development cost increased by the unit service, respectively, and the optimal innovative service type.

To simplify the analysis, the initial utility of bilateral users joining platform A is the same as that of Platform B; that is, $X_A = X_B$, $Y_A = Y_B$. The marginal income generated by the interaction between buyers and sellers is equal; that is, strength of cross-side network effect is equal: $\beta = \gamma$. Next, the degree of heterogeneity of bilateral users is the same: $\phi = \varphi$. Finally, the price sensitivity of users to Platform A is 1, while the price sensitivity to Platform B is 0; that is,$\lambda_A = 1$, $\lambda_B = 0$. The previous equation can be now be simplified as follows:

$$\eta^* = \frac{(\beta^2 - \phi^2)(4f + \omega - \theta) + \nu(\beta\omega - \phi\theta)}{2\beta\theta\omega - \phi(\theta^2 + \omega^2)} \tag{25}$$

(2) Simulation analysis of characteristic parameters and the optimal innovative service type

We first assign values to each parameter, and draw the relationship between characteristic parameters including the strength of cross-side network effect β, degree of user heterogeneity ϕ, platform development cost required by the unit service f, additional value of the platform ν, buyer utility increased by the unit service θ, seller development cost increased by the unit service ω, and optimal innovative service type η^*, as shown in Figs. 1–3.

Fig. 1 shows that the optimal innovative service type increases with strength of cross-side network effect and degree of user heterogeneity. Regarding the cross-side network effect, the optimal innovative service type grows exponentially with the increase in the cross-side network effect because the platform's positioning deviation leads to large-scale user attrition. Further, as the strength of the cross-side network between buyers and sellers increases, more merchants will the platform. To retain bilateral users, the platform needs to develop well-positioned innovative services to meet diverse needs, enhance user stickiness, create a healthy business ecosystem, and generate ecological value for the platform.

Regarding the degree of user heterogeneity, the greater the heterogeneity of buyers, the more varied their needs. In this case, the platform needs to develop more personalised services to supplement buyers' perceived experience to correct and update their one-sided evaluation of the platform. Meanwhile, the greater the heterogeneity between sellers, the more diverse their preferences for value-added services provided by the platform. Therefore, the platform needs to constantly update value-added services, correct the positioning deviation of the platform, and reduce the development cost of sellers. This can help in attracting more high-quality merchants to settle on the platform, and thus, more consumers, thereby creating a positive feedback loop.

Fig. 2 reveals that the optimal innovative service type is negatively proportional to the platform development cost and positively proportional to additional value of the platform. Regarding the former, the platform manager, as an 'economic agent', makes decisions based on the cost-benefit analysis. As the platform development costs increase, platform managers will appropriately reduce the types of innovative services. In particular, when the cost of developing innovative services exceeds the benefits, platform managers will stop the development to maintain positive returns. Meanwhile, the additional value of the platform is the benefit derived from joining the platform when its positioning matches the user's demand state. The greater the additional value of the platform, the higher the utility that buyers gain when joining the platform. However, when the consumer demand state changes from price to quality, the utility gained by joining the price platform decreases significantly due to the lack of additional value and positioning deviation. Then, to retain consumers, the price platform needs to develop more innovative services that match their needs, and thus, mitigate user attrition.

Fig. 3(a) reveals an inverted U relationship between the positive buyer utility increased by the unit service and optimal innovative services. Specifically, during the growth period of the platform, to attract users and address the positioning deviation, managers need to continuously increase the types of innovative services to optimise the shopping experience, improve the utility for bilateral users, and stimulate the network quantity effect. In the mature stage, managers should pay more attention to the quality of innovative services. Here, they can reduce the types of innovative services, improve service quality through governance and other strategies, meet the quality needs of users, and optimise the network quality effect. Therefore, the optimal innovative service type is first increases and then decreases.

Moreover, Fig. 3(b) shows that with the increase in the seller development cost due to the unit service, the change in the optimal innovative service type shows a long-tail trend. The seller development cost is the increased cost of innovative services provided by merchants for the implementation platform. When the development cost is less than the increased profit of innovative services and scale of buyers users, merchants will actively support the development of innovative services to improve revenue. However, when the development cost is too high, merchants will be deterred and may even migrate to competitor platforms. Then, if the platform wants to retain sellers, the types of innovative services should be reduced.

Finally, based on the aforementioned characteristic parameters, we perform a sensitivity analysis of the impact on the optimal innovative service type, along with second-order sensitivity heatmap interaction relationships, using the Sobol global sensitivity analysis method. Further details are provided in the Appendix.

Managerial implications

The simulation results have several principal implications for platform managers to execute positioning deviation correction through platform service innovation. First, managers should fully investigate and adaptively match user needs that are inconsistent with platform positioning. They need to conduct extensive research on consumers and merchants, collect the perceived experience and evaluation information of bilateral users on the platform through big data, artificial intelligence (AI), and blockchain to determine whether the positioning deviation problem exists, and develop innovative services based on the needs that are significantly different from users' preferences. Meanwhile, managers should grasp the value information of characteristic parameters such as users' current preferences and future demand, additional value, evaluation and positioning of competitive platforms, and the degree of consumer heterogeneity, and cross-network effects between bilateral users. This can aid managers' understanding of users, explore the reasons for their attrition to other platforms, and help in more scientifically and appropriately designing innovative service strategies.

Second, managers should undertake service innovation design based on the value of the characteristic parameters by obtaining the market information of each parameter. Specifically, based on the simulation analysis of characteristic parameters and optimal innovative service type, when the interaction between bilateral users is strong and degree of user heterogeneity is high, the platform needs to develop innovative services with multiple functions and high utility value. When the additional value of the platform is relatively high, it should provide more quantity and more full-featured innovative services to offset the decline in value caused by changes in demand. Second, based on the sensitivity analysis results in Table A1 in the Appendix derived from the Sobol global sensitivity analysis method, managers should especially focus on the key variables influencing the optimal innovative service type, such as the seller development cost increased by the unit service, the buyer utility increased by the unit service, and the degree of user heterogeneity. (3) Based on the second-order sensitivity heatmap in Fig. A1 in the Appendix, the positive synergistic effects between parameters warrant close attention, particularly the significant interaction between the degree of user heterogeneity and seller development cost increased by the unit service. This synergy amplifies the impact of the seller development cost on the optimal innovative service type as user heterogeneity increases, necessitating careful management. Platform managers should therefore monitor the 'user heterogeneity–seller development cost' dynamic and adopt a phased resource allocation strategy to ensure sustainable growth. This can be done in four steps. First, they should leverage advanced data analytics tools, such as cluster analysis and user profiling, to identify core user segments, such as high-value users (frequent buyers of premium products) and niche markets with concentrated demand (specialised buyers in certain categories). This can help in optimising resource allocation and mitigating cost-heterogeneity trade-offs. Second, managers should invest in modular seller services, such as standardised templates, enabling sellers to efficiently tailor offerings to diverse user needs while reducing costs through scalability. Third, they should implement a real-time monitoring system with predefined thresholds to track this dynamic, triggering strategy adjustments (e.g. pausing service expansions) when heterogeneity exceeds critical levels, thereby ensuring effective resource use. Fourth, they should balance rising user heterogeneity with controlled seller development cost increases, avoiding excessive growth in both to prevent inefficiencies, such as resource strain, and refine services if costs outpace demand.

