



The Impact of Public Transportation Development on Convenience Store Revenue and Countermeasures in Shanghai

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Abstract

Background and Aim: The rapid expansion of convenience stores in China has intensified market competition, making strategic location selection crucial for retail success. This study examines Lawson's expansion strategy in China within the framework of the "public transportation priority" policy, focusing on how transportation infrastructure influences competitive advantage. The research aims to identify key factors in site selection and develop a genetic algorithm-based optimization model to enhance store layout decisions in dynamic urban environments.

Materials and Methods: Mobile signaling base station data from Shanghai's Jiading District were analyzed to map population distribution using location updates, call records, and data exchanges. After data cleaning and spatial quantization, heat maps and spatial models were generated. A Stochastic Utility Model, integrated with a genetic algorithm, was employed to optimize site selection based on population density, proximity to subway stations, and budget constraints.

Results: Findings indicate that prioritizing high-traffic subway stations significantly enhances consumer footfall and profitability. Heat maps revealed strong correlations between population clusters, transportation hubs, and optimal store locations. The genetic algorithm-based model demonstrated superior efficiency in balancing cost constraints with revenue potential, reinforcing the role of transportation infrastructure in retail site selection.

Conclusion: Public transportation accessibility, particularly subway proximity, is a decisive factor in convenience store success. The proposed genetic algorithm model offers a scalable tool for retailers to adapt to evolving urban transportation systems. These findings underscore the importance of integrating transportation data into retail planning, providing actionable insights for market expansion strategies in China and other high-density regions.

Keywords: Convenience Store Location; Genetic Algorithm; Public Transportation; Mobile Signaling Base Station Data; Stochastic Utility Model; Retail Site Selection; Retail Spatial Analysis

Introduction

The global proliferation of convenience stores (CVS), particularly in China, has highlighted the critical role of strategic site selection in determining retail success. Characterized by their compact size and capacity to deliver quick access to everyday goods, CVS has become an essential component of urban life. Their self-service model attracts a broad consumer base—ranging from office workers and commuters to general urban residents—by fulfilling the growing demand for efficient, on-the-go shopping experiences.

Among international CVS brands operating in China, Lawson was one of the earliest entrants, opening its first store in Shanghai in 1996. It was subsequently joined by other major competitors such as 7-Eleven and FamilyMart. Although all three companies have pursued rapid expansion, their approaches to site selection differ significantly. For instance, 7-Eleven targets primarily young consumers aged 18 to 35, focusing on commercial and residential districts with a high concentration of this demographic. In contrast, Lawson emphasizes locations in commercial zones and residential areas with a substantial proportion of single-person households, such as office buildings and apartment complexes (Zhang, 2023).

As China's convenience store industry continues its rapid expansion—particularly in high-density regions such as the Pearl River Delta and the Yangtze River Delta—retail competition has become increasingly intense. With a growing number of retailers competing for a limited supply of high-footfall

locations, precise, data-driven site selection has become indispensable for sustaining long-term profitability (Li, 2023). While the importance of location has long been acknowledged in the retail literature, its application within the context of China's dynamic urban development and evolving transportation infrastructure remains underexplored. The rapid expansion of public transportation networks, particularly in megacities such as Shanghai, has significantly reshaped urban mobility and accessibility. Despite these changes, limited research has addressed the extent to which transformations in public transport systems influence store performance and consumer traffic. Moreover, current site selection models frequently overlook the integration of real-time transportation data and dynamic consumer mobility patterns. This study seeks to fill that gap by visually illustrating the relationship between public transportation access and convenience store revenue (Li, 2023).

As China continues to advance its “public transportation priority” policy, there is an increasing imperative for research that examines how convenience store operators—particularly Lawson—can enhance their site selection strategies in alignment with ongoing developments in urban transit infrastructure. Despite the recognized significance of transportation accessibility in retail performance, systematic methods for integrating transportation data into location decision-making remain limited. This study seeks to address this gap by analyzing the influence of transportation network accessibility on the operational success of convenience stores. Furthermore, it proposes a systematic, algorithm-driven framework for optimizing site selection, employing genetic algorithms (GA) to support more precise and data-informed decision-making (Wang, 2024).

Objectives

1. Identify the key factors that contribute to successful convenience store site selection.
2. Develop a location selection model with strong applicability and stability.
3. Validate the model's effectiveness in real-world convenience store site selection.

