

Construction and Empirical Research on Dynamic Optimization Mechanism of Express Cabinet Advertising Based on Terminal User Portraits

Haiyan Guo^{1*}

¹ School of Economics and Management, Tarim Polytechnic, Alaer City, China

Email Address

guohaiyanhy@163.com (Haiyan Guo)

*Correspondence: guohaiyanhy@163.com

Received: 5 July 2025; Accepted: 28 July 2025; Published: 20 August 2025

Abstract:

With the exclusive touchpoint of the “last 100 meters”, the express cabinet has become the core entrance of community traffic, but its advertising is still stuck in the static carousel stage, and the average conversion rate of the industry has been below 3% for a long time, which not only wastes customer attention resources, but also restricts the revenue of operators and brands. [1] To solve this pain point, this paper proposes and verifies a set of “end-user portrait-driven dynamic optimization mechanism”. First, integrate the interaction data (pickup time, dwell time, operation path), consumption data (category, customer unit price, repurchase cycle) and community attributes (housing price, demographic structure, weather, holidays) to build a two-wheel drive user portrait of “static label dynamic interest” to solve the data sparse problem caused by scene fragmentation. [2] Subsequently, the collaborative optimization strategy is designed around the four dimensions of “content-timing-form-frequency”, and federated deep reinforcement learning (Fed-DQN) is introduced to complete millisecond-level decision-making at the edge, achieving Pareto improvement between advertising effectiveness, user experience and operating costs. Finally, through the real scene experiment of 100 express cabinets, 100 days, and 500,000 interactions, supplemented by synthetic control and eye movement experiment cross-verification. The results showed that the click-through rate of the experimental group increased by 170% compared to the control group, the conversion rate (CVR) increased by 244%, the (return on investment) ROI of the ad group jumped from 1:2.1 to 1:4.7, the user disgust decreased from 21% to 12%, and the pick-up delay increased by only 0.9 seconds. The portrait-decision-feedback closed-loop mechanism performs steadily in real scenarios, providing an integrated solution that can be replicated, promoted, and takes into account technology, business and compliance for express cabinet advertising operations.

Keywords:

Express Cabinet, Advertising, User Portrait, Dynamic Optimization, Federated Deep Reinforcement Learning

1. Introduction

1.1. Research Background and questions

In the past five years, smart express cabinets have rapidly penetrated communities across the country at a compound annual growth rate of 28%. According to the 2024 report of the State Post Bureau, the advertising business has accounted for 41.7% of the total revenue of express cabinets, making it the second largest cash flow after parcel storage. However, behind the boom data, the industry conversion rate has been hovering between 2%-3% for a long time, far lower than the 15% of online channels. [3] A beauty brand once ran static carousel ads in 300 sets of cabinets, with 9 million impressions and only 250,000 clicks, with a conversion Rate (CVR) as low as 2.8%. Homogeneous content, undifferentiated time periods, and single form are regarded as the three major pain points. At the same time, express cabinet terminals are precipitating massive high-value behavioral data; Micro behavior: pick-up time, dwell time, operation path, screen interaction; Consumption characteristics: parcel category, customer unit price, return and exchange frequency; Scene attributes: community housing prices, demographics, weather, holidays, these data have not been systematically integrated, resulting in the embarrassing situation of "data, no portrait, and no optimization". [4]

The image research has evolved through "population labeling → behavior labeling → scene labeling." Utilizing LSTM (Long Short-Term Memory neural network) to integrate multi-source data enables dynamic updates, yet lacks a delineation of the "terminal interaction scene"; currently, scholars focus primarily on online applications, showing insufficient attention to the fluctuations in attention within the "three-second window for pick-up" offline. [5] Additionally, existing literature centers on discussions of profit models and questionnaire surveys, lacking closed experimental loops of "user portraits - advertisement optimization - effect feedback." Few cases utilize static placements in community types, failing to capture micro-behavioral differences and not providing quantifiable evidence of return on Investment (ROI) improvement. [6] In light of this, this paper proposes three interrelated core questions:

Q1: How to construct a terminal user portrait that balances static characteristics and dynamic behaviors under the conditions of "space constraints and fragmented time" in the express cabinet scenario?

Q2: How to design a dynamic advertisement optimization mechanism that uses portraits as input and reinforcement learning as an engine, ensuring improved effectiveness while maintaining user experience and controllable operational costs?

Q3: How to validate the feasibility and replicability of this mechanism through large-scale real-world experiments, providing directly applicable operational solutions for express cabinet operators and advertisers?

1.2. Research objectives

1.2.1. Portrait Layer

Propose a three-tiered labeling system (static - behavior - scene) that integrates "terminal interaction behavior and community attributes," and design a dynamic updating rule based on federated learning.

1.2.2. Mechanism Layer

Design a dynamic optimization mechanism that coordinates "content - timing - format - frequency" across four dimensions and introduce Fed-DQN to achieve multi-objective balance.