Third, managers should adhere to the principle of utility-cost optimisation, considering both the utility of bilateral users and costs of service innovation. While innovative services can address users' heterogeneous needs unmet due to platform positioning deviations, they simultaneously increase operational expenditures. These costs encompass not only the platform's research and development (R&D) expenditures for service innovation, but also incorporate seller collaboration costs and potential user churn. Therefore, managers should avoid blindly pursuing service development that makes sellers' costs too high, as this can lead to seller attrition or utility spillover caused by excessive investment in services that enhance consumer stickiness. Notably, as revealed in the Appendix through a second-order sensitivity heatmap, there is a significant negative antagonistic effect between the buyer utility increased by the unit service and seller development cost increased by the unit service. Consequently, a rational resource allocation plan is essential to prevent excessive investment in one area that could degrade performance in another. This requires managers to assess the types and scale of resources invested in enhancing buyer utility, evaluate whether these investments result in increased seller development costs, and implement an optimisation strategy that balances utility and cost to effectively convert costs into enhanced user retention. Additionally, when developing innovative services, platform managers should construct an evaluation index system for utility-cost optimisation of innovative services and establish a Cost-Utility Ratio (CUR). Utility indicators can be quantified using metrics like user growth, Gross Merchandise Volume (GMV) improvement, and Net Promoter Score. Costs include algorithm development investments, data collection expenses, and operational expenditures. Special attention should be given to dynamic threshold adjustments based on different stages: During the growth phase, higher CUR levels are acceptable to prioritise capturing users and market share, thereby accumulating long-term network effects. Meanwhile, during the mature phase, stricter control over CUR is necessary, emphasising cost efficiency. This can be achieved through measures such as streamlining service procedures and establishing user feedback mechanisms to effectively contain development costs. These thresholds must also adapt to platform scale, market dynamics, and industry positioning. In competitive markets, smaller platforms may elevate CUR thresholds during early growth, employing subsidies to capture users and expand market share. Conversely, mature platforms—typically larger and operating in stable markets—should reduce CUR thresholds, focusing on retention and monetisation efficiency to optimise resource allocation without escalating costs disproportionately. Industry characteristics further influence CUR thresholds: Transaction-focused e-commerce platforms may prioritise GMV-driven utility, accepting higher CUR thresholds during expansion. Meanwhile, gig economy platforms require stricter CUR thresholds to effectively manage seller scalability costs.

Fourth, managers should strategically update users' evaluated positioning through digital marketing. The initial users form an overall evaluation of the platform based on their own use experience, perceived value, social trends, and word-of-mouth. These evaluations directly influence decision-making processes among existing and potential users through social contagion effects. When a substantial deviation occurs between platform positioning and user preferences, large-scale churn becomes inevitable. To address this challenge, digital marketing can take the following steps: (1) Integrate cross-channel data, including user historical behaviour and social media sentiment, to detect real-time shifts in user demands and experiences; (2) deploy precision content interventions, such as personalised short videos, and interactive question and answers, to reshape users' perceptions with targeted feedback; and (3) institutionalise incentive mechanisms for user-generated content to foster self-organising, sharing-based communities and build a sustainable platform ecosystem (Wang et al., 2022). Collectively, this strategy enables the dynamic recalibration of the user evaluation, enhances retention and acquisition effectiveness, and ultimately, cultivates high-engagement value co-creation ecosystems.

Application case analysis

To provide a clearer understanding and analyse the previously mentioned conclusions, this section employs an application case from Taobao. This can help in comprehending the design strategies of service innovation for bilateral platforms from the perspective of positioning correction, thereby illustrating and confirming the practical value of our theoretical research.

The data are extracted from multiple sources: (1) Alibaba's financial reports, including annual and quarterly reports that provide detailed insights into the company's financial status and operational performance. (2) Official reports and industry publications, such as the *Taotian Group Intellectual Property Protection Reports*, which offer comprehensive analyses of platform operations, market performance, and intellectual property (IP) protection mechanisms. (3) Third-party data agencies, including research reports from institutions like QuestMobile, which provide in-depth analyses of e-commerce trends, consumer behaviour, and market dynamics..(4) Financial media sources, such as research articles and news reports from leading outlets like Sina Finance, which deliver the latest updates and market feedback on Taobao and Alibaba. (5) Interviews and press releases from platform leaders, including those featuring key executives of Taobao. For instance, Cheng Daofang, General Manager of Taobao and Tmall Group (Taotian Group)'s Content E-Commerce Division, presented a performance report at the 2024 Taobao Content E-commerce Gala, providing firsthand data on content e-commerce operations.

Adaptive matching strategy

The Taobao platform, historically positioned as a cost-effective marketplace, faces significant challenges in addressing platform positioning deviations arising from evolving consumer quality expectations in consumption upgrading trends. From a demand-driven perspective, Taobao has transitioned from a passive response to counterfeit crises under a 'price-oriented' demand, driven by consumer expectations, before 2015, to a shift towards a 'quality assurance' user demand after 2015, leveraging digital technologies to actively build user trust in quality. By 2023, Taobao further transformed through content-focused services and ecosystem reconstruction to meet emerging scenario demands, particularly in the area of diversified IP protection needs, thereby reshaping its competitive adaptive matching strategy. These stages are elaborated further:

(1) Passive response to counterfeit crises under a 'price-oriented' user demand (pre-2015). In its early stages, Taobao focused on rapidly accumulating users and product listings by attracting merchants through a 'three-year free' policy. Meanwhile, it also attracted consumers through infrastructure development and free services. After 2010, when the platform entered a phase of rapid growth, it attracted more users with strategies such as coupons, cashback, and Alipay rewards. During this period, the platform's competitive

strategy was primarily 'price-oriented'. Although counterfeit goods were prevalent, Taobao's response was relatively passive due to users' primary demand for low prices.

(2) Actively building trust in quality under a 'quality assurance' user demand (2015–2023). In 2015, China's State Administration for Industry and Commerce published a white paper explicitly identifying five major issues regarding the prevalence of counterfeit products on Taobao. To counter the competitive threat from JD.com, which had established a strong position in quality-focused online retail, Taobao initiated measures to address previously underemphasised consumer quality demands. For instance, it implemented innovative services including merchant credibility verification, buyer evaluation systems, and seven-day unconditional refund policies. These measures leveraged historical transaction evaluations, certification centre assessments, and third-party guarantees to safeguard buyer rights.

As noted above, as consumer demand shifted from 'price-oriented' to 'quality assurance', Taobao proactively began building quality trust starting in 2015 through AI-driven layered control and blockchain technology, marking the beginning of its big data governance era. Specifically, its parent company, Alibaba, established a proactive risk control system that leveraged big data analytics and AI identification technologies for counterfeit detection and prevention. By conducting a comprehensive analysis of product information, merchant behaviour, and user feedback, alongside monitoring nearly a thousand dimensional feature indicators, the platform developed an advanced counterfeit identification framework. The framework integrates text analysis models capable of keyword comparison and syntactic-semantic analysis, image recognition algorithms designed to detect counterfeit indicators in product images, and behavioural recognition models that rapidly identify and address abnormal merchant activities. These models perform real-time monitoring of all platform products and user behaviours, allowing for the immediate interception and handling of suspected counterfeit products and high-risk merchants.

This adaptive matching strategy centred on online counterfeit governance has significantly boosted consumer confidence in Taobao. According to the annual *Taotian Group Intellectual Property Protection Reports*, in 2017, 97 % of counterfeit products were intercepted pre-sale through data technologies, with only 1.49 suspected counterfeit transactions per 10,000 orders. Following the integration of blockchain technology in 2019, 96 % of IP complaints were resolved within 24 h, reducing suspected infringing transactions from 3.1 to 1.03 per 10,000 transactions compared to the 2015 levels.

(3) Offering content-focused services and undertaking ecosystem reconstruction under emerging scenario demands (2023–present). With the rise of short videos and live streaming, users have shifted from 'search-based shopping' to a 'content-driven + instant purchase' model. In response, Taobao has initiated a transformation towards content-focused services and ecosystem reconstruction. In 2023, Taotian Group further enhanced online rights protection for content and live broadcast scenarios, planning to allocate 70 % of the homepage recommendation feed to short videos and live streams, integrating short video content into search entrances, and driving the transition from 'transactions' to 'consumption.' Additionally, the newly revamped store layout includes a dedicated 'Content Homepage,' allowing users to view merchants' published articles, notes, and short videos directly within the store, thereby achieving seamless integration between merchant stores and their published content.

During that year's 618 shopping festival, Taotian Group introduced four new columns: 'Lifestyle Encyclopedia,' 'Interest Culture,' 'Unique Scenarios,' and 'New Lifestyles,' opening up avenues for the content-driven trend. Furthermore, the platform provided traffic support to high-quality influencer content across information feeds, Explore tabs, event pages, and external platforms. During this period, over 50,000 new live streamers made their debut on Taobao, such as the 'Coconut Tree Model Squad,' whose live streams focused solely on pure content without listing products for sale.