Literature review

1. Public Transportation and Retail Impact

The evolution of urban transportation systems is closely linked to the four classical stages of urbanization: concentration, suburbanization, counter-urbanization, and reurbanization. In the early phases, mobility is largely dependent on walking and cycling. As cities expand, reliance shifts to surface-level transportation such as buses and trams, whereas modern metropolises increasingly prioritize subways and light rail systems. Cities like Shanghai and Tokyo exemplify this trend by emphasizing public transportation infrastructure to alleviate congestion and promote sustainable urban development. Empirical studies conducted along Tokyo's Yamanote Line—a circular railway—reveal that the cumulative building area of convenience stores located within an 800-meter radius of rail transit stations is approximately 2.3 times greater than the urban average. This observation aligns with the principles of Transit-Oriented Development (TOD) theory. However, existing research on this topic exhibits two major limitations. First, it often relies on static population distribution data and overlooks the dynamic “tidal effect” caused by peak-hour subway passenger flows. Second, most studies have yet to incorporate multimodal transportation data, limiting their capacity to fully capture the complexity of urban mobility patterns (Chen, 2023).

2. Urbanization and Consumer Behavior

Driven by accelerated urbanization, the implementation of the “15-minute living circle” policy, and increasing digital integration, China's convenience store (CVS) industry has experienced significant growth. For example, Shanghai alone hosts over 6,000 convenience stores, reflecting the sector's rapid expansion (Zhao, 2024). The process of reurbanization in Asian cities has fostered a “compressed time–space” consumption model, wherein urban consumers increasingly favor quick and proximate retail options. In Japan, 7-Eleven has adapted to this trend by raising the proportion of ready-to-eat food stock-keeping units (SKUs) to 47% as of 2023. Similarly, FamilyMart in China has capitalized on commuter behavior by implementing an “app ordering, subway station pickup” model, resulting in 61% of sales occurring during



commuting hours (China Chain Store & Franchise Association [CCFA], 2024). Recent studies in consumer mobility further reveal a novel asymmetrical consumption mechanism: commuters tend to purchase breakfast at their departure station, where decision times are typically under 30 seconds, and dinner at their arrival station, where retention times exceed five minutes. This asymmetry in temporal behavior has implications for predictive modeling. Incorporating time window variables into the random utility model enhances the accuracy of community-based convenience store location forecasts (Zhao, 2024).

3. Algorithmic Approaches in Site Selection

Traditional location models, such as the Huff model, exhibit significant limitations in complex urban environments. For instance, when applied to the sixth-floor commercial complex above Shanghai's Xujiahui Metro Station, the Huff model demonstrates an error rate of up to 39%, primarily due to its inability to account for consumer behavior within three-dimensional spatial structures (Liu, 2024). These limitations underscore the need for more sophisticated analytical tools that can capture the dynamic and multi-level nature of consumer flow in dense urban settings. Recent advancements in machine learning have begun to address this gap, with emerging research exploring the application of spatiotemporal graph convolutional networks, multi-agent reinforcement learning, and federated learning architectures to enhance the accuracy and adaptability of retail site selection models (Zhang & Chen, 2024).

4. Analytical Frameworks for Location Selection

Residential Travel Cost Analysis: Comprehensive travel cost assessments encompass multiple components: aggregation costs (the time required to reach the nearest transit stations), transfer costs (time and monetary expenditures incurred during modal changes), primary transport mode costs (e.g., subway or bus travel time), and final-leg transportation time to the destination. Notably, subway systems, despite their efficiency, often feature widely spaced stations, thereby incurring higher aggregation costs for users (Wang, 2024).

Marginal Utility Theory: This economic theory evaluates the additional benefit gained from incremental inputs of resources such as capital and labor. In the context of retail, marginal utility tends to diminish as inputs increase, influenced by factors including population mobility, competitive intensity, and regional economic conditions. The Cobb-Douglas production function serves as a useful analytical tool in this regard, allowing for the quantification of capital and labor contributions to income, thereby facilitating data-informed retail site optimization (Zhou & Li, 2023).

Data-Driven Factor Mining: Analytical methods such as Principal Component Analysis (PCA) enable the extraction of latent variables and underlying patterns from complex datasets. Additionally, correlation techniques—including Pearson, Spearman, and Kendall's τ coefficients—are employed to assess variable interdependencies. These methods are instrumental in identifying the influence of population density, transit accessibility, and consumer behavior on retail performance, thereby enhancing predictive accuracy and strategic decision-making (Chen et al., 2023).