1.2.3. Verification Layer

Utilize a three-step approach of "simulation - pilot - extrapolation" to complete a randomized controlled trial (RCT) involving 100 cabinets, over 100 days, and 500,000 interactions alongside dual verification with synthetic controls.

1.3. Research significance

1.3.1. Theoretical significance

This research introduces for the first time a three-tier labeling system of "static - behavior - scene," providing a new theoretical framework for user portrait construction in express cabinet advertising; innovatively designs a hybrid model combining federated XGBoost with LSTM, breaking through the limitations of traditional singular algorithms in advertisement forecasting; establishes a four-dimensional collaborative mechanism based on Fed-DQN of "content - timing - format - frequency," enhancing the theoretical application of distributed intelligent decision-making in the advertising operation field.

1.3.2. Practical significance

Through a randomized controlled trial (RCT) covering 100 cabinets over a continuous period of 100 days, this study systematically verifies the effectiveness of the proposed methods. The research results not only offer an actionable technical pathway for transforming express cabinet advertising from extensive exposure to refined operations but also establish a reusable industry practice paradigm, which is of significant reference value for improving advertising efficiency in community retail scenarios.

2. Literature Review

2.1. Research context of intelligent express cabinet advertising

Research context of intelligent express cabinet advertising. The early literature mainly focused on profitability models and business models. The cost-benefit method is used to calculate the break-even point of express cabinet advertising, and the concept of "attention window" is proposed, but there is a lack of objective behavior data verification. [7] With the intelligent upgrade of cabinets, the focus of research has shifted to data-driven delivery: using convolutional Neural Network(CNN) to identify gender-age groups in pick-up videos, realizing the replacement of static posters with thousands of people, and increasing the click-through rate (CTR) by 17%, but not involving timing characteristics and dynamic creativity. Overall, existing research is still stuck in the coarse-grained labeling stage of "population-scene", ignoring the dual constraints of millisecond-level interaction behavior and privacy compliance.

2.2. Evolution of user portrait theory

User portraits have undergone three generations of upgrades in the field of e-commerce and short videos: "population tags→ behavior tags→ and scene tags".

Although federated multitasking learning frameworks are proposed to solve data silos, they are all aimed at long-session scenarios. The ultra-short time series of “pick-up in 3 seconds” and the sparse data of offline terminals make it difficult to directly migrate traditional portrait methods. [8] The latest research attempts to integrate community-level macro characteristics: linking community housing prices with consumption power to achieve static delivery, but lacking a closed loop of micro behavior.

2.3. Application of reinforcement learning in advertising optimization

Existing reinforcement learning research has been verified in the field of feed advertising: DQN algorithm and multi-agent federated reinforcement learning (Fed-RL) can effectively improve click-through rate (CTR) and user dwell time. [9] However, there are significant differences in the advertising scenarios of express cabinets, showing unique characteristics - discretization of action space, sparse reward signals, scarcity of data samples, and strict requirements of “local 5ms + cloud 50ms” for response delay.

2.4. Research Review and Gaps

In this context, how to achieve the collaborative optimization of federated learning and reinforcement learning under millisecond latency constraints is still a blank area of current research. Therefore, the literature gap focuses on three points: (1) the lack of a micro-portrait system for the “3” second attention window of express cabinet users, which is difficult to support accurate advertising matching decisions; (2) A dynamic update mechanism suitable for data sparse scenarios and meeting compliance requirements has not yet been formed, which restricts the real-time performance of the model. (3) There is a lack of closed-loop experimental evidence based on 100,000-level real interaction data, which makes it difficult to verify the practical effectiveness of relevant theoretical methods.

3. Purpose of the Study and Hypothesis Formulation

3.1. Purpose of the study

This study aims to solve the problems of low conversion rate, poor user experience, and high operating costs of express cabinet advertising. By building end-user portraits, we can deeply understand the characteristics, behaviors and interests of users, and provide accurate targeting for advertising. Design a dynamic advertising optimization mechanism, based on user portraits and reinforcement learning algorithms, to realize intelligent adjustment of advertising content, timing, form and frequency to improve advertising effectiveness, improve user experience and control operating costs. [10] Through large-scale real-world scenario experiments, the feasibility and reproducibility of the mechanism are verified, and the operation plan can be directly implemented for express cabinet operators and advertisers, so as to promote the transformation of the express cabinet advertising industry from extensive exposure to precise operation.

3.2. Hypothesis Formulation

The two-wheel drive user portrait of “static tags and dynamic interests” constructed by integrating the interaction data, consumption data and community attributes of the express cabinet can effectively solve the data sparse problem caused by scene fragmentation and accurately portray user characteristics and interests.

A collaborative optimization strategy designed around the four dimensions of “content-timing-form-frequency”, and the introduction of a dynamic advertising optimization mechanism that introduces federated deep reinforcement learning (Fed-DQN) to complete decision-making at the edge, can improve advertising effectiveness (click-through rate, conversion rate) while ensuring user experience (antipathy, pick-up delay) and controllable operating costs.

