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Subsidy Strategies for Drone Food Delivery under Dual Network Externalities: A Four-Party Stackelberg Game Approach

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Abstract: Accurate government subsidy policies are crucial to advancing the large-scale promotion of drone food delivery. To scientifically formulate government subsidy strategies, this paper incorporates indirect network effects, peer effects, and psychological costs into a unified framework, and constructs a four-party Stackelberg dynamic game model consisting of the government, infrastructure construction enterprises, food delivery platforms, and consumers. Using backward induction, this study derives equilibrium results under three scenarios: no subsidy, subsidizing infrastructure enterprises, and subsidizing consumers. It compares subsidy levels, delivery prices, market demand, congestion externalities, and social welfare under different strategies, and verifies the conclusions through numerical simulation. Results show that: First, the optimal subsidy targets and intensity are highly dependent on the relative strength of indirect network effects and peer effects. When indirect network effects are weak, consumers should be subsidized if peer effects are also weak, while infrastructure construction enterprises should be subsidized if peer effects are strong. When indirect network effects reach an intermediate level, subsidizing consumers is more effective in enhancing social welfare. Second, the direction of the impact of peer effects on drone delivery demand is moderated by consumers' psychological costs. Peer effects exert a promoting effect only when psychological costs are below the critical threshold. Third, when indirect network effects exceed the critical threshold, the market can achieve equilibrium spontaneously, and the government should withdraw subsidies in an orderly manner. This paper provides a theoretical basis and quantitative decision-making reference for the phased and differentiated government subsidy policies for drone food delivery.

Keywords: Drone food delivery; Government subsidies; Indirect network effects; Peer effects; Stackelberg game

1. Introduction

Drone delivery is regarded as a core solution to address the development shortcomings of the food delivery market caused by the manual delivery model, including high traffic safety risks, worsening urban traffic congestion, persistently high operating costs, and increasing environmental pollution, and it has broad potential for large-scale commercial application. However, restricted by practical development bottlenecks, drone food delivery has not yet achieved large-scale promotion: on the one hand, insufficient coverage density of drone takeoff and landing points leads to unstable delivery time efficiency¹; on the other hand, as an emerging service model, the service fee of drone delivery is significantly higher than that of traditional manual delivery². The combination of high pricing and consumers' psychological concerns directly affects consumers' willingness to choose between delivery methods. Breaking this development dilemma cannot be achieved solely by the inherent mechanisms of the market. As a key policy tool to promote the implementation of emerging technologies, it has been proven that government subsidies exert a significant guiding and catalytic effect on the initial commercialization of emerging technologies (Gerarden 2023; Zhao et al. 2024; Xiang et al. 2025). Therefore, it is urgent for the government to provide guidance and support through scientific and effective subsidy policies, to advance the construction of infrastructure related to drone food delivery, and to reduce consumers' usage costs.

In the field of drone applications, existing studies have shown that subsidies can effectively promote infrastructure construction (Raghunatha et al. 2023; Li et al. 2026), and can also reduce consumers' usage costs to stimulate market demand (Hwang et al. 2020; Sivaraman et al. 2025). However, specific subsidy policies for drone delivery are still in the exploratory stage, and relevant academic research is relatively scarce. In practice, directly applying the single subsidy logic of traditional industries can easily lead to the dilemma of supply-demand mismatch. Therefore, to construct an effective subsidy policy system for drone food delivery, it is necessary to first identify the core variables that

dominate the dynamic evolution of its market, clarify the core demands of the market at
1 China Civil Airports Association Guidelines for Low Altitude Economic Infrastructure Framework

2 The investment industry The formation of the "three legged" pattern in drone logistics: a game of cost and scale

different development stages, and then establish a dynamic policy adjustment mechanism adapted to market evolution, so as to achieve precise matching between subsidy strategies and market development conditions.

A large body of literature has confirmed that both indirect network effects (Sivaraman et al. 2025; Sui et al. 2024) and peer effects (Cai et al. 2025) significantly shape the implementation effectiveness of government subsidy policies. In addition, consumers' psychological costs associated with emerging technologies constitute a critical boundary condition that constrains their adoption decisions (Dabić et al. 2025; Günther et al. 2025). Specifically, indirect network effects refer to the phenomenon whereby the optimization of scale and layout on one side of the supply-demand network enhances the utility of users on the other side. In the context of drone food delivery, this is reflected in the fact that the improvement of infrastructure such as takeoff and landing points can significantly enhance consumers' service experience and usage utility (Wang et al. 2026; Zhang et al. 2023). Meanwhile, peer effects describe the tendency that consumers' choice of delivery methods is strongly influenced by the adoption behavior of reference groups around them. Existing studies have documented that both infrastructure quality and peer adoption behavior are indeed the two core drivers of user decision-making and market evolution in this field (Dabić et al. 2025; Zhang et al. 2023). The former directly determines service practicality and user experience, while the latter plays a pivotal role in building user trust and accelerating market diffusion. Taken together, these two mechanisms shape the underlying logic of the dynamic evolution of the drone delivery market. Therefore, when formulating subsidy policies for drone delivery, the combined effects of indirect network effects, peer effects and psychological costs should be fully considered, and these core drivers and market evolution laws should be integrated into the policy design to achieve the precise formulation of subsidy strategies.

Based on this, this paper constructs a four-party Stackelberg game model including the government, infrastructure construction enterprises, food delivery platforms, and consumers, and solves the model equilibrium through backward induction. It aims to answer how the government should select optimal subsidy targets and subsidy intensity in the market dynamics shaped by indirect network effects and peer effects and regulated by psychological costs, so as to efficiently break the dilemma of large-scale promotion of

drone food delivery and ultimately achieve the optimization of total social welfare. The research results can not only provide a quantitative decision-making basis for the formulation of industrial policies for drone food delivery under the low-altitude economy but also clarify the interaction mechanism of the two core factors on the effect of subsidy policies, filling the quantitative research gap in drone subsidy policies in the food delivery scenario.

The section structure of this paper is as follows: Section 1 serves as the introduction, outlining the research background and significance; Section 2 presents a literature review that summarizes relevant research advancements and identifies existing research gaps; Section 3 constructs and describes a subsidy allocation model for drone food delivery services; Sections 4~5 derive the equilibrium analytical solution of the model and compare the policy effects of different subsidy strategies; Section 6 employs numerical simulations to identify the subsidy strategy that maximizes social welfare.

2. Literature Review

2.1. Factors Influencing User Choice Behavior in Drone Delivery Services

Existing studies on the influencing factors of users' choice behavior regarding drone delivery are generally rooted in classical behavioral theories, such as the Technology Acceptance Model (TAM) (Waris et al. 2022), Theory of Planned Behavior (TPB) (Hwang et al. 2020; Leong and Koay 2023), and Unified Theory of Acceptance and Use of Technology (UTAUT) (Schmidt and Saraceni 2024; Alhothali et al. 2024), based on which the psychological and cognitive paths of user choice are explored. Research shows that perceived usefulness, perceived ease of use (Waris et al. 2022; Jasim et al. 2022; Koh et al. 2023), attitude, and perceived behavioral control (Kim et al. 2021; Leong and Koay 2023) are fundamental positive factors driving adoption intention. Some studies have explicitly identified reliable delivery time and complete infrastructure as key service attributes affecting users' willingness to pay and choice, while infrastructure coverage is precisely the core carrier of indirect network effects in drone delivery (Katz and Shapiro 1985).

Notably, peer effects, as a core social factor influencing user choice, are often quantified as subjective norms or social influence in existing research, whose essence is the transmission effect of surrounding people's choice behaviors on individual decision-

making (Hwang et al. 2020; Waris et al. 2022). In addition, users' choice of drone delivery is not only driven by positive factors but also constrained by multiple negative factors in the actual decision-making process, among which psychological costs have a particularly prominent impact. On the one hand, consumers are highly sensitive to delivery time, and their willingness to choose will decline significantly once the expected delivery time exceeds the psychological threshold (Woo et al. 2025; Kyi et al. 2026); on the other hand, concerns about emerging technologies constitute an important psychological barrier to drone adoption (Mathew et al. 2021; Choe et al. 2021), with worries such as privacy risks and performance risks directly inhibiting users' decision-making tendencies (Koh et al. 2023). These positive driving factors and negative constraining factors work together to ultimately shape the complete mechanism of users' choice of drone delivery.

2.2. Research on Subsidy Policies for Drone Technology Promotion

Government subsidy policies are generally divided into two categories in public economics research: supply-side and demand-side policies, which focus on improving industrial foundations and activating market demand respectively. Existing studies have further confirmed that a single policy tool often has limited effects, and only the organic combination of supply-side and demand-side policies to form a policy mix can maximize the comprehensive effectiveness of policy intervention (Bacchiocchi et al. 2024).