The shift towards content-focused services and ecosystem reconstruction to address emerging scenario demands has also created a need for convenient support tailored to the diverse IP protection needs of rights holders, particularly their demand for rapid responses to counterfeit products in content and live-streaming scenarios. According to the annual *Taotian Group Intellectual Property Protection Reports*, by the end of 2023, Taotian Group's IP platform had attracted over 690,000 rights holders, protecting more than 850,000 IP rights. Some achievements in this area include the protection of over 900 million images, 89 million short videos, and 720,000 design manuscripts through its original content protection platform by 2023.

Critical parameters' control strategy

The critical characteristic parameters of Taobao also serves as a guiding framework for the design principles of service innovation.

One particularly critical parameter is the distinctive network effect on the Taobao. The strength of this effect is positively correlated with the optimal innovative service type that the platform can offer. This necessitates developing segmented services that provide significant usage value to distinct user groups.

For buyer users, Taobao designs differentiated services to enhance the platform's attractiveness. Examples include 'Taobao Fresh,' tailored for urban white-collar professionals; 'Taobao Rental,' catering to single young adults; and 'Global Purchase,' curating premium overseas merchandise. By enhancing diversity, richness, and sustainability within consumer groups, merchant communities, and transaction models, the platform can further strengthen its competitive advantages. This strategy establishes a self-reinforcing cycle whereby consumer base expansion stimulates merchant network development, subsequently propelling business scale growth and ultimately, enhancing revenue streams.

For seller users, Taobao also offers tailored solutions to meet the diverse needs of merchants across various scales. Specifically, for large-scale merchants of well-established brands, Taobao provides robust support in areas like IP protection and advanced tools. A key initiative within the fashion industry's 2025 strategy is the enhancement of IP protection services, which include advanced facial recognition systems designed to combat image theft and the issue of duplicate product listings by multiple sellers. Additionally, Taobao has introduced the 'New Product Super Window' service, which assists original merchants in rapidly promoting new products. For small and medium-sized merchants, Taobao has developed several services by reducing operational costs and increasing traffic. For instance, the 'Qian Niu-1688 Factory Direct Connection' service allows merchants to operate with a zero-inventory model, significantly reducing operational costs. Furthermore, the upgraded '1688 Expert Selection' system provides extended and differentiated traffic support based on product performance, facilitating faster growth for high-potential products. For merchants without inventory, Taobao has guided non-inventory merchants towards compliant business models, such as 'pure commission influencers,' who earn commissions through product distribution. The platform has also strengthened its control over 'malicious store groups' by enhancing store regulations and blocking third-party software that facilitates unauthorised distribution, addressing the issue at its source.

The symbiotic growth of buyer and seller networks exemplifies the cross-side network effects in action. As reported in *Alibaba's Q1 FY2024 earnings report*, Taobao achieved 402 million daily active users and 887 million monthly active users (MAU) in June 2023. Additionally, the 88VIP membership programme exceeded 35 million subscribers, leading to double-digit growth rates in both user acquisition and transaction value. The rapid expansion of the user base, coupled with the advantages of high user quality, strong retention rates, and efficient conversion mechanisms, has substantially facilitated new business entries into Taobao's marketplace. For instance, during Q1 2024, new merchant registrations on Taobao grew by 75 % year-on-year, while daily active advertising merchants demonstrated over 20 % year-on-year growth, with both maintaining double-digit expansion trajectories. Thus, segmented platform service innovation, underpinned by network effects, drives the acquisition of both consumers and merchants, fostering the growth of the platform's business scale and expansion of revenue streams, ultimately enhancing the prosperity of the merchant ecosystem.

Another main characteristic parameter is the buyer utility increased by the unit service. As service innovations elevate buyer utility, platforms must prioritise quality differentiation over price competition to attract stakeholders. Under this strategic framework, Taobao promotes development by optimising platform systems and rules, enhancing merchant tools, raising product quality standards, upgrading application scenarios, and strengthening ecosystem governance.

For instance, Alibaba's March 2023 organisational restructuring ('1 + 6 + N' model) granted operational autonomy to 'Taotian Group,' which formulated three core strategic priorities: (1) customer-centricity, (2) ecosystem prosperity, and (3) technological leadership. Specifically, based on customer-centricity, Taobao would deliver enhanced offerings through scene innovation, including diversified merchandise, short-form videos, live broadcasts, user-generated content, and personalised storefronts. Based on ecosystem prosperity, Taobao would foster a robust ecosystem integrating millions of merchants, billions of content creators, and third-party service providers through infrastructure innovation. Finally, based on technological leadership, Taobao would pioneering AI-era solutions via technological breakthroughs and comprehensive upgrades to its business tools, encompassing Business Advisor, Damo Disk, and Taobao Express.

Based on the 2023 Double 11 Shopping Carnival data disclosed by QuestMobile, Taobao recorded a significant increase in active users, reaching 507 million on 24 October 2023, during the pre-sale period. This marked a year-over-year growth of over 5 %. Notably, user engagement with Taobao short videos surged, with the number of viewers increasing by 142 % year-over-year, while total viewing time grew by 390 %. Additionally, the average daily output of short videos rose to 17,600 posts per minute. Throughout the entire Double 11 period, 89 live-streaming rooms surpassed the 100-million-yuan mark, with 25 hosted by influencers and 64 by stores. Among them, 8 influencer live streams and 10 store live streams achieved this milestone for the first time, setting multiple historical records.

Utility-cost optimisation strategy

Focusing on sustainable ecosystem development, Taobao strategically integrates utility and cost considerations in its implementation of innovative services. First, regarding utility optimisation, Taobao provides substantial subsidy services to attract core user groups on the ecosystem, including buyers, sellers, and third-party service providers.

(1) For buyer users, Taobao has implemented a scenario-based subsidy strategy to accurately activate demand, encompassing initiatives such as county-targeted red envelopes for the '99 Value Festival', special subsidies for 'green and energy-saving home appliances', and environmental incentives for 'Trade-in for New' programmes. Among these, the most impactful initiative was the 'Double 11 Shopping Carnival,' which featured promotional campaigns including limited-time free deliveries, time-bound flash deals, and selected half-price merchandise. These measures transform price sensitivity into quantifiable consumer behaviour data, enabling precise demand matching while promoting a low-carbon consumption model.

(2) For seller users, Taobao has provided diverse technical support tools based on digital and AI technologies to ensure inclusive access to technology. Specifically, in terms of marketing tools, starting in April 2024, Taobao offered several free marketing tools to all merchants on its platform. These include 'Store Honey Customer Service Robot,' an AI-powered customer service tool designed to provide 24/7 efficient support for merchants; and 'Image Space,' a marketing tool for product display and livestream slicing. In logistics optimisation, Taobao has applied for a patent related to intelligent logistics resource scheduling, which encompasses a logistics resource information processing method and electronic devices. By constructing a logistics network model, Taobao optimises route selection and delivery time forecasting through real-time extraction of product logistics information, enabling merchants to reduce fulfilment costs, particularly during peak sales periods, while improving delivery efficiency. In data support and intelligent analysis, Taobao has developed the 'Business Advisor,' a data analytics tool designed for market insights and opportunity identification. This tool allows merchants to access over 1000 data indicators, including daily store data reports, traffic anomaly alerts, and competitor analysis. Additionally, Taobao leverages large language models for personalised advertising, exemplified by the 'Full-Site Promotion' launched by Alibaba's Alimama. Powered by Large Model Algorithm technology, this feature utilises pre-trained models specifically tailored for e-commerce scenarios, enhancing product matching efficiency, improving user targeting through more precise demographic profiling, and ultimately boosting merchants' return on investment. These tools reduce barriers to innovation for sellers while accelerating the digital intelligence transformation of services.