Through the real-scene experiment of 100 express cabinets, 100 days, and 500,000 interactions, supplemented by synthetic control and eye movement experiments, the proposed portrait-decision-feedback closed-loop mechanism performs robustly in the real scene, has reproducibility and promotionability, and can bring significant ROI improvement to the advertising operation of the express cabinet.

4. Research Design and Methodology

4.1. Research objects and samples

The study subjects are users who use express cabinets in a specific area. The multi-stage sampling method was used to determine the sample, and the representative urban areas were first selected, covering different types of communities (such as high-end residential areas, ordinary residential areas, old residential areas, etc.), office buildings and commercial areas. A certain number of express cabinets are then randomly selected in each selected area to collect data on users who use these express cabinets. Finally, 100 express cabinets were determined as experimental samples, and 500,000 user interaction data were expected to be collected within 100 days to ensure the representativeness of the sample and the sufficiency of the data, as shown in Table 1.

Table 1. Sample data.

Area type	Number of express cabinets	Number of expected interactions
High-end residential area	30	150,000
Ordinary residential area	40	200,000
Old residential areas	15	80,000
Office Building	10	50,000
Business quarter	5	20,000

4.2. Research variables

The independent variables in this study mainly include user portrait characteristics, such as terminal interaction behavior (pick-up time, dwell time, operation path, etc.), consumption characteristics (parcel category, customer unit price, repurchase cycle, etc.), and community attributes (housing price, demographic structure, weather, holidays, etc.). Advertising strategy variables, including advertising content, delivery timing, display format, and delivery frequency. The dependent variables are advertising performance indicators, such as click-through rate (CTR), conversion rate (CVR), and return on investment (ROI). User experience indicators, such as user disgust and pickup delay; and operating costs. The control variables include the geographical location of the express cabinet, equipment model, time period, etc., to ensure the accuracy and reliability of the experimental results, and the specific definitions and measurement methods of each variable are shown in Table 2.

Table 2. *Independent variable.*

Type of variable	Variable name	Definition	Measuring method
Independent variable	Time of pickup	The specific time when the user picks up the item	Record the timestamp of each pickup
Independent variable	Length of stay	The time users spend in front of the delivery cabinet	Record it with a camera or sensor
Independent variable	Operation path	The steps and order of operation on the screen of the express delivery cabinet by the user	Record screen interaction logs
Independent variable	Parcel category	The product category to which the user's express package belongs	Check the product information according to the express number
Independent variable	per customer transaction	The average price at which a user buys a product	Based on consumption records
Independent variable	Repeat purchase cycle	The time interval between when a user buys the same category of goods again	Analyze purchase time in consumer data
Independent variable	Housing price	The average house price in the community	Obtained through real estate agency data or public real estate information
Independent variable	Population structure	The proportion of population in different age groups, genders and occupations in the community	Obtained through community surveys or government statistics
Independent variable	Weather	Real-time weather conditions in the area where the delivery cabinet is located	Connect with meteorological data
Independent variable	Festival and holiday	Whether it is a statutory holiday or special holiday	Judging by the calendar information
Independent variable	Content of advertisements	Specific information about the advertisement displayed	Record advertising copy, pictures, videos, etc
Independent variable	Timing of deployment	When the advertisement is displayed	Set different release times
Independent variable	Format of presentation	The presentation of advertisements, such as pictures, videos, text, etc	Record the format of the advertisement
Independent variable	Frequency of delivery	Number of times an AD is displayed per unit of time	Statistics on the number of ads displayed
Independent variable	Click-through rate (CTR)	The ratio of clicks to exposures	Track AD clicks and exposures
Independent variable	Conversion rate (CVR)	The ratio of the number of users who completed the purchase to the number of users who clicked on the AD	Track users from click to purchase
Independent variable	Return on investment (ROI)	The ratio of advertising revenue to advertising costs	Calculate the revenue and input cost of advertising
Independent variable	User aversion	The percentage of users who are repulsed by the ads	Collect through questionnaire survey or user feedback
Independent variable	Operating costs	Advertising costs, such as server costs, data processing costs, etc	Statistics of related expenses
Independent	Time delay in	The increase in the average time	Compare the time of

variable	pickup	it takes for users to pick up items	retrieving the sample before and after the experiment
Controlled variable	Geographical position	The specific address of the express delivery cabinet	Record the longitude and latitude of the delivery cabinet
Controlled variable	Unit type	Brand and model of express cabinet	View device identifiers
Controlled variable	Time quantum	Divide the day into different time periods, such as morning, afternoon, evening, etc	By time period

4.3. Selection of Research Methods

4.3.1. Data Collection Methods

This study employs multiple methods to collect data. Firstly, user interaction behavior data is collected through the log data of the express cabinet terminal system, including pickup time, duration of stay, and operation path; this data can accurately reflect users' behavior in front of the express cabinet in real-time. Secondly, in collaboration with express companies and e-commerce platforms, consumer data is obtained from users, such as package categories, average transaction value, and repurchase cycles, in order to understand consumption characteristics. [11] Simultaneously, a questionnaire survey is utilized to gather users' attitudes towards advertisements, their level of aversion, and basic personal information. The questionnaire content covers aspects such as users' age, gender, occupation, and income, as well as their views on the content, form, and frequency of advertisements. A sample of the questionnaire is provided in Table 3.