In the drone industry, existing research on subsidies and related policy practices is largely concentrated in mature application scenarios. The implementation effects of subsidy policies for plant protection drones have been systematically analyzed (Deng et al. 2024; Ding et al. 2024), and the income-increasing effect of agricultural drone subsidies on farmers has also been empirically tested (Yu et al. 2024). Collectively, these studies and policy practices have formed a unified subsidy framework characterized by supply-side dominance and demand-side supplementation.

On the supply side, studies show that subsidy policies are mainly tilted toward drone manufacturers and agricultural service organizations, reducing equipment procurement costs for agricultural plant protection drones and technological innovation costs through agricultural machinery purchase subsidies and R&D subsidies (Cao et al. 2025). On the demand side, existing subsidy policies are mostly supplementary to supply-side subsidies,

with relatively limited coverage and incentive intensity, and mainly benefit farmers indirectly in the form of operation subsidies and usage subsidies.

2.3. Research on Game Analysis of Traditional Food

Multi-agent game research in the food delivery field has formed a mature analytical framework centered on platforms, which incorporates government regulation and user decision-making. Its core logic focuses on supply-demand matching, cost allocation, and policy guidance for traditional delivery services, providing a fundamental paradigm for constructing the game model of drone delivery in this paper.

Existing research on multi-stakeholder games in the food delivery sector has evolved around three core hierarchical relationships. At the micro platform-user level, studies focus on the two-way interaction between pricing strategies and service quality, revealing the core decision-making logic of platforms balancing market share and profitability through fee structure design (Oh et al. 2026; Seo et al. 2025). At the meso operational level, scholars have examined the allocation of decision-making power and efficiency optimization between platforms and delivery entities, confirming that the independence and decision-making mechanisms of delivery entities have a critical impact on overall service capacity (Simoni and Winkenbach 2023). At the macro government regulation level, three-party game studies involving governments, enterprises, and users have clarified that subsidy and regulatory policies are essential tools to guide the upgrading of delivery models and balance corporate profits with social welfare (Ji et al. 2024; Plazier et al. 2024).

2.4. Literature Review

The preceding sections have systematically sorted out the literature around three core directions: users' choice behavior in drone delivery, subsidy policies for drone technology promotion, and multi-agent game in food delivery. In the research field of user choice behavior, the existing literature has respectively identified and empirically verified the core impacts of indirect network effects, peer effects, and psychological costs on users' choice behavior of drone delivery. In the field of subsidy policies for drone technology promotion, existing achievements highly focus on mature application scenarios such as agricultural plant protection and emergency rescue, fully verifying the positive guiding role of fiscal subsidies in the commercial promotion of drone technology. In the research field of multi-agent game in food delivery services, existing literature, based on the scenario of traditional

manual delivery, has constructed a well-established game analysis paradigm around the four core agents: food delivery platforms, consumers, delivery riders, and the government, and clarified the formation mechanism of equilibrium in the strategic interactions among multiple agents in the food delivery market.

To systematically compare the research dimensions, methodologies and coverage of existing studies, and clearly highlight the incremental contributions of this paper, we construct a comparative analysis table as shown in Table 1.

Table 1

Comparative analysis of existing research streams and this paper

Research Stream	Main Literature	Methodology	Core Research Dimensions					
			Indirect Network Effects	Peer Effects	Psychological Costs	Four-party Game	Subsidy Strategy Design	Subsidy Exit Mechanism
Drone Delivery User Adoption	Hwang et al. (2020)	Empirical Survey	○	√	√			
	Waris et al. (2022)	Empirical Survey	○	√	√			
	Leong and Koay (2023)	Empirical Survey	○	√	√			
	Dabić et al. (2025)	Systematic Review	√	√	√			
	Zhang et al. (2023)	Empirical Survey	√	√	√			
Drone Industry Subsidy Policies	Raghunatha et al. (2023)	Policy Analysis	√				√	
	Deng et al. (2024)	Empirical Estimation					√	
	Yu et al. (2024)	Quasi-natural Experiment					√	
	Li et al. (2026)	Game Theory	√			Three-party	√	
	Ji et al. (2024)	Game Theory				Three-party	√	
Food Delivery Multi-agent Game	Oh et al. (2026)	Game Theory				Two-party		
	Plazier et al. (2024)	Scenario Analysis					√	
Network Externalities & Peer Effects	Sui et al. (2024)	Game Theory	√			Two-sided Market		
	Cai et al. (2025)	Evolutionary Game		√		Three-party	√	
This Paper	This Paper	Four-party Stackelberg Game	√	√	√	√	√	√

Notes: $\surd$ = Explicitly incorporated; $\circ$ = Mentioned but not quantitatively modeled.

Through the above comparative analysis, it can be found that the existing literature still has obvious shortcomings: First, extant studies have not incorporated indirect network effects, peer effects, and psychological costs into a unified analytical framework, and have not yet clarified the interaction mechanism of the three on the effect of subsidy policies. Second, there is relatively little quantitative research on subsidy policies specifically targeting the drone food delivery scenario, making it difficult to accurately depict the policy transmission mechanisms on both the supply and demand sides in this scenario. Third, most analytical frameworks are still constructed based on the traditional manual delivery scenario, neither incorporating the independent infrastructure construction enterprise entity that is crucial in the drone delivery ecosystem nor combining the characteristics of market dynamic evolution to clarify the optimization path and exit mechanism of subsidy policies.

3. Drone Food Delivery Subsidy Allocation Model

This section adopts the backward induction method to solve the market equilibrium results under three scenarios: the benchmark model without government subsidies (Model N), the model subsidizing infrastructure construction enterprises (Model S), and the model subsidizing consumers (Model C), and analyzes the mechanism of core variables.

3.1. Model Assumptions

To accurately characterize the laws of multi-agent strategic interactions in the drone food delivery market under dual network externalities, and to quantify the social welfare effects of different government subsidy strategies, the model sets forth the following assumptions with respect to the dimensions of spatial market distribution, agents' decision-making rationality, specification of utility functions, costs and benefits, and characterization of externalities:

Assumption 1: Referring to the classical Hotelling linear city model, assume that consumers are uniformly distributed on the interval $[0,1]$ (Zhang et al. 2026). With full market coverage, i.e., all consumers will choose one delivery method, satisfying $D_T + D_D = 1$, where D_T is the demand for traditional delivery and D_D is the demand for drone delivery.

Assumption 2: Consumers are perfectly rational and choose delivery methods based on the principle of utility maximization. They choose traditional delivery when $U_T(x) \geq U_D(x)$, and drone delivery otherwise.

Assumption 3: Infrastructure construction enterprises are uniformly distributed on the interval $[0,1]$. The steady-state periodic operation scale of a single infrastructure enterprise is normalized to 1 unit order per cycle. Enterprises choose to invest in traditional delivery or drone delivery infrastructure based on the principle of utility maximization.

Assumption 4: The food delivery platform operates both traditional and drone delivery services simultaneously, and sets the prices of the two types of delivery services to maximize profit. The platform and infrastructure construction enterprises realize value connection through fixed revenue sharing.

Assumption 5: Traditional manual ground delivery generates positive traffic congestion externalities, while drone air delivery does not occupy ground road resources and does not generate additional traffic congestion costs.

Assumption 6: τ_T and τ_D represent the psychological costs of consumers for traditional delivery and drone delivery respectively, which are used to characterize consumers' perceived risks and concerns about the two delivery methods and are the core negative factors affecting consumer decision-making. Assuming that $\tau_T > \tau_D$ reflects the relative advantages of drone delivery in terms of time efficiency stability and controllability (Hu et al. 2025; Lemardel é et al. 2021).

Assumption 7: To prevent the intensity of peer effects from excessively distorting the inherent preference heterogeneity of consumers, the intensity coefficient is restricted within the interval $(0, t_c)$.

3.2. Model Establishment

(1) Consumers

The core focus of this paper is on indirect network effects and peer effects. Consumers' decision-making on the choice of drone delivery mode is susceptible to the maturity of infrastructure and the behavior of surrounding peers. The more complete the infrastructure and the higher the proportion of consumers choosing drone delivery, the greater the probability that an individual's choice willingness will be translated into actual action. Based on the above, let the utility of consumers choosing traditional delivery be $U_T(x)$, and

the utility of choosing drone delivery be $U_D(x)$, with their utility functions shown in Formula (1) and Formula (2):

$$U_T(x) = u_0 - t_c \cdot x + \gamma \cdot D_T + \eta \cdot y_T - (p_T + \tau_T) \quad (1)$$

$$U_D(x) = u_0 - t_c \cdot (1 - x) + \gamma \cdot D_D + \eta \cdot y_D - (p_D + \tau_D) + e_c \quad (2)$$

Where, u_0 is the base utility of consumers from food delivery services; t_c is the intensity of consumers' preference heterogeneity for delivery modes; x is the location of a consumer in the linear city; γ is the peer effect coefficient; D_T and D_D are the equilibrium demand of traditional delivery and drone delivery, respectively; η is the indirect network effect coefficient; y_T and y_D are the number of infrastructure facilities for traditional delivery and drone delivery, respectively; p_T and p_D are the service prices of traditional delivery and drone delivery, respectively; τ_T and τ_D are consumers' psychological costs of traditional delivery and drone delivery, respectively; e_c is the unit subsidy provided by the government to consumers who choose drone delivery. In the formula, the impact of indirect network effects on consumer utility is quantified by $\eta \cdot y_D$; the peer effect is adjusted in combination with the characteristics of consumption decision-making for drone delivery, and its mechanism of action is reflected by $\gamma \cdot D_D$.