(3) For third-party service providers, Taobao has taken several measures to promote the development of its ecological infrastructure, including content ecosystem traffic incentives, and technology development and promotion subsidies. Specifically, in 2023, Taobao launched an incentive policy for Multi-Channel Network (MCN): each qualified new talent streamer (i.e. one who, within their first month after the debut broadcast, meets specific GMV requirements and completes at least four effective live streams) can receive cash incentives of up to RMB 500,000. Additionally, Taobao has introduced an Independent Software Vendors (ISV) support programme as part of its technology development and promotion subsidies: newly certified ISV can use Taobao's open platform interfaces and data interfaces for free, and have the opportunity to be featured on Taobao's homepage, search results, and within stores. These measures aim to construct a collaborative infrastructure network that facilitates the extension of service capabilities and ecological boundaries.

Second, in terms of cost reduction, Taobao has continuously optimised and improved its high-cost innovative services. To reduce operational costs for sellers caused by buyer responsibility, in 2017, Taobao standardised its return and exchange processes by introducing the 'Taobao 7-Day No-Reason Return Policy,' which stipulated detailed regulations for unserviceable return categories, including custom-made products, perishable goods, digital products, periodicals, service-oriented products, second-hand items, and auctioned goods.

In August 2024, Taobao further updated these rules to include additional criteria for specific product categories: (1) For apparel, fitness equipment, bedding, home essentials, and handicrafts, anti-theft tags and anti-damage labels must remain intact, and products must be in a reasonable condition without visible signs of wear, washing, or cosmetic residue. (2) For swimsuits and pants, the crotch protection tape must remain undamaged. (3) For personal care products, such as cleaning agents, hair care, skincare, and cosmetics, the items must remain sealed and unopened in their original packaging. (4) For digital appliances, anti-theft tags must be intact and undamaged by liquid. For mobile phones specifically, they must not have been activated. (5) For flatscreen TVs and air conditioners, simple power testing is permitted; however, installation or usage on the wall is prohibited.

Strategic digital marketing strategy

Taobao's strategic digital marketing initiative, structured to optimise holistic user evaluations, comprises five specific targeted components: First, event marketing and trend leveraging. By aligning with major cultural events and social trends, Taobao designs thematic campaigns to enhance user engagement and brand exposure metrics. For instance, as the exclusive e-commerce partner for the 2025 CCTV Spring Festival Gala, Taobao launched the 'Make Wishes, Claim Red Packets, Share 2.5 Billion' campaign during the event, enabling users to generate AI-powered Spring Festival Gala avatars and participate in interactive wishing. The campaign attracted 118 million participants, generating 753 million user interactions.

Second, dynamic contextualisation and personalised recommendations. Various user groups can exhibit significant differences based on factors such as age, geographic location, and purchasing power. Therefore, Taobao leverages this user heterogeneity to provide tailored recommendations. Specifically, in terms of age differences, younger users are typically recommended trendy clothing, electronics, and popular products, while middle-aged and older users are more likely to see cost-effective and practical items such as home goods and health supplements. By geographic location, users in first-tier cities are often recommended imported products and express delivery services, with an emphasis on brand and quality. Meanwhile, users in lower-tier cities are more price-sensitive, favouring regional specialties, daily necessities, and actively engaging in group-buying and discount activities. Finally, in terms of purchasing power segmentation, low-spending users are primarily shown low-priced promotional items, while high-spending users are shown branded products, and even luxury or designer items.

Moreover, Taobao constructs consumer trajectory profiles based on historical behavioural data of purchases, collections, browsing, etc. This enables precise product-service matching. Simultaneously, by monitoring real-time parameters such as page dwell time, geolocation, and temporal patterns, Taobao evolves recommendation systems from static labelling to context-aware adaptive frameworks. A representative case is Taobao's 'Shopping Walk' feature, which employs real-time geolocation and meteorological data (e.g. precipitation levels) to recommend context-specific merchandise such as rain protection equipment. According to *Alibaba's Q2 FY2023 financial report*, Taobao's core user retention rate for users spending over 10,000 yuan remained stable at 98 % for three consecutive quarters, with the user base reaching 124 million. This sustained retention rate can be attributed to the precise alignment of user needs through personalised recommendations.

Third, content ecosystem and IP Synergistic operations. Through the strategic integration of multidimensional tools spanning Taobao Live, Weitao, short-form videos, Taobao communities, content-centric stores, interest-based communities, and personalised customer service, the platform drives the evolution from single-product operations to an IP-driven, entertainment-oriented, and diversified business ecosystem. For instance, the Palace Museum's Taobao store has cultivated a 'cute-style' IP through social media campaigns featuring cultural merchandise, such as Emperor Yongzheng meme collections and Forbidden City cat-themed products. Its WeChat articles have garnered an average of over 100,000 views per post, while annual sales have reached CNY 1 billion. This model enhances user retention while facilitating the emergence of influencer commerce, livestream shopping guides, and global sourcing agents. According to the performance report released by Taotian Group's Content E-commerce Division during the 2024 Annual Summit, the number of content consumers on Taobao grew by 44 % year-over-year in 2023. Additionally, the number of live-streaming rooms with monthly transactions exceeding CNY 1 million reached 12,000, while 8.63 million new content creators and 770,000 newly launched live-streaming accounts were added.

Fourth, engendering cross-platform traffic closed-loops. Strategic collaborations with platforms like WeChat and REDnote enable embedded redirect-free transactional loops. Specifically, the September 2024 Taobao-WeChat payment integration allows direct WeChat Pay transactions and in-app order placement without link redirection. QuestMobile data indicates this converted 245 million exclusive WeChat users (190 million active e-commerce users) into potential Taobao consumers. During the first month post-implementation, Taobao experienced 55 % year-on-year growth in new installations, with MAUs increasing by 18.67 million to reach 944 million.

Fifth, emotionally-driven social responsibility marketing. The platform implements user engagement through socially impactful campaigns, as exemplified by the 2024 Spring Festival 'Hometown Treasures on Board' public welfare initiative. In collaboration with the Ministry of Culture and Tourism, Taobao organised agricultural livestreams leveraging narratives of hometown specialties from returning travellers, encompassing all 34 provincial-level administrative regions and mobilising millions of agricultural support resources. The campaign's promotional video garnered over 20 million views, attracting participation from more than 150 local agricultural brands and 3 automobile manufacturers.

Limitations and future research

First, this study relies on a static duopoly competition model to preliminarily explore the realisation mechanisms of positioning deviation correction through platform service innovation. While this approach illuminates the core mechanisms, it oversimplifies the dynamic nature of real-world markets, and fails to adequately capture shifts in user demand and strategic interactions among platforms. Additionally, the model does not fully reflect the complexity of platform ecosystems, which encompass multiple competitors, multi-sided participants, and intricate interdependencies.

A significant limitation arises from the simplification of external factors, such as brand loyalty and social network effects, which influence user behaviour and platform strategies. To highlight the key mechanisms and maintain the model's operationality, this study simplifies these complex external variables by incorporating key parameters (e.g. the strength of the cross-side network effect and degree of user heterogeneity). These parameters abstractly represent the influence of such external factors. For instance, a strong cross-side network effect indicates that users' decisions are influenced not only by their individual utility but also by feedback from the behaviours of other users. This indirectly captures the impact of social network effects and brand loyalty on the platform ecosystems. Similarly, user heterogeneity reflects the diverse preferences seen in real markets, such as variations in brand loyalty or social influences among users. Although the model does not explicitly consider specific user preferences, it incorporates user heterogeneity to account for the varying needs of buyers and sellers, which are closely linked to complex factors such as brand effects and social network influences. However, this simplification introduces potential biases in the findings. Specifically, by not explicitly modelling brand loyalty, the model may underestimate user retention rates, particularly in markets where brand effects are pronounced, such as luxury e-commerce platforms. Likewise, the omission of social network effects may fail to explain clustered user churn, especially on platforms reliant on social interactions, like social media marketplaces, where user departures can trigger network-driven cascades. These biases limit the model's ability to accurately interpret specific platform scenarios, potentially reducing its practical relevance.

Future research can incorporate such external factors influencing user behaviour and platform strategies. For instance, brand loyalty could be quantified using metrics such as repurchase rates, customer satisfaction levels, and customer lifetime value. Meanwhile, social network effects may be evaluated through indicators like network density, information diffusion rates, user activity levels, or the influence of key opinion leaders. Additionally, validating the model's conclusions across diverse contexts through comparative case studies—such as comparing platforms with strong brand loyalty (e.g. Apple's App Store) to those driven by pronounced social network effects (e.g. WeChat Mini Programs)—can bolster its robustness and practical utility. Furthermore, scholars can develop dynamic multi-agent computational models that integrate demand evolution, multi-platform competition, and user preference heterogeneity, thereby enhancing the explanatory power for service innovation in complex market environments.