Table 3. Questionnaire samples.

Problem types	Problem Statement
Personal information	Your age? Your gender? Your occupation? What's your monthly income range?
Advertising attitude	Do you hate the advertising of express delivery cabinets? Is the frequency of the current advertising of express delivery cabinets appropriate?
Content of the advertisement	What kind of express cabinet advertising are you interested in? What information do you want to see in the express cabinet advertising?
Form of advertising	What form do you prefer to express the advertisement of express delivery cabinet? (picture/text/video)
Frequency of advertising	How many express cabinet ads are appropriate to see in a week?

By interviewing express cabinet operators and advertisers, we aim to understand their experiences, issues, and needs in the advertising operation process, providing a practical business perspective for the study. The interview outline focuses on aspects such as advertising deployment strategies, cost control, and effectiveness evaluation. For specific interview questions, see Table 4.

Table 4. Interview questions.

Interviewees	Interview questions
Express cabinet operator	What are the main strategies for advertising placement? What are the biggest problems encountered in the process of advertising operation? How to evaluate the effectiveness of advertising? What are the main indicators to focus on? What are the main aspects of advertising operation costs?
Advertiser	What are the reasons for choosing express cabinet advertising? What are your expectations for the target audience of advertising? How effective is the current advertising effect? Does it meet the expectation? What aspects do you pay the most attention to in the process of advertising?

4.3.2. Data collection steps

The data collection mainly covers three aspects: log data, questionnaires and interviews. Log data collection is automated through the express cabinet terminal system, using sensors and logging programs to record the user's pickup time, dwell time, operation path and other interactive behavior data in real time, and the data collection frequency is set to once per minute to ensure that the obtained behavior data is timely and complete, and these data are directly stored in the local database of the express cabinet terminal, waiting for subsequent summary and analysis. The questionnaire is distributed in a combination of online and offline. With the help of a professional questionnaire platform, questionnaires are distributed to users online through channels such as express cabinet APP push, community WeChat group and official account release; offline, users are randomly selected for on-site distribution in areas with high traffic such as communities, office buildings and commercial districts around the express cabinets.

The questionnaire distribution time lasts for four weeks, and is fixed every week during peak user pickup periods such as weekday evenings and weekend afternoons to improve the collection rate of the questionnaire. A total of 5,000 questionnaires were distributed, and 4,500 valid questionnaires were collected, with an effective recovery rate of 90%. During the interview, a detailed interview outline was formulated for express cabinet operators and advertisers. Interviews with express cabinet operators focused on advertising strategies, cost control, equipment operation status, and observation of user behavior. Interviews with advertisers revolve around advertising goals, expectations for express cabinet advertising, advertising effectiveness evaluation, and understanding of user needs. A combination of face-to-face interviews and telephone interviews was used to interview a total of 15 express cabinet operators and 10 advertisers, and the time of each interview was controlled at 30-60 minutes.

4.4. Portrait construction process

To construct a user profile based on multi-source data, data cleaning is carried out first. For the collected log data, consumption data, and community attribute data, data cleaning algorithms are used to identify and handle missing values, outliers, and duplicate values. [12] For the missing values, mean filling and regression prediction are used to fill in the missing values. For outliers, identify and correct them by setting reasonable data ranges and statistical test methods. For duplicate values, delete them directly to ensure data accuracy and consistency. [13] In the feature engineering process, key features are extracted from the cleaned data. For the terminal interaction behavior data, extract the hourly characteristics of pick-up time, segmentation characteristics of dwell time, and key step characteristics of operation paths. For

consumption data, extract the first-level classification characteristics of the parcel category, the quantile characteristics of the customer unit price, and the length of the repurchase cycle. For community attribute data, extract the characteristics of housing prices, the age proportion characteristics of population structure, the weather type characteristics of weather, and the characteristics of holidays. At the same time, feature selection algorithms, such as chi-square test and information gain, are used to screen out features that make important contributions to the construction of user portraits, remove redundant features, reduce data dimensions, and improve model training efficiency.

The label system is constructed using a three-layer structure of “static-behavioral-scene”. The static tag layer includes the user's basic information labels, such as age, gender, occupation, income, etc. The behavior label layer is generated based on the user's interaction behavior and consumption behavior data, such as high-frequency pickup user tags, high-consumption user tags, and user labels that prefer a certain category of products. The scene tag layer is constructed based on community attributes and time factors, such as high-end community user tags, holiday active user tags, rainy day pickup user tags, etc. [14] Through the fusion and analysis of multi-source data, each user is labeled accordingly to form a comprehensive and accurate user profile.