(2) Infrastructure Construction Enterprises

The infrastructure construction enterprises are the second-tier decision-making agents in the game, whose investment decisions directly determine the scale of infrastructure coverage for traditional delivery and drone delivery. Enterprises choose their investment direction based on the principle of utility maximization, and their utility is mainly composed of the base investment utility and the per-order revenue share paid by the platform. Government subsidies for infrastructure construction enterprises will directly increase the utility of enterprises that invest in drone delivery infrastructure. Based on this, the model of the utility function for enterprises investing in traditional infrastructure $U_{infra,T}(y)$ and the utility function obtained by enterprises investing in drone infrastructure $U_{infra,D}(y)$ are shown in Formula (3) and Formula (4):

$$U_{infra,T}(y) = v_0 - t_s \cdot y + r_T \quad (3)$$

$$U_{infra,D}(y) = v_0 - t_s \cdot (1 - y) + r_D + e_s \quad (4)$$

Where, v_0 is the base investment utility; t_s measures the intensity of enterprises' investment preference heterogeneity; y is the investment preference location of infrastructure construction enterprises uniformly distributed over the interval $[0,1]$; r_T and r_D are the per-order revenue obtained from the platform, which constitute the main source of enterprises' utility; e_s is the unit subsidy provided by the government to enterprises investing in drone delivery infrastructure.

(3) Food Delivery Platform

Food delivery platforms are the third-tier decision-making agents in the game, who maximize their total profit by setting differentiated service prices. To clearly characterize the value flow path between the platforms and infrastructure construction enterprises, it is assumed that the unit cost of the platforms includes the fixed revenue share paid to infrastructure construction enterprises. Based on this, the model of the food delivery platform's profit under the traditional food delivery model $\max_{p_T} \pi_T$ and the food delivery platform's profit under the drone delivery model $\max_{p_D} \pi_D$ are shown in Formula (5) and Formula (6):

$$\max_{p_T} \pi_T = (p_T - c_T) \cdot D_T \quad (5)$$

$$\max_{p_D} \pi_D = (p_D - c_D) \cdot D_D \quad (6)$$

Where, $c_T = c_{Top} + r_T$, $c_D = c_{Dop} + r_D$. Where, r_T and r_D are the per-order revenue paid to the corresponding infrastructure construction enterprises, and c_{Top} and c_{Dop} are the other operating costs of the platform.

(4) Government

In the overall model, the government formulates subsidy policies and selects the optimal subsidy targets and subsidy levels to maximize total social welfare. The total social welfare function should comprehensively cover the interests of all market participants and social public costs, including consumer surplus, the surplus of infrastructure construction enterprises, and the total profit of food delivery platforms, while deducting the traffic congestion externalities generated by traditional manual delivery and the total government subsidy expenditure. Based on this, the social welfare function model is shown in Formula (7):

$$\max_e SW = \Pi + CS_C + CS_S - EI - TS \quad (7)$$

In the formula, $\Pi = \pi_T + \pi_D$ is the total profit of the food delivery platform; CS_C is consumer surplus, defined as:

$$CS_C = \int_0^{D_T} U_T(x)dx + \int_{D_T}^1 U_D(x)dx \quad (8)$$

CS_S is infrastructure construction enterprise surplus, defined as:

$$CS_S = \int_0^{y_T} U_{\text{infra},T}(y)dy + \int_{y_T}^1 U_{\text{infra},D}(y)dy \quad (9)$$

Where, EI is congestion externalities, whose expression is $EI = \theta_T \cdot D_T$; TS is total government subsidy expenditure. If subsidizing consumers, $TS = e_c \cdot D_D$; if subsidizing infrastructure construction enterprises, $TS = e_s \cdot y_D$. To ensure the non-negativity of subsidies and traditional food delivery, the government's decision must satisfy the constraints $e \geq 0$ and $D_T(e) \geq 0$.

3.3. Model Description

This research system conducted a quantitative analysis of the subsidy strategy for drone food delivery. As shown in Fig.1, a four-party Stackelberg dynamic game framework is constructed to describe the interactive relationship between multi-agent strategies. By using this framework, the model equilibrium solution, policy effect comparison, and social welfare maximization analysis are sequentially completed, providing theoretical support for the formulation of differentiated subsidy policies.

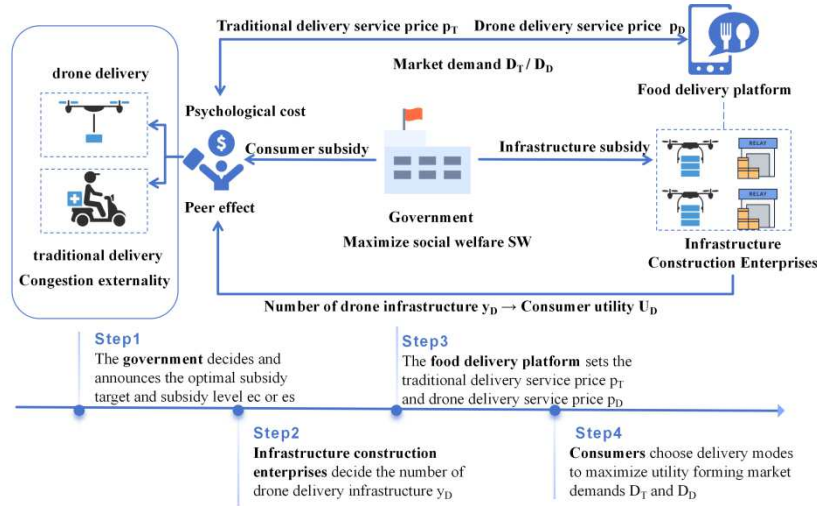


Fig.1. Game mechanism framework of drone food delivery subsidy policies under dual network externalities

(1) Model Equilibrium Solution

Based on the four-party Stackelberg game framework, three subsidy scenarios are established by controlling the values of subsidy variables: the benchmark non-subsidy scenario with $e_c = e_s = 0$ serving as the blank reference, the scenario of subsidizing infrastructure construction enterprises with $e_s > 0$ and $e_c = 0$, and the scenario of subsidizing consumers with $e_c > 0$ and $e_s = 0$. The subgame perfect Nash equilibrium under each scenario is solved to explore how peer effects and indirect network effects affect the optimal subsidy level and the government's exit threshold. Backward induction is adopted throughout the solution process. Specifically, the consumer selection rules under given p_T , p_D , y_T and y_D are first derived to obtain D_T and D_D . On this basis, the optimal pricing of platforms and the optimal investment scale of enterprises are deduced in reverse order, followed by the derivation of the government's optimal unit subsidy level e_c or e_s . The complete derivation is presented in the appendix.

(2) Policy Effect Comparison

To comprehensively evaluate the implementation effectiveness of supply-side and demand-side subsidies and scientifically identify the optimal subsidy strategy for the large-scale promotion of drone food delivery and social welfare maximization, this study conducts a horizontal comparison across four core dimensions, namely subsidy level, delivery price, market share, and congestion externalities, based on the analytical equilibrium solutions of the three scenarios. First, the optimal unit subsidy intensities of the two subsidy policies are compared to quantify the differences in fiscal input costs under distinct market conditions. Second, the differentiated impacts of various subsidy policies on platforms' pricing strategies are analyzed to reveal the price transmission mechanisms of subsidies on both supply and demand sides. Third, the equilibrium delivery volumes under the three scenarios are compared to assess the effectiveness of the two subsidy policies in expanding the market share of drone delivery and guiding the optimal allocation of market resources. Finally, the levels of congestion externalities under different subsidy policies are measured to quantify the urban traffic improvement benefits brought by the promotion of drone food delivery services.