Second, this study primarily employs numerical simulation method, which lacks empirical validation of the model's predictive capabilities. Although the simulation results provide valuable theoretical insights and the Taobao case study corroborates the implementation process and practical implications of the theoretical framework, the scarcity of real-world data may limit the generalisability of the conclusions. Meanwhile, key characteristic parameters, such as demand states and the strength of cross-side network effect, lack established quantification schemes. Still, in the Appendix, we do use the Sobol global sensitivity analysis method, along with Python software and Monte Carlo sampling, to preliminarily explore the sensitivity of characteristic parameters to the optimal innovative service type, as well as the interaction mechanisms among these parameters, including the synergistic and antagonistic effects.

However, this analysis relies on a final simplified model derived through mathematical derivation and conditional assumptions, rather than the original, more complex framework. The original model, incorporating numerous parameters such as user price sensitivity and platform registration fees, proved computationally infeasible for comprehensive analysis. These parameters were simplified through assumptions and derivations and, while indirectly reflected in the simplified model, were not subjected to direct sensitivity analysis. Consequently, their specific variability and potential influence on the mechanisms and design principles of platform service innovation remain underexplored. Further limitations arise from the scope of the sensitivity analysis, particularly concerning the higher-order interaction effects. Given the multitude of parameters, analysing these interactions demands significant computational resources. Further, the resulting high-dimensionality risks overwhelming the analysis with noise, reducing the interpretability of higher-order terms. Consistent with mainstream research, our Sobol global sensitivity analysis prioritises the first-order sensitivity indices, total effect sensitivity coefficients, and second-order sensitivity heatmaps to identify key parameter influences and pairwise interaction effects; these methods are widely recognised as robust and actionable. Nevertheless, this focus excludes higher-order interactions, which may constrain our ability to fully capture the complex relationships among parameters and their collective impact on model outcomes. Moreover, service innovation design depends on multiple characteristic parameters with varying degrees of importance, necessitating robust methods for reasonable weight allocation. This challenge has not been adequately resolved.

Furthermore, the preliminary managerial implications derived from the simulation results require further validation across heterogeneous platform types and scale dimensions. For instance, platforms of varying scales may face distinct implementation challenges in pursuing service innovation. While the case study in this study focuses on Taobao, a mature e-commerce platform, its ecosystem characteristics (e.g. user scale, resource allocation, and market positioning) may not directly apply either to smaller or medium-sized platforms, or niche or vertically-focused platforms. Specifically, in terms of resource allocation, large platforms like Taobao can harness substantial resources to drive extensive R&D, such as AI-driven recommendation systems, though their scale may reduce agility. Conversely, smaller platforms, limited by budgets and manpower, excel in flexibility, rapidly deploying tailored innovations. Further, regarding market positioning, large platforms favour scalable, universal solutions to serve broad user bases. Meanwhile, small platforms, such as Etsy (handmade goods) or Depop (second-hand fashion), target specific markets with customised offerings.

Future research should address these limitations. First, empirical data (such as large-scale user surveys or experimental results) can be integrated to enhance the model's robustness and applicability. Second, the scope of sensitivity analysis can be expanded to include the parameters simplified in the current model (e.g. user price sensitivity and registration fees). Additionally, advanced techniques, such as machine learning, can be employed to analyse higher-order interaction effects. This can provide a more comprehensive understanding of the intricate relationships among parameters and their impact on model outcomes. Third, the methodological approaches for parameter weight optimisation by building upon the existing sensitivity analysis and using an expanded analytical scope. For instance, the entropy weight method can be used to objectively determine the weights by analysing parameter variability derived from large-scale survey data. Meanwhile, the analytic hierarchy process can yield subjective weights through expert surveys and case-specific analyses. Integrating these objective and subjective weights can establish a robust baseline for parameter allocation, which can be further refined through Bayesian dynamic adjustment. This iterative process, incorporating real-time data or simulation outcomes, can yield a final adaptive reference framework that balances theoretical rigour with practical utility. Fourth, cross-platform comparative case studies can be performed to elucidate scale-dependent heterogeneity in governance strategies. Specifically, while identifying the key common factors, these studies should examine how resource allocation, market positioning, and innovation strategies vary between large-scale platforms and smaller or niche platforms. This can enable the development of a robust, universally applicable governance framework, enhancing its relevance and utility across diverse platform ecosystems, from mature giants to specialised markets.

Third, this study overlooks the broader, complex ecosystem in which the platform operates. We solely focus on service innovation within the platform, thereby neglecting other pivotal participants in the platform ecosystem, such as third-party service providers. While the Taobao case study provides a preliminary exploration of the impact of third-party service providers (such as MCNs and ISVs), the complexity and interactivity of these parameters have led to their exclusion from the simulation model. Nevertheless, these third-party actors shape platform service innovation through distinct cooperative and competitive dynamics. In cooperative contexts, they collaborate with platforms to co-develop services that enhance functionality and user experience. For instance, ISVs might supply tools like inventory management or marketing analytics, integrating these with the platform to boost seller efficiency. This accelerates innovation by leveraging external expertise. However, it poses governance challenges as well, such as aligning tools with platform standards or negotiating revenue-sharing terms. In competitive scenarios, third-party actors like MCNs may introduce services that rival the platform's core offerings. For example, MCNs could deploy live-streaming or branded content that competes with the platform's marketing efforts, driving enhancements like live-commerce to retain users and sellers. While this rivalry can spur innovation, it risks ecosystem fragmentation if third-party services divert traffic or revenue. This oversight results in an overly narrow and one-sided perspective on the topic. Furthermore, the study does not adequately consider the impact of changes in the broader social and technological environment on platform service innovation. Factors such as advancements in emerging technologies, and shifts in policies and regulations significantly influence these innovations but remain underexplored.

Future research should adopt a more holistic perspective, broadening the analytical scope to encompass the wider platform ecosystem through targeted case studies. These studies should employ a multi-case study approach to investigate how third-party service providers shape service innovation through cooperative and competitive dynamics, focusing on the following: (1) Identifying the distinct roles and contributions of various third-party actors—such as MCNs, ISVs, and other partners—and their unique value propositions in driving service innovation. (2) Exploring how specific cooperative mechanisms, including joint development and resource complementarity, enhance platforms' innovation capabilities. (3) Analysing innovation drivers in competitive settings, particularly how market pressures incentivise platforms and third-party providers to invest in R&D and optimise service offerings.

Furthermore, given challenges in data acquisition and processing, this study employed the simulation analysis of key parameters and optimal service types, supplemented by a preliminary sensitivity analysis. To extend this, future research should designate critical drivers of platform service innovation as independent variables. Meanwhile, platform service innovation performance is the dependent variable, and quantified via adoption rates, usage frequency, and user satisfaction. Then, panel data can be constructed for empirical testing, including the use of macroeconomic indicators, such as gross domestic product growth rate, digital economy penetration index, and industry prosperity index, as moderating variables. Such an approach can facilitate a more robust assessment of model stability across varying environmental conditions.

Moreover, conducting exogenous shock tests by incorporating variables related to emerging technologies, such as AI and blockchain, can offer valuable insights into their impact on service innovation. Future research can effectively employ a difference-in-differences methodology to assess the influence of emerging technologies on platform service innovation. Specifically, by comparing platforms that adopt these technologies (treatment group) with those that do not (control group) across pre- and post-adoption periods, researchers can establish an interaction term between time (1 for the post-technology adoption period, 0 otherwise) and treatment dummy variables (1 for technology-adopting platforms, 0 otherwise) as an exogenous shock variable. This approach can provide a clearer estimation of the technologies' influence on platform service innovation both before and after their introduction. Overall, by addressing these gaps, future research could enhance our understanding of how platforms can effectively design service innovations within a complex ecological environment.