4.5. Optimize mechanism design

According to the constructed user portrait, the four-dimensional collaborative optimization mechanism of “content-timing-form-frequency” is designed. In terms of content, based on the interests and consumption characteristics in the user portrait, personalized advertising content is pushed for different users. For example, for young female users who prefer beauty categories, push the latest beauty product advertisements; For high-income business people, push high-end electronics and business service ads. In terms of timing, combine the user's pickup time and behavioral habits to choose the best advertising time. Through data analysis, it is found that when users pick up the package from 7 to 9 pm, their attention is more focused, and the advertising effect is better at this time; For users who frequently pick up on weekends, pushing ads on weekend mornings can increase exposure and click-through rates.

In terms of form, choose the appropriate display form according to the user's preference for different advertising forms. Through questionnaire surveys and user behavior analysis, it is understood that some users prefer advertising in the form of pictures because of its simplicity and intuitiveness. Some young users are more interested in advertising in the form of videos, believing that it is rich in content and vivid and interesting. Therefore, for different user groups, push image ads and video ads respectively.

In terms of frequency, by controlling the number of advertisements, users are avoided from being disgusted. Utilize reinforcement learning algorithms to dynamically adjust ad delivery frequency based on users' historical behavior and feedback. for users with high acceptance of advertising, appropriately increase the frequency of advertising; For users with high antipathy, reduce the frequency of delivery. Federated deep reinforcement learning (Fed-DQN) was introduced to achieve multi-objective balance. The Fed-DQN model works together at the edge and in the cloud, with the edge responsible for collecting real-time behavior data from

local users and making initial decisions based on the on-premises model. The cloud summarizes the data of each edge, updates and optimizes the global model, and distributes the optimized model parameters to the edge. Through continuous training and learning, the Fed-DQN model can improve advertising effectiveness (click-through rate, conversion rate) while ensuring user experience (antipathy, pickup delay) and controllable operating costs, achieving an optimal balance of multiple goals.

5. Experimental Design and Validation

5.1. Experimental grouping

A total of 100 parcel lockers were randomly divided into an experimental group and a control group, with 50 units allocated to each. During the grouping process, factors such as geographical location, community type, and surrounding population density were comprehensively considered. Stratified random sampling was employed to ensure comparability between the two groups in these aspects, thereby minimizing experimental errors and ensuring the accuracy of the results. The specific grouping details are shown in Table 5.

Table 5. Grouped experiments.

Group	Number of express cabinets	Regional distribution of locations	Density range of surrounding population (people/km ²)
Experimental group	50	15 high-end residential units, 20 units in ordinary residential area. There are 7 old residential buildings, 5 office buildings and 3 commercial buildings	3000-10000
Control group	50	15 high-end residential units, 20 units in ordinary residential area, There are 8 units in the old residential area, 5 units in the office building and 2 units in the commercial area	2000-10000

5.2. Experimental process

The experimental period was 100 days, during which the control group used the traditional static carousel ad delivery strategy to display ads in a fixed sequence and time intervals; The experimental group adopts the dynamic optimization mechanism of advertising based on user portraits for advertising. Collect data such as the number of ad impressions, clicks, user pick-up time, and stay time of the two groups of express cabinets regularly every day, and record user feedback on advertisements, including antipathy survey results. Preliminary collation and analysis of the collected data are conducted weekly, and detailed data summary and in-depth analysis are conducted once a month to evaluate changes in indicators such as advertising effectiveness, user experience, and operating costs.

5.3. Result verification

The experimental results were verified by synthetic control method. By constructing a synthetic control model, the advertising effect and user experience indicators of the experimental group without the dynamic optimization mechanism of advertising were simulated, and the actual results of the experimental group were compared and analyzed to further verify the effectiveness of the dynamic optimization mechanism. At the same time, eye movement experiments are performed. During the pick-up process, 100 representative users were selected and used eye tracking equipment to record the eye movement trajectory, fixation time, fixation point distribution and other data when watching the advertisement, analyze the user's attention allocation to different advertising contents, forms and display positions, and verify the effect of the advertising dynamic optimization mechanism on improving advertising effectiveness from the perspective of user attention, and enhance the reliability of the experimental results.

6. Presentation and Analysis of Research Results

6.1. Data descriptive statistics

Descriptive statistical analysis of the collected data of 500,000 user interactions is shown in Table 6. In terms of pickup time, the average pickup time is concentrated between 7 - 9 pm, which is in line with the user's daily routine, when users have more time to pick up their items after work. The average dwell time is 30 seconds and the standard deviation is 10 seconds, indicating that there is a certain difference in the time users spend in front of the delivery locker, and some users may spend more time viewing ads or performing other actions. Among the parcel categories, e-commerce parcels accounted for the highest proportion of 70%, reflecting the dominance of e-commerce shopping in the express delivery business. The average unit price of customers is 150 yuan, and the standard deviation is 50 yuan, indicating that the user's consumption amount fluctuates to a certain extent. The average community housing price is 5,000 yuan per square meter, and the housing price varies greatly from community to community, which also reflects the difference in the consumption power and living standards of residents in different communities. The specific grouping details are shown in Table 6.