(3) Social Welfare Analysis

Social welfare serves as the ultimate indicator for measuring the overall market resource allocation efficiency and multi-stakeholder welfare. To identify the optimal subsidy strategy that maximizes total social welfare, a systematic social welfare analysis is conducted based on the aforementioned multi-dimensional policy effect comparison results. First, according to the theoretically derived critical thresholds of indirect network effects η_1 and η_2 , the evolution of the drone food delivery market is divided into three stages, including weak, moderate, and strong stages. The analytical equilibrium solutions are adopted to compare social welfare differences between the two subsidy strategies in moderate and strong market stages, thereby clarifying the exit boundary of subsidy policies in the mature market stage. Given the complex form of analytical social welfare solutions under weak indirect network effects, core model parameters are calibrated with empirical data of China's food delivery industry. Numerical simulation is applied to plot the variation curves of social welfare increment, optimal unit subsidy level, market delivery volume, and congestion externalities with peer effects. The net social welfare return and fiscal input-output ratio of the two subsidy strategies under diverse parameter combinations are compared to determine the optimal subsidy strategy for total social welfare maximization at each market evolution stage.

4. Equilibrium Solution of the Drone Food Delivery Subsidy Allocation Model Under Different Scenarios

4.1. No Government Subsidy

To provide a benchmark for evaluating the effect of government subsidy policies, this section first analyzes the scenario without government subsidies (Model N), where $e_c = 0$ and $e_s = 0$. By solving this four-stage Stackelberg game using backward induction, the equilibrium demands for traditional delivery and drone delivery are obtained, as shown in Formula (10) and Formula (11), respectively.

$$D_T^{N*} = [-(r_D - r_T)\eta + t_s(c_D - c_T + 3t_c - 3\gamma + \tau_D - \tau_T)]/6t_s(t_c - \gamma) \quad (10)$$

$$D_D^{N*} = [(r_D - r_T)\eta + t_s(-c_D + c_T + 3t_c - 3\gamma - \tau_D + \tau_T)]/6t_s(t_c - \gamma) \quad (11)$$

Based on the equilibrium results, this study first focuses on the influence mechanism of two key behavioral factors, peer effects and psychological costs, on drone delivery demand. Intuitively, peer effects are generally expected to unconditionally promote the

adoption of new technologies. However, this model reveals a more complex internal relationship.

Proposition 1. In the benchmark model without government subsidies, the direction of the effect of peer effects on the equilibrium demand for drone delivery D_D^{N*} is strictly moderated by consumers' psychological cost τ_D . Specifically:

(a) When the psychological cost τ_D is below the critical value τ_D^{critical} , the enhancement of peer effects promotes drone delivery demand;

(b) When the psychological cost τ_D is above the critical value τ_D^{critical} , the enhancement of peer effects instead inhibits drone delivery demand.

Where the critical psychological cost $\tau_D^{\text{critical}} = [-(c_D - c_T)t_s - (r_T - r_D)\eta]/t_s + \tau_T$.

Proposition 1 reveals a counterintuitive yet critical phenomenon: peer effects do not always promote the adoption of drone delivery, and their direction of action depends on consumers' psychological costs. When consumers have low concerns about drone delivery, peer effects promote consumers' adoption of drone delivery; conversely, when psychological costs are high, peer effects may instead inhibit consumers' adoption of drone delivery.

4.2. Subsidies for Infrastructure Construction Enterprises

In Model S, the government chooses to subsidize the drone delivery infrastructure construction enterprises, that is, sets the unit subsidy $e_s \geq 0$, while the subsidy for consumers is set at $e_c = 0$. The equilibrium solutions of the subsidy level, traditional delivery price and drone delivery price in Model S are shown in Formula (12), Formula (13) and Formula (14), respectively:

$$e_s^{S*} = \begin{cases} \frac{\eta(5t_s(c_D - c_T + \tau_D - \tau_T) + 5(-r_D + r_T)\eta - 3t_s\theta_T)}{9t_s(\gamma - t_c) + 5\eta^2}, & \text{若 } \eta \leq \eta_1, \text{ 且 } \gamma \leq \gamma_1 \\ -r_D + r_T + \frac{t_s(c_D - c_T + 3t_c + \tau_D - \tau_T - 3\gamma)}{\eta} = \bar{e}_s, & \text{若 } \eta \leq \eta_1, \text{ 且 } \gamma > \gamma_1 \\ 0, & \text{若 } \eta > \eta_1 \end{cases} \quad (12)$$

$$p_T^{S*} = \begin{cases} \frac{t_s(c_D + 2c_T + 3t_c + \tau_D - \tau_T - 3\gamma) + \eta[9(r_D - r_T)(t_c - \gamma) + a]}{3[9t_s(\gamma - t_c) + 5\eta^2]}, & \text{若 } \eta \leq \eta_1, \text{ 且 } \gamma \leq \gamma_1 \\ c_T, & \text{若 } \eta \leq \eta_1, \text{ 且 } \gamma > \gamma_1 \\ \frac{t_s(c_D + 2c_T + 3t_c + \tau_D - \tau_T - 3\gamma) + (-r_D + r_T)\eta}{3t_s}, & \text{若 } \eta > \eta_1 \end{cases} \quad (13)$$

$$p_D^{S*} = \begin{cases} \frac{(t_c - \gamma)b + c_D(6t_s t_c - 6t_s \gamma - 5\eta^2) + \eta^2 \theta_T}{9t_s(\gamma - t_c) - 5\eta^2}, & \text{若 } \eta \leq \eta_1, \text{ 且 } \gamma \leq \gamma_1 \\ c_D + 2t_c - 2\gamma, & \text{若 } \eta \leq \eta_1, \text{ 且 } \gamma > \gamma_1 \\ \frac{t_s(2c_D + c_T + 3t_c - \tau_D + \tau_T - 3\gamma) + (r_D - r_T)\eta}{3t_s}, & \text{若 } \eta > \eta_1 \end{cases} \quad (14)$$

Where $a = \eta(-5c_D + 5(c_T - \tau_D + \tau_T) + 3\theta_T)$, $b = 3t_s(c_T + 3t_c - \tau_D + \tau_T - 3\gamma) + (3r_D - 3r_T - 5\eta)\eta$; η_1 is the critical threshold of indirect network effects; γ_1 is the critical threshold of peer effects, and their specific expressions are shown in the Appendix.

Proposition 2. The impacts of heterogeneous indirect network effects and peer effects on the optimal unit subsidy for infrastructure construction enterprises:

(a) When indirect network effects are weak ($\eta \leq \eta_1$), peer effects have a non-monotonic effect on the optimal unit subsidy level e_s^{S*} : (i) When peer effects are weak ($\gamma \leq \gamma_1$), e_s^{S*} increases with the enhancement of γ ; (ii) When peer effects are strong ($\gamma > \gamma_1$), e_s^{S*} is 0.

(b) When indirect network effects are strong ($\eta > \eta_1$), the optimal unit subsidy level e_s^{S*} is always 0 and is not affected by peer effects.

This relationship reveals the dynamic balance between policy intervention and spontaneous market forces: in a market environment with weak indirect network effects, when peer effects have not yet emerged, the market lacks the impetus for spontaneous growth, and the government needs to strengthen infrastructure supply through subsidies to lay a solid foundation for market launch. When peer effects have formed a strong market pull, the platform will spontaneously adapt to demand growth through pricing strategies. At this time, the marginal benefit of infrastructure subsidies decreases rapidly, and the government can appropriately reduce the subsidy intensity to avoid redundant fiscal resources. When indirect network effects are strong and the infrastructure network is relatively complete, the market can achieve spontaneous growth through its own supply-demand matching, so no additional subsidy intervention is required.

In addition, from the perspective of consumers' psychological costs in choosing delivery modes, let the psychological cost difference between the two delivery modes be $\Delta\tau = \tau_T - \tau_D$. The market dominance of drone delivery requires $\Delta\tau > \Delta\tau^* = (c_D - c_T) - (e_s + r_D - r_T)\eta t_s$. This indicates that drone delivery needs to establish a sufficient psychological cost advantage to offset its potential disadvantages in operational costs.

According to the expression of $\Delta\tau^*$, subsidizing infrastructure construction enterprises directly reduces the critical threshold of psychological cost for market entry, and such a reduction is magnified as the indirect network effect η increases. It provides a core condition for drone delivery to break through competitive barriers and achieve large-scale market penetration in the early stage of market promotion.