Conclusions

Despite the growing recognition within the industry of platform service innovation's pivotal role in positioning deviation correction on bilateral platforms, the majority of extant research primarily focuses on determining whether, in what manner, and to what extent service innovation impacts enterprise performance from various theoretical standpoints. A notable gap remains on integrating service innovation design with the underlying causes of user attrition caused by positioning deviation on bilateral platforms. Addressing this gap, based on the perspective of positioning deviation correction, this study uses the Hotelling model to construct users' utility function and MATLAB-based numerical simulations to examine how platform service innovation can address this deviation, the influence of key parameters on the optimal innovation service type, and elucidate the design principles for such innovation. Overall, we provide a comprehensive understanding of the complex interactions between user churn, platform positioning deviation, and service innovation, thereby enriching platform economics theory, and offering new insights into the dynamics of user retention and churn in bilateral platforms. Moreover, it provides valuable guidance for designing platform service innovation strategies and developing effective operational approaches, offering practical insights for platform managers seeking to enhance long-term competitiveness and stability.

The main conclusions are as follows: (1) After a change in the future demand state, the deviation between platform positioning and user preferences is the main reason for the loss of users and even the collapse of the platform. We derive the following condition for this: $\beta\gamma < \phi\varphi$. (2) When the type of innovative service satisfies $\eta > \frac{2(\nu\gamma+\nu\phi)}{\theta\phi-\omega\beta+\theta\gamma-\omega\varphi}$, positioning deviation can be addressed via service innovation. (3) Platform managers should design service innovation based on the demand areas where there is a large deviation from user preferences. Here, it should use the principle of cost-benefit matching. Further, it should combine the influences of the strength of cross-side network effect, degree of user heterogeneity, platform development cost required by the unit service, additional value of the platform, buyer utility increased by the unit service, and seller development cost increased by the unit service, among other characteristic parameters, on the optimal innovative service. Simultaneously, managers should leverage digital marketing to update users' evaluated positioning of the platform in a timely manner.

CRediT authorship contribution statement

Xiao Xuan: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Data curation, Conceptualization. **Wenqi Duan:** Writing – review & editing, Validation, Supervision, Project administration, Conceptualization. **Lijia Kong:** Software, Methodology, Data curation.

Declaration of competing interest

The authors declare no conflict of interest.

Appendix

To further investigate the influence of characteristic parameters on the optimal innovative service type, this study conducts a sensitivity analysis and the results are presented here. The aim is to identify the relative impacts of key parameters and provide a basis for future research, particularly regarding parameter weight allocation.

Sensitivity analysis is a well-established methodology for examining the relationships between input parameters and model outcomes. This approach offers both quantitative and qualitative insights into how variations in individual input parameters affect the system's behaviour. Among various sensitivity analysis techniques, the Sobol global sensitivity analysis is particularly effective for analysing complex, non-linear systems—such as the platform examined in this study—by evaluating both the global influence of input parameters and their interdependencies.

(1) Sobol global sensitivity analysis method

We use variance-based Sobol sensitivity indices to quantify how changes in input parameters affect model outputs. Specifically, we decompose the variance of the output into contributions from individual parameters and their interactions. Assume that the model can be expressed as $\eta = f(x)$, where η denotes the model response and x is a vector comprising n input parameters. The model response can be decomposed as follows:

$$f(x) = f_0 + \sum_{i=1}^{n} f(x_i) + \sum_{1\le i\le j\le n}^{n} f_{ij}(x_i, x_j) + \cdots + f_{12\cdots k}(x_1, x_2, \cdots, x_n) \tag{A1}$$

Here, f_0 is the mean of $f(X)$, f_i represents the first-order function of the input parameters, and f_{ij} represents the second-order function, with higher-order terms continuing in this manner. All terms in the model response are orthogonal; that is, their expectations satisfy $\int f(x_i) f(x_j) dx_i dx_j = 0$.

Therefore, these decomposed terms can be calculated through the conditional expectation of η.

$$f_0 = E(\eta) \tag{A2}$$

$$f_i = E(\eta|x_i) - E(\eta) \tag{A3}$$

$$f_{ij} = E\left(\eta|x_i, x_j\right) - f_i - f_j - E(\eta) \tag{A4}$$

The conditional expectation $E(\eta|x_i)$ is the average of $\eta|x_i$ over the domain of X_i. A larger value of $E(\eta|x_i)$ indicates a greater influence of parameter x_i on the output. Therefore, variance serves as a measure of sensitivity, while the total variance $Var(\eta)$of the model can be expressed as:

$$Var(\eta) = \sum_i^n Var_i + \sum_i^n \sum_{i<j}^n Var_{ij} + \cdots + Var_{12\cdots n} \tag{A5}$$

Here, Var_i is $Var[E(\eta|x_i)]$, and Var_{ij} is the covariance between parameters $Var_i$and Var_j.

Dividing Eq. (A5) by $Var(\eta)$ yields the Sobol sensitivity indices:

$$S_i = \frac{Var[E(\eta|X_i)]}{Var(\eta)} \tag{A6}$$

Here, S_i represents the first-order sensitivity index, which directly quantifies the contribution of the independent variable x_i to the output target variable η, without considering the interactions with other variables. Meanwhile, the total effect sensitivity index S_{T_i}, which incorporates contributions from both the direct effect and interactions with other variables, can be expressed as follows:

$$S_{T_i} = \frac{Var(\eta) - Var_{\sim X_i}[E(\eta|x_{\sim i})]}{Var(\eta)} \tag{A7}$$

Where $x_{\sim i}$ denotes all variables except x_i.

Additionally, we compute the second-order sensitivity index, which are termed as interaction indices. These indices reflect the synergistic or antagonistic effects between two parameters. The specific formula is given by the following:

$$S_{ij} = \frac{Var\left[E\left(\eta|x_i, x_j\right)\right] - S_i - S_j}{Var(\eta)} \tag{A8}$$

(2) Parameter sensitivity test results and analysis based on Sobol method

Next, we adopt the Monte Carlo sampling method, consistent with extant research practices, with a sample size of 1000. Using Python software, we further conduct a Sobol global sensitivity on the six characteristic parameters mentioned earlier: the strength of cross-side network effect β, degree of user heterogeneity ϕ, platform development cost required by the unit service f, additional value of the platform ν, buyer utility increased by the unit service θ, and seller development cost increased by the unit service ω. This analysis aims to investigate the influence of these input variables on the optimal innovative service type.

As shown in the Table A1, the total effect sensitivity coefficients of the characteristic parameters, ranked from highest to lowest, are $\omega(0.797) > \theta(0.648) > \phi(0.647) > f(0.119) > \beta(0.057) > \nu(0.011)$. Among these, ω, θ, and ϕ are classified as highly sensitive; f and β are moderately sensitive; and ν is weakly sensitive. Thus, the seller development cost increased by the unit service, buyer utility increased by the unit service, and degree of user heterogeneity are the key variables influencing the optimal innovative service type. However, the additional value of the platform has a negligible impact and can be disregarded in future optimisation studies.

Table A1
Total effect sensitivity coefficients of the characteristic parameters.

Parameter	S_{T_i}	Sensitivity degree
β	0.057	Moderate
ϕ	0.647	High
f	0.119	Moderate
ω	0.797	High
θ	0.648	High
ν	0.011	Weak

Based on the calculated second-order sensitivity index S_{ij}, we construct an interaction effect heatmap, as illustrated in Fig. A1.

Clearly, the degree of user heterogeneity ϕ and seller development cost increased by the unit service ω exhibit a significant positive interaction effect. Thus, these two parameters demonstrate a synergistic effect in influencing the optimal innovative service type. In other words, higher user heterogeneity significantly amplifies the influence of seller development costs on determining the optimal service type.

The reasons can be explained from two perspectives. On the one hand, heterogeneous users may require more customised services, which increases cost sensitivity. On the other hand, when sellers raise their development costs to improve product or service quality in response to higher demand diversity among users, they may inadvertently face challenges in achieving cost efficiency.

Additionally, the combined effect of rising seller development costs and highly differentiated user demands can lead to increased uncertainty in business outcomes. While the data-driven precision matching of user needs may convert high costs into greater user retention and market share, excessive costs could result in resource wastage or reduced returns if user demands are too diversified to be effectively met.