Table 6. Data Profile Overview.

Variable quantity	Mean value	Standard deviation	Minimum	Maximum	Frequency distribution (major category percentage)
Time of pickup	7-9 PM (peak time)	/	2 a.m	11 p.m	7-9 PM: 40%; 10-12AM: 20%; 4-6 PM: 25%
Length of stay	30s	10s	10s	60s	10-20s:30%; 20-30s:40%; 30-40s:20%
Operation path	Clicking the item code input accounted for the highest proportion	/	Simply click to pick up your item	Complex operations (multiple clicks, queries, etc.)	Click the pickup code to input: 70%; check package information: 15%; other operations: 15%
Parcel category	E-commerce parcels	/	/	/	E-commerce parcels: 70%; documents: 10%; fresh food: 15%

	account for 70%				
per customer transaction	150yuan	50yuan	20yuan	500yuan	100-150:40%; 150-200:30%; 200-250:15%
Repeat purchase cycle	30days	10days	7days	90days	7-14days:20%; 14-30days:50%; 30-60days:25%
Housing price	5000 yuan/square meter	2000 yuan/square meter	4000 yuan/square meter	10,000 yuan/square meter	4000-6000 yuan/square meter: 50%; 6000-8000 yuan/square meter: 35%; 8000-10000 yuan/square meter: 15%
Population structure	The 30-45 age group accounts for 40%	/	/	/	The 30-45 age group accounts for 40%
Weather	Sunny account for 60%	/	/	/	Sunny: 60%; rainy: 20%; cloudy: 15%
Festival and holiday	Weekends and public holidays account for 30%	/	/	/	Weekends and public holidays: 30%; weekdays: 70%

6.2. User portrait results

This paper constructs a three-layer label system of “static-behavior-scene” to realize the all-round portrait portrayal of express cabinet users, and lays a micro-decision-making foundation for accurate advertising delivery.

In the static label dimension, the user group presents distinct demographic characteristics: the age distribution as a whole conforms to the normal distribution law, with the highest proportion of users in the age group of 30-45 years old, reaching 40%, and this group usually has strong spending power and stable living needs; The gender ratio is basically balanced, with 52% of men and 48% of women; In the occupational composition, office workers account for 50%, students account for 20%, freelancers account for 15%, and other occupational types account for 15%, reflecting the breadth of penetration of express cabinet services in different social roles.

Behavioral labels further reveal users' interaction patterns and consumption tendencies: high-frequency pick-up users (more than 3 times a week) account for 35%, and their dependence on express lockers is significantly higher than that of other groups. high-consumption users (customer unit price exceeding 200 yuan) accounted for 20%, constituting the core potential group for advertising conversion; In terms of category preferences, 15% prefer beauty categories, 12% prefer electronic products, and 10% prefer fresh food.

The scene label focuses on the environmental context in which user behavior occurs: high-end community users account for 15%, and the consumption power and consumer taste of this group are relatively prominent; 30% of active users during holidays showed a significant increase in users' shopping and pickup behavior during

holidays; 20% of users picked up on rainy days, reflecting the specific impact of weather factors on the use of express cabinets.

The synergy of the above three layers of labels clearly outlines the characteristics and needs of different user groups, and provides quantifiable decision-making support for the transformation of advertising from “casting a wide net” to “precise reach”.

6.3. Advertising optimization effect

6.3.1. Increase click-through rate and conversion rate

The click-through rate and conversion rate of the experimental group and the control group are compared, and the results are shown in Table 8. The click-through rate (CTR) of the experimental group increased by 170% compared with the control group, from the original 3% to 8.1%; The conversion rate (CVR) increased by 244%, from 2.8% to 9.6%. This shows that the dynamic optimization mechanism based on user portraits can significantly improve the attractiveness of advertisements and users' purchase intentions. By accurately targeting user needs, pushing personalized advertising content, and displaying advertisements in the right form at the right time, it effectively stimulates users' interest and purchasing behavior, and greatly improves the advertising effect. [15] The specific grouping details are shown in Table 7.

Table 7. Experimental result.

Group	Click-through rate (CTR)	Conversion rate (CVR)
Control group	3%	2.8%
Experimental group	8.1%	9.6%

6.3.2. User rejection and pickup delay

The optimization mechanism also has a significant impact on user disgust and pickup delay. User disgust dropped from 21% in the control group to 12% in the experimental group, indicating that the optimized ad delivery strategy can better meet user needs and reduce user resistance to ads. In terms of pickup delay, the experimental group only increased by 0.9 seconds, which is almost negligible, which shows that while improving the advertising effect, the optimization mechanism does not have a significant negative impact on the user's pickup experience, ensuring that users can pick up the package quickly and conveniently, and maintain a good user experience. [16]

6.3.3. ROI Improvement

The ROI comparison for ad groups before and after optimization shows that the ROI before optimization was 1:2.1, and after optimization, it jumped to 1:4.7. This means that under the same advertising cost, the optimized advertising dynamic optimization mechanism can bring more revenue and create higher business value for express cabinet operators and advertisers.[17] By increasing the click-through rate and conversion rate of advertisements, more users are attracted to purchase products or services, thereby achieving a significant increase in the return on advertising investment, which strongly proves the effectiveness and feasibility of this optimization mechanism in business operations.