4.3. Subsidies for Consumers

This section constructs and solves the model (Model C) where the government provides a unit subsidy e_c to consumers who choose drone delivery, i.e., sets the consumer unit subsidy $e_c \geq 0$, while the subsidy to infrastructure construction enterprises $e_s = 0$. The equilibrium solutions of the subsidy level, traditional delivery price and drone delivery price in Model C are presented in Formula (15), (16) and (17), respectively.

$$e_c^{C*} = \begin{cases} -2c_D + 2(c_T - \tau_D + \tau_T) + \frac{2(r_D - r_T)\eta}{t_s} + 3\theta_T, & \text{若 } \eta \leq \eta_2 \text{ 且 } \gamma \leq \gamma_2, \\ c_D - c_T + 3t_c + \tau_D - \tau_T - 3\gamma + \frac{(-r_D + r_T)\eta}{t_s} = \bar{e}_c, & \text{若 } \eta \leq \eta_2 \text{ 且 } \gamma > \gamma_2, \\ 0, & \text{若 } \eta > \eta_2. \end{cases} \quad (15)$$

$$p_T^{C*} = \begin{cases} c_D + t_c + \tau_D + \frac{(-r_D + r_T)\eta - t_s(\tau_T + \gamma + \theta_T)}{t_s}, & \text{若 } \eta \leq \eta_2 \text{ 且 } \gamma \leq \gamma_2, \\ c_T, & \text{若 } \eta \leq \eta_2 \text{ 且 } \gamma > \gamma_2, \\ \frac{t_s(c_D + 2c_T + 3t_c + \tau_D - \tau_T - 3\gamma) + (-r_D + r_T)\eta}{3t_s}, & \text{若 } \eta > \eta_2. \end{cases} \quad (16)$$

$$p_D^{C*} = \begin{cases} c_T + t_c - \tau_D + \tau_T - \gamma + \frac{(r_D - r_T)\eta}{t_s} + \theta_T, & \text{若 } \eta \leq \eta_2 \text{ 且 } \gamma \leq \gamma_2, \\ c_D + 2t_c - 2\gamma, & \text{若 } \eta \leq \eta_2 \text{ 且 } \gamma > \gamma_2, \\ \frac{t_s(2c_D + c_T + 3t_c - \tau_D + \tau_T - 3\gamma) + (r_D - r_T)\eta}{3t_s}, & \text{若 } \eta > \eta_2. \end{cases} \quad (17)$$

Where, η_2 and γ_2 are critical thresholds, and their specific values are shown in the Appendix.

Proposition 3 : The effects of indirect network effects and peer effects on the optimal unit subsidy for consumers:

(a) When indirect network effects are weak ($\eta \leq \eta_2$): (i) If peer effects are also weak ($\gamma \leq \gamma_2$), the optimal subsidy e_c^{C*} does not change with γ ; (ii) If peer effects are strong ($\gamma > \gamma_2$), the optimal subsidy e_c^{C*} decreases with the increase of γ .

(b) When indirect network effects are strong ($\eta > \eta_2$), the optimal subsidy is always zero and is not affected by peer effects.

Proposition 3 reveals another counterintuitive phenomenon: when both effects are weak, the optimal consumer subsidy level does not change with the enhancement of peer effects. This is because in this context, consumers pay more attention to the reliability of delivery rather than peer influence, and simply increasing economic subsidies cannot effectively improve their willingness to choose. When peer effects are significant, platforms tend to seize market share by cutting prices, and the government can appropriately reduce the subsidy intensity to avoid resource redundancy. In addition, under some equilibrium paths, the traditional delivery price p_T^{C*} may be equal to its marginal cost c_T , which reflects that under strong peer effects, the market penetration rate of drone delivery increases rapidly, and traditional delivery platforms have to adopt aggressive competitive strategies of marginal cost pricing to maintain market share.

Psychological costs affect total social welfare through three core paths: first, changing the level of consumer utility and directly affecting the scale of consumer surplus; second, adjusting the demand structure of traditional delivery and drone delivery, and indirectly affecting platform profits and congestion externalities levels; third, interacting with peer effects and indirect network effects to regulate the welfare transmission efficiency of subsidy policies. The model derivation results show that the marginal sensitivity of total social welfare to the traditional delivery psychological cost τ_T is $\frac{(r_D - r_T)\eta + t_s(-c_D + c_T - t_c - \tau_D + \tau_T + \gamma + \theta_T)}{2t_s(t_c - \gamma)}$. This expression indicates that the marginal impact of psychological costs on social welfare is not a fixed value but is synergistically moderated by peer effects and indirect network effects, further confirming that psychological costs are a key boundary condition determining the welfare effect of consumer subsidy policies.

5. Multi-dimensional Comparative Analysis of the Effects of Drone Food Delivery Subsidy Policies

5.1. Subsidy Levels

Based on the equilibrium subsidy level e_s^{S*} in Model S and the equilibrium subsidy level e_c^{C*} in Model C derived above, this section compares the optimal unit subsidy intensity of the two subsidy policies and quantifies the differences in fiscal input costs between the two schemes. It provides a fundamental basis for the subsequent

comprehensive evaluation of policy efficiency and the selection of optimal subsidy recipients.

Proposition 4. Comparison of the optimal unit subsidy levels under the two subsidy policies yields the following results:

(a) When indirect network effects are weak ($\eta \leq \eta_1$), there exists a peer effect threshold γ_3 such that: (i) If peer effects are weak ($\gamma \leq \gamma_3$), the unit subsidy to consumers is higher than that to infrastructure construction enterprises, i.e., $e_c^{C*} \geq e_s^{S*} > 0$; (ii) If peer effects are strong ($\gamma > \gamma_3$), the unit subsidy to infrastructure construction enterprises is higher than that to consumers, i.e., $e_s^{S*} > e_c^{C*} > 0$;

(b) When indirect network effects are moderate ($\eta_1 < \eta \leq \eta_2$), the unit subsidy to consumers is always higher than that to infrastructure construction enterprises, i.e., $e_c^{C*} > e_s^{S*} = 0$;

(c) When indirect network effects are strong ($\eta > \eta_2$), the government does not need to provide subsidies, i.e., $e_c^{C*} = e_s^{S*} = 0$.

Proposition 4(a) reveals the core decision-making logic in the early stage of drone delivery promotion. At this time, indirect network effects are weak, and the intensity of peer effects is the key to determining the direction of subsidy investment. In the context of weak peer effects, consumers' psychological costs and usage concerns about drone delivery are the core decision-making obstacles. Subsidizing consumers at this time can directly reduce usage costs and effectively improve consumers' willingness to try, resulting in more significant policy effects. In the context of strong peer effects, social influence has been able to effectively stimulate consumers' willingness to try, but problems such as long waiting times and uneven service coverage caused by weak infrastructure have become the main bottlenecks restricting user experience and repeat purchases. At this time, the government's core task is to shift from stimulating trial use to ensuring experience. By subsidizing infrastructure construction enterprises to expand network coverage and enhance indirect network effects, the strong potential social demand can be transformed into solid market growth.

Proposition 4(b) indicates that when indirect network effects reach an intermediate level, service convenience is no longer the primary obstacle. At this time, subsidizing

consumers to directly stimulate demand is a more cost-effective strategy, which can rapidly increase platform order volume and infrastructure utilization rate, forming a virtuous cycle between supply and demand.

Proposition 4(c) points out a clear government exit mechanism. When the drone delivery network is highly developed, the market can achieve effective growth through its own competition and peer effects, and the marginal benefit of government subsidies is zero. Canceling subsidies at this time can avoid the waste of fiscal resources and market price distortion.

5.2. Delivery Prices

The pricing decisions of food delivery platforms are directly related to consumers' willingness to choose and the market competition landscape. This section systematically reveals the differentiated impacts of different government subsidy policies on platform pricing strategies by comparing the equilibrium drone delivery prices under the three models.

Proposition 5. Comparison of the equilibrium drone delivery prices under the three models yields the following results:

(a) When indirect network effects are weak ($\eta \leq \eta_1$), there exists a peer effect threshold γ_4 such that: (i) If peer effects are weak ($\gamma \leq \gamma_4$), the drone price under consumer subsidies is the highest, i.e., $p_D^{C*} \geq p_D^{S*} \geq p_D^{N*}$; (ii) If peer effects are strong ($\gamma > \gamma_4$), the drone price under infrastructure subsidies is the highest, i.e., $p_D^{S*} \geq p_D^{C*} > p_D^{N*}$;

(b) When indirect network effects are moderate ($\eta_1 < \eta \leq \eta_2$), the drone price under consumer subsidies is higher than that under infrastructure subsidies or no subsidies, i.e., $p_D^{C*} \geq p_D^{S*} = p_D^{N*}$;

(c) When indirect network effects are strong ($\eta > \eta_2$), the drone prices under different subsidy policies tend to be consistent, i.e., $p_D^{C*} = p_D^{S*} = p_D^{N*}$.

Proposition 5(a) reveals the differentiated impacts of subsidy policies on platforms' pricing power. Under weak peer effects, subsidizing consumers will lead to the highest drone delivery price. The internal logic is that government subsidies directly increase consumers' willingness to pay for drone delivery, which is equivalent to creating price increase room for the platform. Under the goal of maximizing profits, the platform will

partially extract the consumer surplus brought by consumer subsidies through price increases, thereby achieving profit growth at a higher equilibrium price. Under strong peer effects, subsidizing infrastructure will lead to the highest drone delivery price. This is because government subsidies for infrastructure have greatly improved the network coverage and indirect network effects of drone delivery, significantly enhancing its service quality advantage over traditional delivery. This improvement in service quality endows the platform with stronger market power and pricing power, enabling it to set higher prices without causing massive customer churn.