Therefore, platform managers should closely monitor the ‘user heterogeneity–seller development cost’ combination and adopt a phased resource allocation strategy to ensure sustainable growth, comprising the following steps: The first step involves utilising data analytics to precisely identify core user segments. Platforms should leverage advanced tools, such as cluster analysis and user profiling, to pinpoint key user groups, including high-value users (e.g. frequent buyers of premium products) and niche markets with concentrated demand (e.g. specialised buyers in certain categories). By leveraging these insights, managers can optimise resource allocation and mitigate trade-offs between seller development costs and user heterogeneity, ensuring investments align with actual user needs. Taobao illustrates this with its ‘Thousand People, Thousand Faces’ system, wherein it uses big data and cloud computing to match granular product features to buyer preferences via behavioural profiles. Tailored recommendations in the ‘Guess You Like’ section enable sellers to engage potential customers. Through cluster analysis, users are segmented into specific groups (e.g. ‘Generation Z’ or high-value spenders), allowing for customised offerings that enhance efficiency and align with diverse demands.

Second, modular seller service solutions should be developed to cost-effectively address user heterogeneity. Platforms should prioritise investments in adaptable tools, such as standardised service templates, which enable sellers to tailor offerings efficiently while leveraging scalability to reduce development costs. This approach enhances cost efficiency and operational flexibility, accommodating diverse user demands without excessive resource expenditure. For instance, Taobao demonstrates this strategy by offering sellers modular tools such as ‘Business Advisor,’ a flexible analytics platform tailored to individual seller needs, thereby enhancing operational efficiency and reducing costs. Additionally, via the Taobao Open Platform, sellers utilise pre-built design templates to craft customised storefronts or product pages for diverse buyer segments, such as fashion enthusiasts or budget-conscious shoppers. These modular solutions minimise the expense of personalised service development, effectively aligning offerings with heterogeneous user demands while reinforcing platform efficiency.

The third step involves establishing real-time monitoring and early warning mechanisms. A robust system should track shifts in the ‘user heterogeneity–seller development cost’ dynamic, with predefined thresholds and resource allocation priorities. When heterogeneity exceeds critical levels, automated alerts should prompt managers to recalibrate strategies, such as pausing new service expansions in favour of optimising existing solutions, thereby ensuring that resources are effectively allocated. For instance, Taobao leverages Alibaba’s artificial intelligence-driven system to monitor seller performance and user behaviour in real time, and uses advanced algorithms to analyse big data (e.g. sales trends and consumer preferences) and achieve precise demand forecasting. This facilitates responsive inventory adjustments and efficient supply chain optimisation. Moreover, the system establishes thresholds for key metrics, such as request volumes across user scenarios including search, promotions, and live-streaming. During major events, it predicts traffic peaks and pre-emptively reallocates resources to avert disruptions. This illustrates a robust real-time monitoring and early warning mechanisms aligned with managing user heterogeneity and seller costs.

Fourth, user heterogeneity should be balanced with seller development costs. As heterogeneity rises, managers must carefully control the corresponding cost increase, avoiding excessive growth in both to prevent negative impacts, such as resource strain or diminished platform efficiency. If cost escalation outpaces diverse user demand, managers should refine service offerings to curb unnecessary expenditure. Taobao exemplifies this balance through differentiated strategies for users and sellers. For high-value users, the platform provides premium product recommendations and enhanced services, while supporting small-scale sellers by lowering entry barriers and offering free foundational tools. Additionally, charging for advanced features (e.g. virtual reality previews) and redirecting long-tail demand to third-party Application Programming Interface (API) markets further mitigate costs. This balanced approach not only accommodates diverse user needs but also prevents excessive seller development expenses, ensuring sustained platform efficiency.

Moreover, as observed in Fig. A1, the buyer utility increased by the unit service θ and seller development cost increased by the unit service ω form a significant negative antagonistic effect. This is because platforms need to enhance consumer utility by increasing service functionalities, which typically requires sellers to incur higher costs. However, as sellers increase their marginal cost per additional unit of service, this may compress their profit margins, potentially forcing them to reduce service supply or even exit the platform. In other words, when resources are limited, one party’s gains come at the expense of the other. Therefore, formulating a rational resource allocation plan to prevent excessive investment in one aspect from leading to performance degradation in the other. Managers should assess the types and scale of resources invested in enhancing buyer utility, identify whether these investments lead to increased seller development costs, and implement an optimisation strategy that balances utility and cost to effectively convert costs into user retention.

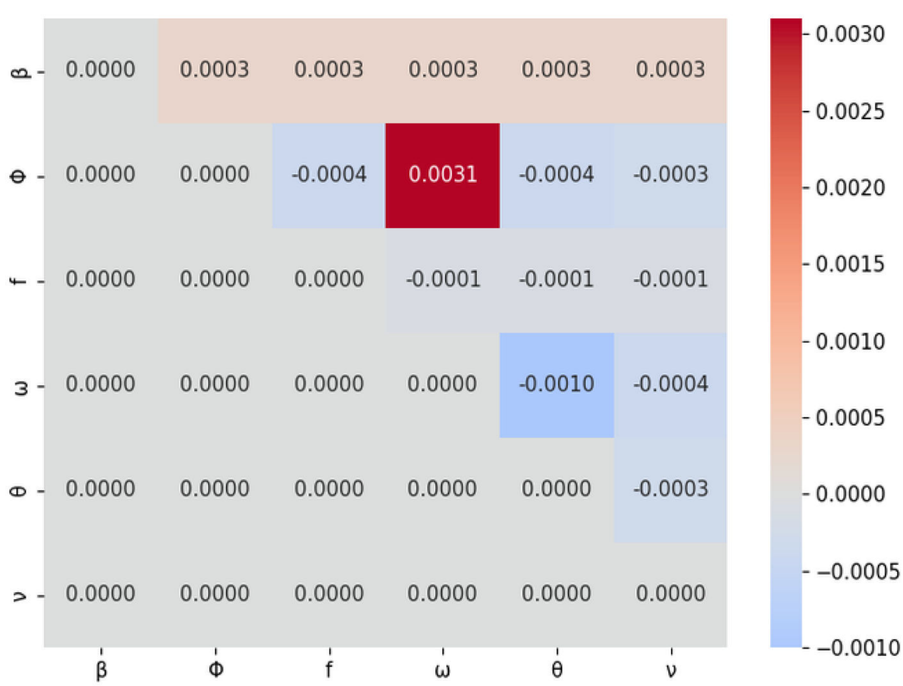


Fig. A1. Second-order sensitivity heatmap.

References

Akbar, Y. H., & Tracogna, A. (2022). The digital economy and the growth dynamics of sharing platforms: A transaction cost economics assessment. *Journal of Digital Economy, 1*(3), 209–226. https://doi.org/10.1016/j.jdec.2023.01.002

Alaimo, C., Kallinikos, J., & Valderrama, E. (2020). Platforms as service ecosystems: Lessons from social media. *Journal of Information Technology, 35*(1), 25–48. https://doi.org/10.1177/0268396219881462

Brunswicker, S., Almirall, E., & Majchrzak, A. (2019). Optimizing and satisficing: The interplay between platform architecture and producers design strategies for platform performance. *MIS Quarterly, 43*(4), 1249–1277. https://doi.org/10.25300/MISQ/2019/13561

Cenamor, J., & Frishammar, J. (2021). Openness in platform ecosystems: Innovation strategies for complementary products. *Research Policy, 50*(1), Article 104148. https://doi.org/10.1016/j.respol.2020.104148

Daradkeh, M. (2023). Exploring the boundaries of success: A literature review and research agenda on resource, complementary, and ecological boundaries in digital platform business model innovation. *Informatics, 10*(2), 41. https://doi.org/10.3390/informatics10020041

Gui, Y. M., Wu, Z., & Gong, B. G. (2021). Value-added service quality investment competition decision of bilateral platform in competitive environment. *Chinese Journal of Management Science, 29*(05), 65–76. https://doi.org/10.16381/j.cnki.issn1003-207x.2018.1245

Guo, L. (2006). Consumption flexibility, product configuration, and market competition. *Marketing Science, 25*(2), 116–130. https://doi.org/10.1287/mksc.1050.0169

Hagiu, A. (2009). Two-sided platforms: Product variety and pricing structures. *Journal of Economic & Management Strategy, 18*(4), 1011–1043. https://doi.org/10.1111/J.1530-9134.2009.00236.X

Hotelling, H. (1990). Stability in competition. In H. Hotelling (Ed.), *The collected economics articles of Harold hotelling* (pp. 50–63). New York, NY: Springer.