6.4. Analysis of verification results

The results of synthetic control method show that the advertising effect and user experience indicators of the synthetic control group are significantly lower than those of the experimental group without the dynamic optimization mechanism of advertising. In terms of click-through rate, the synthesis control group was only 4.5%, which was far lower than the 8.1% of the experimental group; In terms of conversion rate, the synthesis control group was 5.2%, while the experimental group reached 9.6%. This further verifies the effectiveness of the dynamic advertising optimization mechanism, excludes the interference of other factors on the experimental results, and proves that the mechanism can significantly improve the advertising effect in real scenarios.

The results of the eye tracking experiment showed that when users watched the optimized ad, their gaze time was longer, and the focus was more on the key information area of the ad. For personalized recommended beauty ads, female users spent an average of 5 seconds on a fixed gaze, compared to just 3 seconds on traditional static ads. For electronic product advertising, the focus of target user groups (such as young men and business people) is more focused on the product features and advantages introduction area, which shows that the optimized advertisement can better attract users' attention and convey advertising information, and verifies the positive effect of the advertising dynamic optimization mechanism on improving advertising effectiveness from the perspective of user attention, and provides strong evidence support for the promotion and application of this mechanism.

7. Research Conclusions

In this study, the end-user portrait of the “static-behavior-scene” three-layer label system is successfully constructed, which effectively solves the data sparseness problem caused by the fragmentation of the express cabinet scene. By integrating express cabinet terminal interaction data, consumption data and community attribute data, it accurately portrays the characteristics, behaviors and interests of users, providing strong support for accurate advertising delivery. The designed four-dimensional collaborative advertising dynamic optimization mechanism of “content-timing-form-frequency” introduces federated deep reinforcement learning (Fed-DQN) to complete millisecond-level decision-making at the edge, realizing Pareto improvement between advertising effectiveness, user experience and operating costs. [18] The results of large-scale real-world experiments show that the click-through rate (CTR) of the experimental group is increased by 170%, the conversion rate (CVR) is increased by 244% compared with the control group, and the return on investment (ROI) of the ad group jumps from 1:2.1 to 1:4.7, and the user antipathy decreases from 21% to 12%, and the pick-up delay is only increased by 0.9 seconds, which verifies the effectiveness and reproducibility of the mechanism in real scenes.

8. Research Contributions and Innovations

In terms of theory, for the first time, a three-layer labeling system of “static-behavior-scene” suitable for express cabinet scenarios is proposed, and federalization is designed. The XGBoost + LSTM fusion framework is used for user portrait construction, which enriches the application of user portrait theory in offline terminal scenarios. The Fed-DQN-driven four-dimensional collaboration mechanism of “content-timing-form-frequency” provides a new application paradigm for reinforcement learning in the field of advertising optimization, and expands the

application boundaries of reinforcement learning in short-time-sequence, low-action dimensional scenarios.

At the practical level, it provides an integrated solution that can be directly implemented for the advertising operation of express cabinets, helping express cabinet operators and advertisers realize the transformation from extensive exposure to precise operation, effectively improving advertising effectiveness and commercial value, while taking into account user experience and privacy compliance requirements. [19] The feasibility of the mechanism is verified through real-world scene experiments, providing reference practical cases and data support for the industry, and promoting the technological upgrading and innovative development of the express cabinet advertising industry.

9. Study Limitations

In terms of sample scope, although different types of express cabinets in communities, office buildings and commercial areas are selected in this study, they are mainly concentrated in specific areas, which may not fully represent the use and user characteristics of express cabinets nationwide, and there are certain geographical limitations. In terms of data dimension, despite the integration of multi-source data, some factors that have a potential impact on user portraits and advertising optimization may still be missed, such as users' social relationships, in-depth exploration of interests and hobbies, etc., resulting in the completeness and accuracy of user portraits that need to be further improved. In terms of time span, the 100-day experimental period is relatively short, making it difficult to capture the impact of long-term user behavior changes and market dynamics on advertising effectiveness, which may affect the long-term effectiveness and stability of the research results.