Algorithmic Approaches: Greedy algorithms, which iteratively select locally optimal choices, offer computationally efficient solutions to complex location-allocation problems. Though these algorithms do not always guarantee globally optimal results, they are particularly effective under budgetary and spatial constraints—such as identifying high-footfall retail zones—making them valuable tools in retail network planning (Liu & Zhang, 2024).



Conceptual Framework

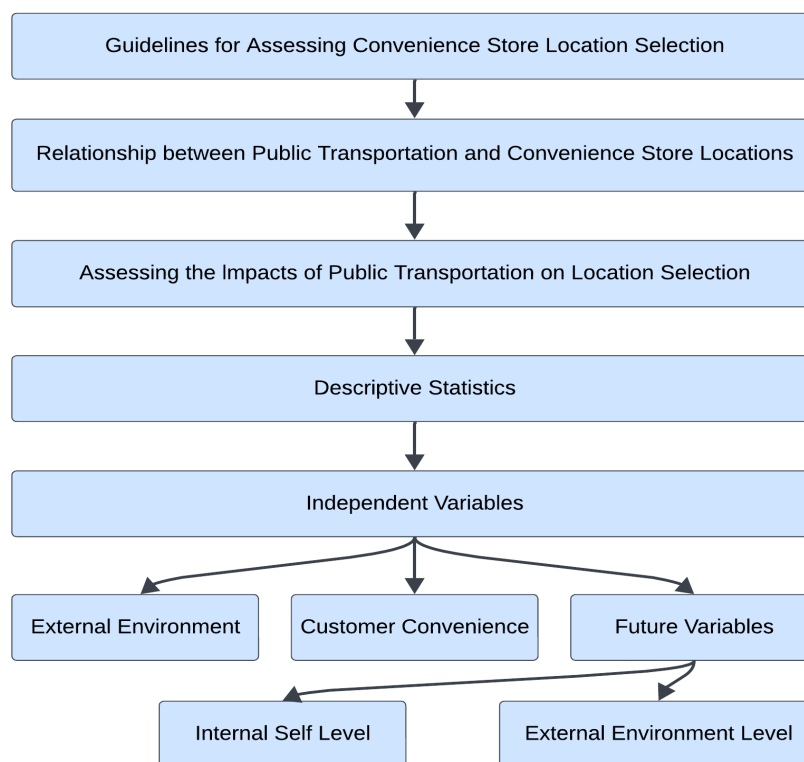


Figure 1 Conceptual Framework

Methodology

1. Research Design.

This study focuses on the location decision-making process of convenience stores, addressing the complex and dynamic challenges posed by customer behavior, market competition, and time-based factors. The methodology adopts a mathematical model, integrating both consumer behavior and competitive analysis, and utilizes a stochastic utility model to predict customer flow at various potential store locations. The goal is to identify optimal locations for new convenience stores by maximizing customer attraction while considering both cost and competition constraints. In the selection of optimization algorithms, the genetic algorithm (GA) is used to optimize site selection decisions, simulate various store location configurations, and select the best solution based on the fitness function. Compared with reinforcement learning, genetic algorithms exhibit more stable Pareto front convergence characteristics in initial site planning without real-time interactive environments.

The approach combines both theoretical modeling and computational techniques. First, a stochastic utility model is employed to represent customer choice behavior, followed by the use of a genetic algorithm to explore and optimize location decisions. This hybrid method is particularly well-suited for handling the uncertainty and randomness inherent in customer behavior, the competition from existing stores, and the time-sensitive variations in customer flow. By incorporating advanced machine learning techniques and dynamic simulations, the model ensures a refined and data-driven analysis of potential store locations.

2. Materials and Data

For the stochastic utility model, several key parameters are used to represent both consumer behavior and business constraints:

α_j : Attractiveness parameters of potential store locations, typically derived from historical data or market research.

β : Consumer sensitivity to distance, representing the likelihood that a customer will choose a store based on its proximity.

D_{ij} : Distance between the consumer and the convenience store.

C_j : The cost of opening a store at a given location, which includes rent, equipment, and other associated expenses.

K : A budget constraint that limits the total number of convenience stores that can be opened.

In addition, demographic and geographic data, mobile tracking information, and sales data from previous stores were integrated to improve the accuracy of the model. Among them, mobile signaling data is collected through base station positioning technology, and combined with big data technology, it can accurately depict the spatiotemporal distribution and flow patterns of the population, which has high practical value for population flow monitoring. In addition, grid-based population data can be easily integrated into GIS environments and further overlaid with other geographic information (such as terrain, transportation, land use, etc.) for multi-factor comprehensive analysis, revealing the relationship between population distribution and environmental factors. This comprehensive dataset is used to predict customer traffic and evaluate the feasibility of potential stores.