Jiang, Q. W., Luo, J. Q., & Li, Y. J. (2024). Digital intellectualization on the operation decision of manufacturing enterprises' service innovation. *Journal of Systems & Management, 34*(2), 123–145. Retrieved from http://82.156.45.170:8085/kcms/detail/31.1977.N.20240621.1056.002.html Accessed November 8, 2024.

Latinovic, Z., & Chatterjee, S. C. (2024). Value co-creation: Balancing B2B platform value and potential reverse-value effects. *Journal of Business Research, 175*, Article 114518. https://doi.org/10.1016/j.jbusres.2024.114518

Leong, C., Pan, S. L., Leidner, D. E., & Huang, J. S. (2019). Platform leadership: Managing boundaries for the network growth of digital platforms. *Journal of the Association for Information Systems, 20*(10), 1531–1565. https://doi.org/10.17705/1jais.00577

Li, W., Sun, C., Li, Y., & Ertz, M. (2024). Effects of business to business e-commerce platform-governance mechanisms on seller firms' performance. *Research in International Business and Finance, 67*, Article 102121. https://doi.org/10.1016/j.ribaf.2023.102121

Liu, B. Q., Li, D. T., Wang, J., Wang, Z. H., Li, B., & Zeng, C. (2024). Integrating user short-term intentions and long-term preferences in heterogeneous hypergraph networks for sequential recommendation. *Information Processing & Management, 61*(3), Article 103680. https://doi.org/10.1016/j.ipm.2024.103680

Luo, J., Luo, J., Nan, G., & Li, D. (2023). Fake review detection system for online E-commerce platforms: A supervised general mixed probability approach. *Decision Support Systems, 175*, Article 114045. https://doi.org/10.1016/j.dss.2023.114045

Malgonde, O., Zhang, H., Padmanabhan, B., & Limayem, M. (2020). Taming complexity in search matching: Two-sided recommender systems on digital platforms. *MIS Quarterly, 44*(1), 48–84. https://doi.org/10.25300/MISQ/2020/14424

Mao, K., Jing, X., Wang, G., Chang, Y., Liu, J., Zhao, Y., Yu, S., & Liu, J. (2024). A novel open-source CADs platform for 3D CT pulmonary analysis. *Computers in Biology and Medicine, 169*, Article 107878. https://doi.org/10.1016/j.compbiomed.2023.107878

Miremadi, I., Khoshbash, M., & Saeedian, M. M. (2023). Fostering generativity in platform ecosystems: How open innovation and complexity interact to influence platform adoption. *Research Policy, 52*(6), Article 104781. https://doi.org/10.1016/j.respol.2023.104781

Shafiloo, R., Kaedi, M., & Pourmiri, A. (2024). Considering user dynamic preferences for mitigating negative effects of long-tail in recommender systems. *Information Sciences, 669*, Article 120558. https://doi.org/10.1016/j.ins.2024.120558

Shi, H. R., Sun, G. Q., & Zhang, B. J. (2018). System archetypes of the evolution of platform ecosystem and policies' explanation. *Forum on Science and Technology in China, 07*, 113–123. https://doi.org/10.13580/j.cnki.fstc.2018.07.015

Sui, R., Liu, M., Liu, Y., & Zha, X. (2024). Two-sided dynamic pricing and value-added service investment strategies of competitive platforms considering indirect network effects. *International Journal of Production Economics, 272*, Article 109262. https://doi.org/10.1016/j.ijpe.2024.109262

Tian, J., & Xu, J. B. (2020). The influence of multidimensional proximity on patent technology transaction in integrated circuit industry. *Studies in Science of Science, 38*(05), 949–960. https://doi.org/10.16192/j.cnki.1003-2053.2020.05.020

Trabucchi, D., & Buganza, T. (2020). Fostering digital platform innovation: From two to multi-sided platforms. *Creativity and Innovation Management, 29*(2), 345–358. https://doi.org/10.1111/caim.12320

Urbaniak, R., Ptaszyński, M., Tempska, P., Leliwa, G., Brochocki, M., & Wroczynski, M. (2022). Personal attacks decrease user activity in social networking platforms. *Computers in Human Behavior, 126*, Article 106972. https://doi.org/10.1016/j.chb.2021.106972

Wang, L., Zhang, R.-S., & Zhang, C.-X. (2024). Live streaming e-commerce platform characteristics: Influencing consumer value co-creation and co-destruction behavior. *Acta Psychologica, 243*, Article 104163. https://doi.org/10.1016/j.actpsy.2024.104163

Wang, Y., Tian, Q. H., Li, X., & Xiao, X. H. (2022). Different roles, different strokes: How to leverage two types of digital platform capabilities to fuel service innovation. *Journal of Business Research, 144*, 1121–1128. https://doi.org/10.1016/j.jbusres.2022.02.038

Wei, T., & Lu, R. Y. (2013). Differentiation strategy of service innovation based on Hotelling advanced model. *Journal of Industrial Engineering, 27*(03), 69–73. https://doi.org/10.13587/j.cnki.jieem.2013.03.002

Wu, M., Liu, Y. L., Jasimuddin, S. M., & Zhang, Z. P. (2023). Rethinking cross-border mobile payment ecosystems: A process study of mobile payment platform complementors, network effect holes and ecosystem modules. *International Business Review, 32*(1), Article 102026. https://doi.org/10.1016/j.ibusrev.2022.102026

Yang, J., & Kwon, Y. (2024). Are digital content subscription services still thriving? Analyzing the conflict between innovation adoption and resistance. *Journal of Innovation & Knowledge, 9*(4), Article 100581. https://doi.org/10.1016/j.jik.2024.100581

Zhang, K. Y., Tang, X. F., Su, H. X., & Wang, Y. (2018). Innovation strategy: A comparative study on brand relationship-driven and service innovation-driven. *Forecasting, 37*(04), 39–45. https://doi.org/10.11847/fj.37.4.39

Zhang, S. K., & Tang, T. Y. (2019). Managing same-side and cross-side innovations in two-sided platforms. *Marketing Intelligence & Planning, 37*(7), 770–790. https://doi.org/10.1108/MIP-03-2019-0156

Zhang, X., Sui, R., Dan, B., & Guan, Z. (2021). Bilateral value-added services and pricing strategies of the third-party platform considering the cross-network externality. *Computers & Industrial Engineering, 155*, Article 107196. https://doi.org/10.1016/j.cie.2021.107196

Zhao, L. L., Liu, Y., Wei, J., & Wang, L. (2017). Service innovation strategies and competitive advantages for manufacturing firms: Mechanisms and contingencies. *Science Research Management, 38*(05), 20–29. https://doi.org/10.19571/j.cnki.1000-2995.2017.05.003

Zhao, Y., Von Delft, S., Morgan-Thomas, A., & Buck, T. (2020). The evolution of platform business models: Exploring competitive battles in the world of platforms. *Long Range Planning, 53*(4), Article 101892. https://doi.org/10.1016/j.lrp.2019.101892

Zheng, D. J., Li, Y., Shen, J. W., & Zheng, M. Z. (2019). A study on the influence factors of user exodus in mobile reading platform: Taking "WeChat reading" as an example. *Information Studies: Theory & Application, 42*(08), 78–82. https://doi.org/10.16353/j.cnki.1000-7490.2019.08.015

Zhou, L., Mao, H., Zhao, T., Wang, V. L., Wang, X., & Zuo, P. (2022). How B2B platform improves buyers' performance: Insights into platform's substitution effect. *Journal of Business Research, 143*, 72–80. https://doi.org/10.1016/j.jbusres.2022.01.060