10. Future Research Directions

In the future, the scope of the sample can be further expanded to cover cities and villages in different regions of the country and different levels of economic development, increase the number of express cabinets and user samples, and improve the universality and representativeness of the research results. In terms of data dimension expansion, we will dig deep into users' social network data, in-depth information on interests and hobbies, and combine IoT devices to obtain more user life scene data, further improve user portraits, and improve the accuracy of advertising delivery. [20] Extend the experimental time span, conduct long-term tracking research, analyze the long-term trend of user behavior and market environment, optimize the dynamic optimization mechanism of advertising, and achieve continuous improvement of advertising effect and long-term maintenance of user experience. [21] At the same time, explore how to apply the latest artificial intelligence technologies, such as generative adversarial networks (GANs) and transfer learning, to the field of express cabinet advertising optimization to promote technological innovation and development in this field.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

Funding

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

References

- [1] Jiang, T.C.; Wang, Y.; Liu, J. Research on Intelligent Parcel Locker Information Service Based on WeChat Public Platform. *Enterprise Reform and Management*, 2015, 12, 2. DOI: 10.13768/j.cnki.cn11-3793/f.2015.5822.
- [2] Qian, M. Research on Profit Model and Performance Evaluation of B2C E-commerce Enterprises: A Case Study of Vipshop. East China University of Technology, 2021.
- [3] Feng, Q. Analysis of Profitability of SF Holding under Differentiation Competition Strategy [D]. University of Electronic Science and Technology of China, 2022. Construction and Empirical Research on Dynamic Optimization Mechanism of Express Cabinet Advertising Based on Terminal User Portraits
- [4] Zhang, X.W. Research on Urban Logistics Collaboration in the E-commerce Environment. University of Science and Technology Beijing, 2023.
- [5] Chen, Z.L. Research on the Design and Application of Data-driven LSTM Neural Network Structure. Beijing University of Technology, 2022.
- [6] Lin, L.Q.; Ji, H.Y. Application and Challenges of Personalized Recommendation Systems in Modern Marketing. *Business Observer*, 2024, 35.
- [7] Zhu, L. Research on Text Classification Method of Self-media Based on CNN Deep Learning. *Computer Knowledge and Technology: Academic Edition*, 2021.
- [8] Dong, X.T.; Zhou, Q.; Miao, R.F. et al. Grouping Method for Enterprise Load Peak Shaving Based on User Portraits. *Journal of Anhui Electrical Engineering Vocational and Technical College*, 2023, 28(4), 16-24. DOI: 10.3969/j.issn.1672-9706.2023.04.004.
- [9] Software Engineering. Research and System Design of Personalized Recommendation Method Based on DeepFM and Double DQN. 2023.
- [10] You, Y.Q. Optimization Research on Precision Marketing Strategy of Y Brand Home Furnishing Internet Advertising. East China Normal University, 2023.
- [11] Zhou, L.X.; Xiong, C.W.; Lin, J. Investigation and Analysis of Community Fresh Food O2O Consumers and Development Suggestions. *Journal of Liuzhou Vocational & Technical College*, 2023, 23(1), 36-40. DOI: 10.16221/j.cnki.issn1671-1084.2023.01.008.
- [12] Qian, Z.K.; Ding, X.O.; Sun, Z. et al. Intelligent Selection Method of Evidence Sets for Diverse Data Cleaning Tasks. *Computer Science*, 2024, 51(8), 124-132. DOI: 10.11896/jsjx.230900003.
- [13] Jin, L. Research on Key Technologies for Missing Value Imputation in Incomplete Data. Harbin Institute of Technology [2025-08-01]. DOI: CNKI:CDMD:2.1014.001204.

- [14] Tai, Y.F.; Wang, Z.Q.; Liu, H.F. et al. Analysis of User Annotation Behavior Characteristics Based on Tag and Short Comment Data. *Intelligence Engineering*, 2023, 9(4), 68-78. DOI: 10.3772/j.issn.2095-915x.2023.04.006.
- [15] Hou, D.Q. The Use of Technology and Countermeasures for User Profiling in Computational Advertising. *Finance (Market Edition)*, 2024, 2, 74-76.
- [16] Yuan, L.P. Research on Different Native Advertising Features and Their Impact on User Rejection and Product Perception in a Social Context. Shanghai International Studies University, 2023.
- [17] Chen, S.W.; Liu, M. Dynamic Allocation Optimization of Storage Space for Express Lockers Based on Spatio-Temporal Network [C] // “Two Types of Society” Construction and Management Innovation - The 15th China Management Science Academic Conference. 0 [2025-08-01].
- [18] Zhou, R.S.; Wang, Y.H. Research on Dynamic Scheduling Problems Based on DQN Algorithm. *Microprocessors*, 2025, 46(1), 55-59.
- [19] Wang, Y.R. Design of Campus Express Lockers Based on Sustainable Design and User Needs. *Design*, 2024, 37(4), 118-121. DOI: 10.3969/j.issn.1003-0069.2024.04.033.
- [20] Gong, Ke. Current Status, Challenges and Future Trends of Internet of Things Development. *New Economy Weekly*, 2024, 11.
- [21] Bai, N.; Shan, N. The Impact of Digital Scene Interaction on Design from the Perspective of Cognitive Behavioral Theory. *Journal of Jiamusi University (Natural Science Edition)*, 2024, 42(1), 157-159.



© 2025 by the author(s); licensee International Technology and Science Publications (ITS), this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (<http://creativecommons.org/licenses/by/4.0/>)