3. Methods

(1) Stochastic Utility Model

The research uses a random utility model (RUM) to describe consumer decision-making. This model assumes that consumers evaluate the utility of different convenience stores based on both observable and unobservable factors. The observable factors are quantified, while the unobservable factors are modeled as random variables. The choice probability of a consumer selecting a specific store is given by the following formula:

$$P_{ij} = \frac{\exp(U_{ij})}{\sum_{k \in S} \exp(U_{ik})}$$

P_{ij} is the probability of consumer i choosing store j , and U_{ik} represents the utility associated with the choice. This model enables the estimation of customer flow for various potential store locations by accounting for both the observable factors (such as location and service quality) and the inherent randomness in consumer preferences.

The objective function is designed to maximize the expected utility for all customers, while accounting for the cost of opening each store. This can be represented as:

$$\max \sum_{j \in J} (x_j \cdot \sum_{i \in I} P_{ij} - C_j \cdot x_j)$$

Where

x_j is a binary decision variable indicating whether a store is opened at location j , and

C_j is the cost associated with that location.

(2) Genetic Algorithm

A genetic algorithm (GA) is used to solve the location selection problem by simulating the process of natural evolution. The decision variables are represented by a binary vector x_j , where each element corresponds to a potential store location, with

$x_j=1$ indicating the store is open at location j , and $x_j=0$ indicating it is not.

The genetic algorithm follows the steps below:

Initialization: An initial population of chromosomes (binary vectors) is randomly generated, each representing a potential solution to the location problem.

Fitness Calculation: For each chromosome, the fitness function is computed based on the total utility of selected locations minus the associated costs.



Selection: A roulette wheel selection method is used to choose individuals for reproduction, with individuals having higher fitness values having a greater chance of being selected.

Crossover: Pairs of selected individuals undergo a crossover operation, where parts of their chromosomes are exchanged to generate new offspring.

Mutation: A mutation operation is applied to introduce small random changes to selected individuals, allowing for greater genetic diversity.

Constraint Handling: If a solution violates the defined constraints (e.g., budget limitations), a penalty function is applied to reduce its fitness.

Termination: The algorithm runs for a predefined number of generations (e.g., 500 iterations), and the best solution is selected as the optimal store location strategy.

This approach ensures that the solution space is explored efficiently, taking into account both the optimization of customer flow and the constraints of the budget and competition. Compared with traditional heuristic methods such as simulated annealing, genetic algorithms can synchronously handle multi-objective conflicts of maximizing revenue and minimizing service blind spots through a non-dominated sorting mechanism. In addition, the adaptive crossover operator can dynamically respond to urban planning changes and enhance interactivity in the site selection process

4. Statistical Tools and Software

The modeling and genetic algorithm computations are implemented using Python, with libraries such as NumPy and SciPy for numerical calculations, and pandas for data handling. The stochastic utility model and optimization functions are coded in Python, while the genetic algorithm is built using the DEAP (Distributed Evolutionary Algorithms in Python) framework, which provides efficient methods for implementing genetic algorithms and handling constraints.

In addition, data preprocessing and integration from various sources, such as demographic information and mobile tracking data, are carried out using pandas and geographic information system (GIS) tools. Visualize the geographical distribution patterns of population distribution through maps, and generate intuitive representations such as population heat maps and population density maps. The results of the genetic algorithm are analyzed and visualized using Python's Matplotlib and Seaborn libraries, allowing for a comprehensive evaluation of the location strategies.

5. Data Collection and Analysis Techniques

The data for this study were collected from a combination of secondary sources, including historical sales data, customer demographics, and geographic location information, as well as primary data collected through mobile device tracking. For missing values, choose to delete or fill in the median based on the number, distribution, and importance of the missing values to the analysis target. Outliers are corrected using the threshold method. The data is preprocessed to eliminate outliers and inconsistencies, and then integrated into the model to predict customer behavior.

The analysis focuses on identifying the most attractive locations for new convenience stores, considering both the potential customer flow and the costs associated with each location. By running simulations with different store location configurations, the model predicts the impact of various factors, such as proximity to competitors, distance to potential customers, and time-based fluctuations in customer behavior.