Proposition 5(b) indicates that when indirect network effects reach an intermediate level, the price-increasing effect of infrastructure subsidies disappears. This is because the basic services of the market are already relatively convenient, and the marginal improvement of additional infrastructure subsidies on service quality is limited, making it difficult to support higher premiums. At this time, only consumer subsidies can still maintain a higher price level by directly affecting willingness to pay.

Proposition 5(c) once again confirms the policy neutrality characteristic after market maturity. When the drone delivery network is highly developed, its services have become a standardized and fully accessible commodity, and prices are completely determined by market competition and cost structure. The choice of government subsidy targets no longer affects the equilibrium price.

5.3. Market Share

The ultimate goal of subsidy policies is to encourage consumers to choose drone delivery and guide the optimal allocation of market resources. This section systematically evaluates the effectiveness of the two subsidy policies in expanding the market share of drone delivery by comparing the equilibrium sales volumes D_D^* and D_T^* under the three models.

Proposition 6. Comparison of the equilibrium delivery volumes of drone delivery and traditional delivery under the three models yields the following results:

(a) When indirect network effects are weak ($\eta \leq \eta_1$), there exists a peer effect threshold γ_5 such that: (i) If peer effects are weak ($\gamma \leq \gamma_5$), consumer subsidies are the most effective in promoting drone delivery choices, i.e., $D_D^{C*} \geq D_D^{S*} \geq D_D^{N*}$, and the traditional delivery volume decreases accordingly, i.e., $D_T^{C*} \leq D_T^{S*} \leq D_T^{N*}$; (ii) If peer

effects are strong ($\gamma > \gamma_5$), infrastructure subsidies are the most effective in promoting drone delivery choices, i.e., $D_D^{S*} \geq D_D^{C*} > D_D^{N*}$, and the traditional delivery volume decreases accordingly, i.e., $D_T^{S*} \leq D_T^{C*} < D_T^{N*}$;

(b) When indirect network effects are moderate ($\eta_1 < \eta \leq \eta_2$), consumer subsidies are the most effective in promoting drone delivery choices, i.e., $D_D^{C*} \geq D_D^{S*} = D_D^{N*}$, and the traditional delivery volume decreases accordingly, i.e., $D_T^{C*} \leq D_T^{S*} = D_T^{N*}$;

(c) When indirect network effects are strong ($\eta > \eta_2$), different subsidy policies have no impact on sales volumes, i.e., $D_D^{C*} = D_D^{S*} = D_D^{N*}$ and $D_T^{C*} = D_T^{S*} = D_T^{N*}$.

Proposition 6(a) further refines the decision-making basis for subsidy targets in the early promotion stage. In an environment with weak peer effects, consumers have insufficient awareness and interest in drone delivery. At this time, direct subsidies to consumers can most effectively lower the trial threshold, create initial demand, and thus rapidly increase the sales volume of drone delivery. In an environment with strong peer effects, social influence has been able to effectively stimulate consumers' willingness to try, but time unreliability caused by sparse takeoff and landing points has become a bottleneck restricting the realization of demand. At this time, subsidizing infrastructure construction enterprises can transform potential trial willingness into actual orders by expanding network coverage and enhancing indirect network effects, thereby exerting the greatest promoting effect on drone delivery volume.

Proposition 6(b) indicates that when indirect network effects reach a moderate level, the infrastructure for drone delivery has begun to take shape, and its marginal improvement in driving demand has weakened. At this time, direct subsidies to consumers are still the most effective means to stimulate demand and expand market share. In this stage, the main contradiction of the market shifts from service inaccessibility to price sensitivity, so economic incentive policies that directly reduce usage costs have more critical effects.

Proposition 6(c) once again confirms that when the drone delivery network is highly developed, its services have become standardized and highly accessible commodities, and the market has entered a mature stage. At this time, market share is determined by consumers' inherent preferences and the relative cost-effectiveness of services, and subsidy policies cannot further change the sales volume structure.

5.4. Congestion Externalities

In addition to promoting technology adoption, another important social benefit of drone food delivery promotion is that it may alleviate traffic congestion caused by traditional ground delivery. This section evaluates the derivative benefits of different subsidy policies in improving urban traffic congestion by comparing the equilibrium congestion externalities $EI^* = \theta_T \cdot D_T^*$ under the three models.

Proposition 7. Comparison of the equilibrium congestion externalities under the three models yields the following results:

(a) When indirect network effects are weak ($\eta \leq \eta_1$): (i) If peer effects are weak ($\gamma \leq \gamma_5$), consumer subsidy policies are the most effective in alleviating congestion, i.e., $EI^{C*} \leq EI^{S*} \leq EI^{N*}$; (ii) If peer effects are strong ($\gamma > \gamma_5$), infrastructure subsidy policies are the most effective in alleviating congestion, i.e., $EI^{S*} \leq EI^{C*} < EI^{N*}$;

(b) When indirect network effects are moderate ($\eta_1 < \eta \leq \eta_2$), consumer subsidy policies are the most effective in alleviating congestion, i.e., $EI^{C*} \leq EI^{S*} = EI^{N*}$;

(c) When indirect network effects are strong ($\eta > \eta_2$), different subsidy policies have no impact on congestion externalities, i.e., $EI^{C*} = EI^{S*} = EI^{N*}$.

Proposition 7 shows that the effectiveness of subsidy policies in alleviating traffic congestion is isomorphic to their effectiveness in promoting drone delivery choices and replacing traditional delivery. Within the framework of the model setting in this paper, the internal logic presents a linear characteristic: policies that can more effectively reduce traditional delivery volume will directly and proportionally reduce road occupancy, traffic conflicts, and congestion caused by ground transportation vehicles for traditional manual delivery.

In the early promotion stage ($\eta \leq \eta_1$), the optimal congestion reduction policy is completely consistent with the optimal promotion policy. Under weak peer effects, subsidizing consumers can most effectively transfer price-sensitive users from traditional delivery to drone delivery; under strong peer effects, subsidizing infrastructure achieves the largest-scale demand shift by solving the core pain point of service reliability. Both paths can produce significant congestion alleviation effects through the maximum substitution of traditional delivery.

In the mid-promotion stage ($\eta_1 < \eta \leq \eta_2$), consumer subsidies continue to be the most effective tool for alleviating congestion. At this time, the marginal benefit of further investment in infrastructure on improving reliability diminishes, while direct price incentives remain the strongest driving force for marginal users to switch to drone delivery.

In the market maturity stage ($\eta > \eta_2$), the market share of drone delivery has reached a stable equilibrium at this stage, and the equilibrium sales volume of traditional delivery is no longer affected by subsidy policies, so congestion externalities also remain unchanged.

6. Subsidy Strategies for Social Welfare Maximization Under Numerical Simulation

6.1. Social welfare

Social welfare is the ultimate indicator for measuring the efficiency of overall social resource allocation and the well-being of all stakeholders. Based on the comprehensive analysis of platform profits, consumer surplus, enterprise surplus, congestion externalities, and government expenditures in the previous sections, this section compares the equilibrium social welfare SW^* under the three models, aiming to identify the optimal subsidy strategy that maximizes total social welfare for the government.

Proposition 8. Comparison of the equilibrium social welfare under the three models yields the following results:

(a) When indirect network effects are moderate ($\eta_1 < \eta \leq \eta_2$), consumer subsidy policies yield the highest social welfare, i.e., $SW^{C*} \geq SW^{S*} = SW^{N*}$;

(b) When indirect network effects are strong ($\eta > \eta_2$), social welfare under different subsidy policies tends to be consistent, i.e., $SW^{C*} = SW^{S*} = SW^{N*}$.

Proposition 8(a) indicates that when indirect network effects are no longer the main bottleneck, continuously stimulating demand by subsidizing consumers is the most effective way to improve total social welfare, and the marginal social benefit of subsidizing infrastructure has declined at this time.

Proposition 8(b) reconfirms the endpoint of policy neutrality. In a mature and efficient market, government intervention cannot create additional net social welfare, and the spontaneous equilibrium of the market is the optimal state.

Since social welfare under weak indirect network effects is too complex to be solved analytically, this paper adopts the numerical simulation method to conduct a comparative analysis of social welfare in this scenario. The market size in the model is normalized to 1, and all parameter values are normalized to the interval $[0,1]$ and calibrated based on industry realities and relevant studies to ensure the rationality of their economic implications.