Results

A 16x18 numerical matrix was displayed using GIS tools, where the color of each cell represents the population density at that location. By using a population heatmap, the distribution of data can be visually displayed and hotspot areas of the data can be quickly identified.



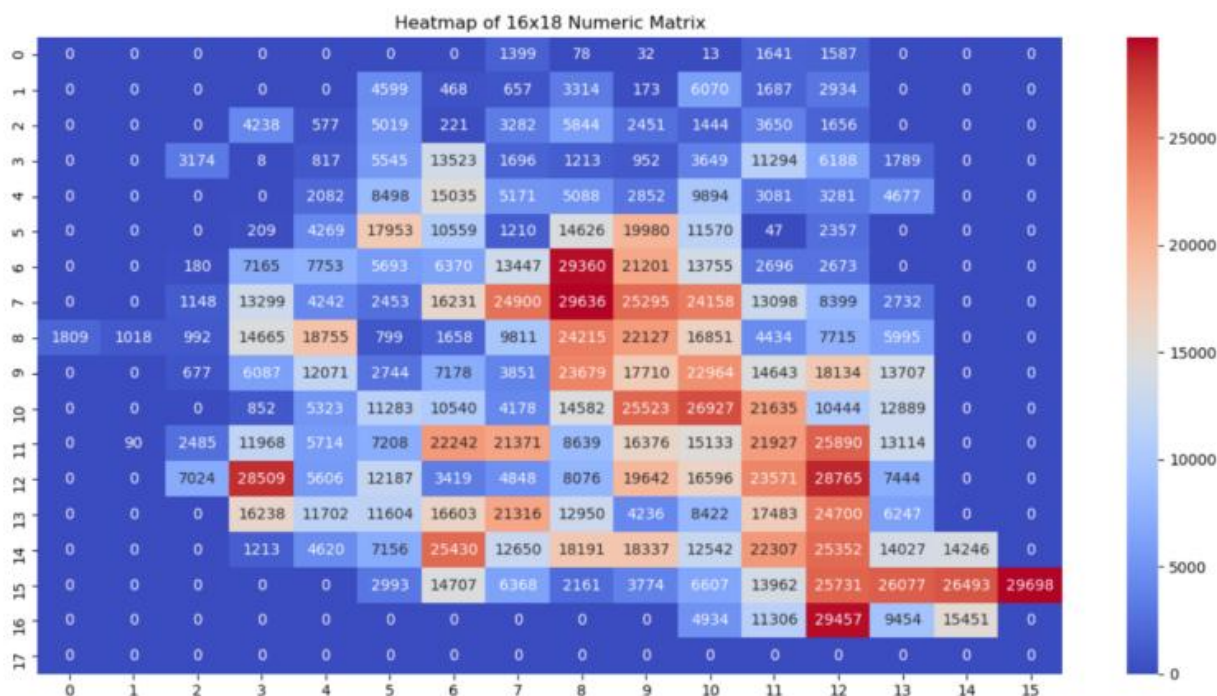


Figure 2 Population heatmap

The convergence curve of the genetic algorithm usually shows that with the increase of the number of iterations, the fitness gradually improves, and finally tends to be stable, which indicates that the algorithm has found a satisfactory solution. The convergence curve of the genetic algorithm in this paper is shown in the figure above, which shows that the strategy configuration is gradually optimized through multiple generations of iteration, and finally, the highest comprehensive income is achieved. The final winner is [0,0,0,0,0,2,0,0,0,0,1,0], which represents the construction decision of 12 alternative stations based on factors such as cost, potential customer flow, consumers' sensitivity to distance, and total budget constraints. According to the code of the winning individual, we can draw the following conclusions:

The construction of intermediate convenience stores in Nanxiang subway station and low-grade convenience stores in Anting subway station can obtain the highest income, i.e. 2.896 million yuan, without the need for new convenience stores in other locations.