6.2. Model Validation

Referring to the report of the China Internet Network Information Center (CNNIC), the scale of online food delivery users in China accounts for approximately 50% of the total number of Internet users, which reflects that this service has a broad foundation of moderate willingness to pay. Accordingly, the basic utility of consumers for food delivery services u_0 is set to 0.5. For infrastructure construction enterprises, their basic investment utility v_0 is set to a matching 0.5. To simplify the analysis and highlight the core mechanism, the intensity of preference heterogeneity for consumers t_c and enterprises t_s are both normalized to 1. One of the key bottlenecks faced by drone delivery is the problem of indirect network effects caused by insufficient coverage of takeoff and landing point networks, and the coefficient η representing its intensity is set to 0.5 in this paper.

In terms of cost and psychological parameters, considering the operational complexity of drone delivery at the current technological stage, its platform unit cost c_D is set to 0.15, slightly higher than the traditional delivery cost $c_T = 0.10$. Drawing on traffic behavior research, traditional delivery brings higher psychological costs to consumers due to traffic risks, time efficiency volatility and other issues, so τ_T is set to 0.12. In contrast, drone delivery has perceived advantages in time efficiency certainty and avoiding ground congestion, so its psychological cost is set to a lower $\tau_D = 0.05$. In addition, to quantify the negative impact of the traditional rider model on urban traffic, referring to congestion cost research, its unit congestion externalities cost θ_T is set to 0.01.

Based on the above parameters, this study focuses on analyzing the changes in social welfare with peer effects. Fig.2 shows the welfare increments of the two subsidy strategies relative to the no-subsidy benchmark, as well as the welfare difference between the two subsidy strategies.

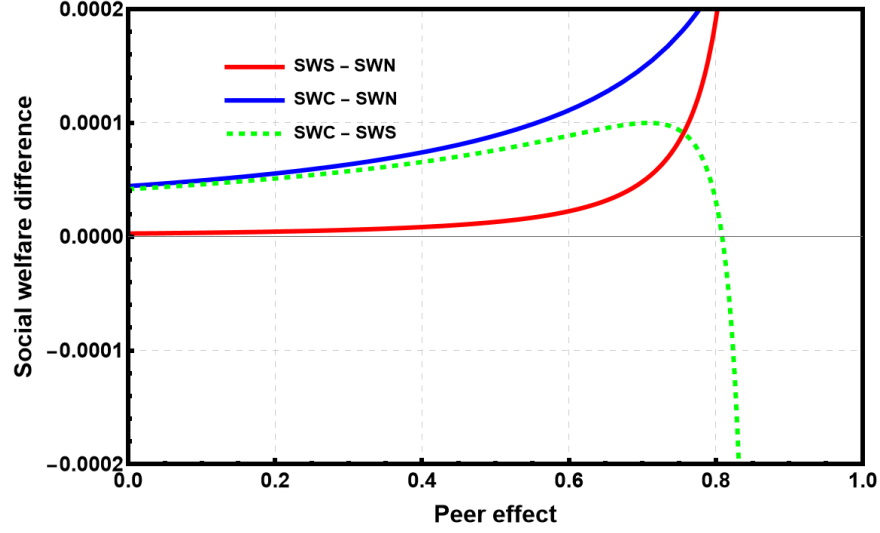


Fig.2. Three Social Welfare Differences.

The simulation results clearly reveal a dynamic law based on market conditions: when peer effects are weak ($\gamma < 0.8$), the improvement in social welfare brought by subsidizing consumers is significantly better than that by subsidizing infrastructure construction enterprises, with $SW^C - SW^S > 0$ at this time. This indicates that in the early market incubation stage, when the social demonstration effect has not yet formed, consumers' psychological costs are the main obstacle to choice, and direct demand-side subsidies can more effectively launch the market and create welfare. However, when peer effects strengthen and exceed approximately 0.8, the situation reverses, with $SW^C - SW^S < 0$, meaning that subsidizing infrastructure construction enterprises becomes the optimal strategy. The internal logic is that strong peer effects can already spontaneously drive demand growth, but the bottleneck constraint of indirect network effects becomes prominent at this time. By subsidizing the supply side to expand the takeoff and landing point network and improve service stability, the market demand brought by social influence can be met and further stimulated, thereby achieving a higher level of social welfare.

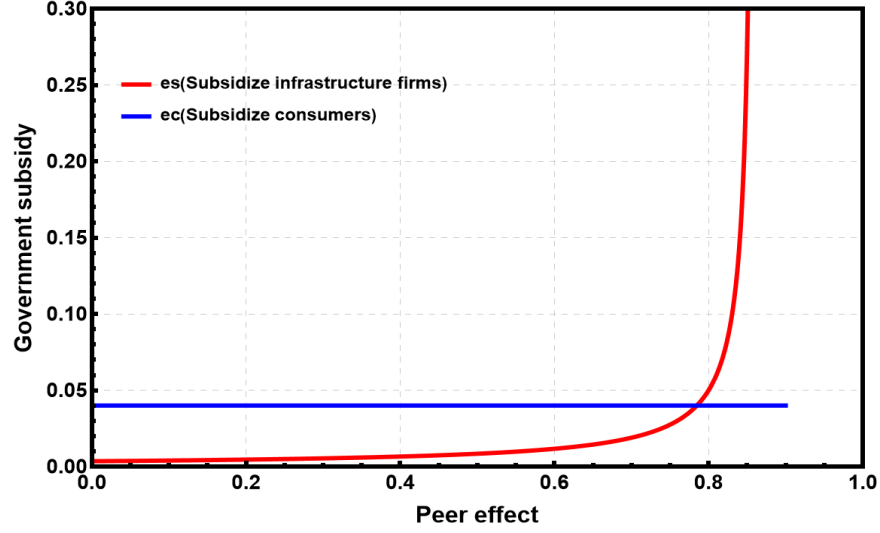


Fig.3. Trend of Government Subsidies with Peer Effects

Fig.3 depicts the dynamic trajectory of the government's optimal unit subsidy with peer effects under the two subsidy strategies. When the government subsidizes drone infrastructure construction enterprises, the unit subsidy level e_s and peer effect γ present a non-monotonic change characteristic of first rising and then rapidly dropping to 0: in the early market stage with weak peer effects, e_s gradually increases with the enhancement of γ ; when γ breaks through the critical value, e_s directly drops to 0. This change law reveals the dynamic adaptation relationship between policy subsidies and spontaneous market driving: in the early market stage with insufficient peer effects, government subsidies are needed to promote infrastructure construction and activate the low-altitude delivery network; when peer effects are strong enough, the market can operate spontaneously relying on platform pricing and user diffusion, the marginal benefit of subsidies returns to zero, and the government does not need to continue investment.

From the comparison of the two subsidy curves, when peer effects are below approximately 0.79, the consumer unit subsidy e_c is higher than the infrastructure unit subsidy e_s , meaning that the unit fiscal input of demand-side subsidies is higher; when peer effects exceed 0.79, e_s surpasses e_c , and the unit intensity of supply-side infrastructure subsidies is higher. This comparison result is highly consistent with the previous social welfare analysis conclusions: in the early stage of market promotion, even though consumer subsidies are more costly, they can more efficiently leverage initial demand and improve social welfare; after entering the market self-growth stage, shifting

to infrastructure subsidies, although the unit input increases slightly, can break the bottleneck of service reliability and achieve better social welfare. This provides a quantitative basis for the government to accurately allocate fiscal subsidy resources at different development stages of drone food delivery.

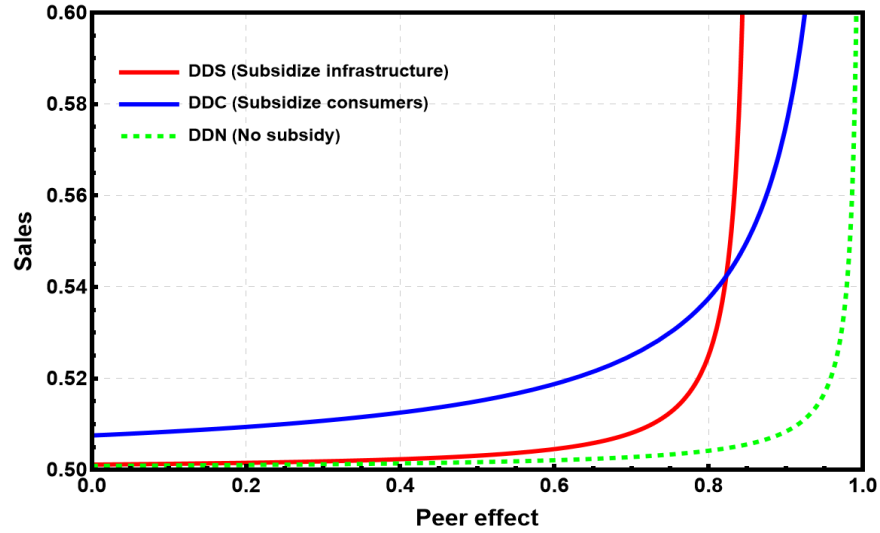


Fig.4. Trend of Delivery Volumes with Peer Effects

Fig.4 compares the drone delivery volumes under different strategies. Overall, any subsidy can significantly increase sales volume, and its effect is amplified with the enhancement of γ . Specifically, when $\gamma < 0.825$, the sales volume corresponding to the consumer subsidy strategy is the highest; when $\gamma > 0.825$, the infrastructure subsidy strategy achieves a reversal and continues to lead. This turning point is consistent with the conclusion of welfare analysis, indicating that when peer effects are strong, improving service reliability can promote market acceptance more effectively than direct price incentives. The sales volume under the no-subsidy scenario is always the lowest, once again confirming the necessity of policy intervention.

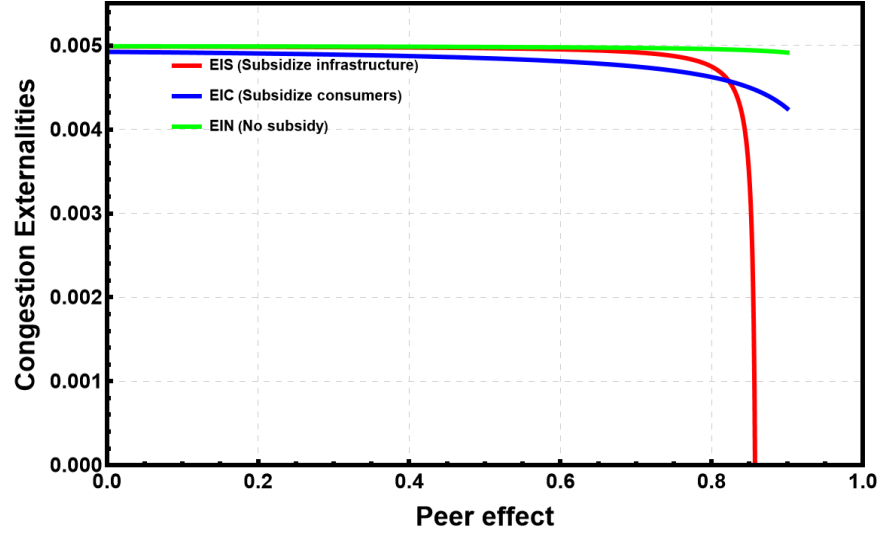


Fig.5. Trend of Congestion Externalities with Peer Effects

Fig.5 depicts the changes in congestion externalities with peer effects under different subsidy strategies. The results show that the implementation of subsidies can effectively reduce congestion externalities, and its effect becomes more significant with the enhancement of γ . Specifically, when $\gamma < 0.825$, the congestion externalities corresponding to the consumer subsidy strategy are the lowest; while when $\gamma > 0.825$, the infrastructure subsidy strategy becomes a better choice for alleviating congestion. This critical point is highly consistent with the turning point in sales volume analysis, once again confirming the shift of dominant constraints at different development stages: in the early stage, congestion is reduced by directly replacing traditional delivery through subsidizing consumers; in the later stage, it is necessary to continuously expand the scale of replacement by improving the reliability of drone services. The congestion externalities in the no-subsidy scenario are always the highest, highlighting the positive externality value of policy intervention in improving urban traffic.

7. Conclusions and Policy Implications

This paper constructs a four-party Stackelberg dynamic game model consisting of the government, infrastructure construction enterprises, food delivery platforms, and consumers. Focusing on the core issue of how the government should select subsidy recipients and subsidy intensity to address the dilemmas in the large-scale promotion of drone food delivery under the joint influences of indirect network effects and peer effects, the main conclusions are summarized as follows:

(1) Psychological cost is a key variable affecting the effectiveness of drone delivery subsidy policies, and it influences total social welfare through three core channels: consumer surplus, demand structure, and the interaction between dual network effects. To compensate for potential operational cost disadvantages, drone delivery must satisfy the psychological cost gap condition $\Delta\tau > \Delta\tau^* = (c_D - c_T) - (e_s + r_D - r_T)\eta t_s$.

(2) Peer effects do not inevitably promote the adoption of drone delivery, and their influence direction is critically regulated by consumers' psychological cost. When the psychological cost of drone delivery τ_D is lower than the critical value $\tau_{D_{critical}} = -(c_D - c_T)t_s - (r_D - r_T)\eta t_s + \tau_T$, stronger peer effects significantly increase drone delivery demand; conversely, when τ_D exceeds this threshold, enhanced peer effects exert a restraining impact on demand.

(3) The government's optimal subsidy target and intensity are jointly determined by the magnitude of indirect network effects and peer effects. Based on horizontal comparisons of subsidy level, delivery price, market share, and congestion relief, as well as taking social welfare as the judgment criterion: under weak indirect network effects, consumer-side subsidies are preferable when peer effects are weak, which reduces consumer entry barriers, expands drone delivery demand, and alleviates traffic congestion by substituting traditional delivery; when peer effects are strong, subsidizing infrastructure construction enterprises helps improve service reliability. Under moderate indirect network effects, subsidizing consumers achieves social welfare maximization. When indirect network effects are sufficiently strong, subsidy policies become ineffective, and the government should phase out subsidies in an orderly manner.

(4) The timing of government subsidy withdrawal is clarified. When the intensity of indirect network effects exceeds the critical threshold $\frac{t_s[2c_D - 2(c_T - \tau_D + \tau_T) - 3\theta_T]}{2(r_D - r_T)}$, the infrastructure system forms a self-sustaining operation mode. The market can achieve sustainable growth relying on market competition and dual network effects. At this stage, the marginal benefit of government subsidies approaches zero, and the government should withdraw from subsidy intervention and shift its focus to industry regulation and standard formulation.

Based on the above conclusions, this paper puts forward the following policy implications:

(1) Implement phased and differentiated subsidy strategies. In the market incubation stage with weak peer effects and insufficient indirect network effects, align with local consumption promotion policy systems, focus on issuing demand-side subsidies such as drone food delivery consumption experience vouchers and order discounts to quickly cultivate initial user groups. When the market enters the growth stage, shift the subsidy focus to the supply side, providing lump-sum subsidies and operational support for the construction of infrastructure such as drone takeoff and landing points to break the bottleneck of service reliability.

(2) Support with psychological cost mitigation measures. Establish a full-process safety information disclosure system for drone food delivery, disclose core information such as the compliance qualifications and flight safety records of delivery drones to consumers to eliminate their core concerns about technical safety. Simultaneously incorporate psychological costs into the subsidy intensity calculation model, carry out drone delivery safety popularization and exclusive subsidy activities in conjunction with communities and food delivery platforms, form a linkage with the national digital literacy improvement policy, and expand the user coverage of emerging services.

(3) Clarify quantitative standards for subsidy exit. Take the critical threshold of indirect network effects and the market coverage ratio of drone infrastructure proposed in this paper as core quantitative indicators, establish a rigid trigger mechanism for subsidy exit, give full play to the decisive role of the market in resource allocation, and align with the overall requirements of the national market-oriented development of the low-altitude economy.

This study has three limitations:

First, based on the uniform distribution assumption of the Hotelling linear city model, it standardizes the spatial distribution of market entities and fails to fully capture the spatial heterogeneity of urban low-altitude delivery. In reality, airspace policies and infrastructure conditions show significant localized differences. Incorporating full-dimensional heterogeneity requires constructing complex nested models, and the lack of publicly available refined data poses objective research barriers.

Second, based on the static equilibrium framework, it sets consumers' psychological costs as steady-state variables and fails to capture the learning effects in consumers' multi-

period decision-making and the dynamic evolution of psychological costs. Its dynamic changes rely on long-cycle micro-tracking data that is mostly internal non-public information of enterprises and inaccessible to external researchers. Meanwhile, incorporating multi-period dynamic games tends to generate multiple equilibria, making it difficult to extract clear policy implications.

Third, to focus on the core mechanism of subsidy policies, this study simplifies the market structure and does not incorporate the multi-platform oligopolistic competition pattern. Multi-platform competition will add multiple strategic interactions, making it difficult to accurately isolate the net effect of subsidy policies. Meanwhile, drone food delivery is still in the pilot stage, and a mature competitive pattern has not yet formed, lacking effective data to calibrate model parameters.

Future research can construct heterogeneous extended models combined with spatial panel data, depict the dynamic evolution law of psychological costs through micro-tracking data, and explore the optimization of subsidy strategies under multi-platform competition after the industry pattern matures, to further improve the practical adaptability of the research.

CRedit authorship contribution statement

Haonan He: Writing-review and editing Conceptualization, Data curation, Formal analysis, Methodology, Supervision, Validation.

Jingjing Li: Writing-original draft Formal analysis, Investigation, Visualization.

Ying Sun: Funding acquisition, Project administration, Resources.

Conflict of interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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