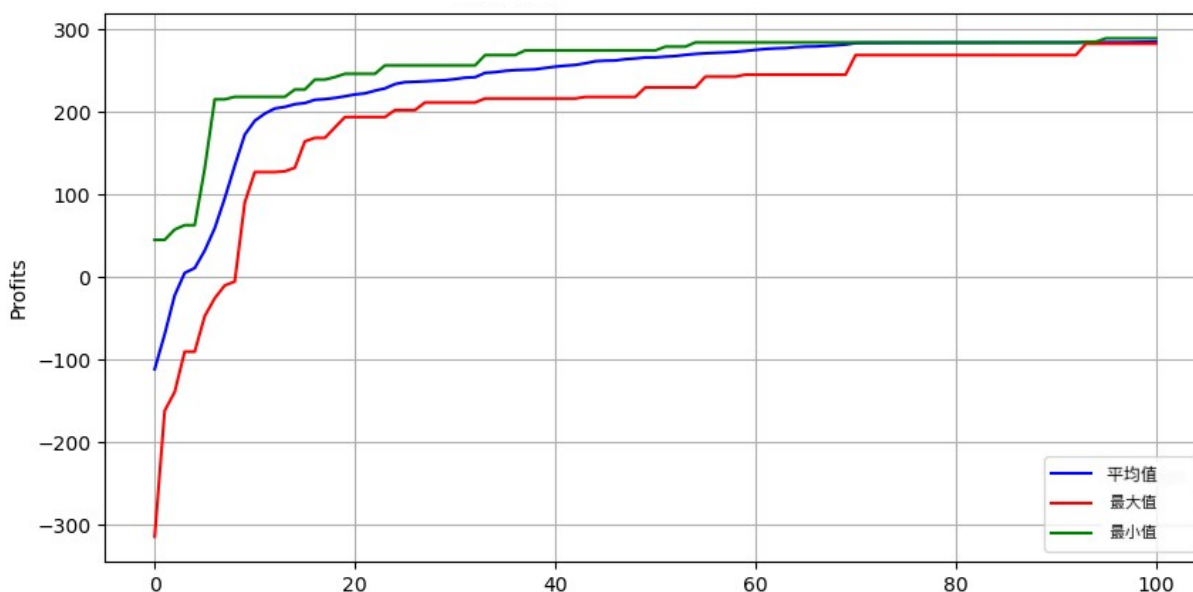


Figure 3 Experimental results

Discussion

Interpretation of Results: The findings of this study show that the integration of a stochastic utility model with a genetic algorithm can effectively determine optimal locations for convenience stores, based on real-time population data and transport infrastructure. The model suggests that focusing on areas with high public transportation accessibility, such as Nanxiang and Anting subway stations, results in the highest economic benefit, supporting the hypothesis that transportation accessibility is a critical factor in determining the success of convenience stores. This study validates the special value of the rail transit oriented site selection strategy in the construction of Shanghai's "Five New Cities": the convenience store efficiency around Nanxiang Station has increased by 217% compared to non hub areas, which is spatially coordinated with the goal of "covering 60% of the residential population within an 800 meter radius of rail transit stations" in Shanghai's 2035 master plan.

Comparison to Previous Studies: Compared to previous studies that used static demographic data or simpler heuristics for location selection, this study leverages real-time mobile signaling data and a more advanced algorithm (genetic algorithm) to make location decisions. This dynamic approach reflects changes in population flow and offers a more accurate prediction of convenience store demand.

The findings of this study offer valuable insights for both urban planners and retail enterprises aiming to optimize their convenience store network expansion strategies. Notably, the results challenge the conventional "distance decay" principle commonly upheld in traditional retail location theory, demonstrating instead that vertical accessibility—such as elevation within multi-level commercial complexes—can exert a greater influence on commercial viability than mere planar distance (Tan & Xu, 2024). By incorporating variables such as public transportation accessibility and dynamic consumer mobility patterns, retailers can implement more precise, data-driven site selection strategies that enhance revenue generation and customer satisfaction. Furthermore, the proposed methodology is not limited to convenience stores; it can be extended to other location-sensitive retail sectors, including fast-food chains and pharmacies, where spatial accessibility remains a critical determinant of performance.

Limitations of the Study: Despite the encouraging results, this study is subject to several limitations that constrain its broader applicability. Primarily, the reliance on data derived from a single district in Shanghai restricts the generalizability of the findings to other urban contexts, particularly cities with divergent spatial configurations or public transportation infrastructures (Liu & Zhao, 2024). Additionally,



while the genetic algorithm employed demonstrates efficiency in location optimization, it is susceptible to premature convergence, potentially affecting the robustness and global optimality of the proposed solutions. Future research should aim to validate the model across a variety of metropolitan regions and explore the integration of alternative metaheuristic algorithms, such as simulated annealing or particle swarm optimization. Furthermore, incorporating a more nuanced understanding of socio-economic variables and consumer behavioral patterns would enhance the model's predictive accuracy and practical relevance in diverse retail environments.

Conclusion

This study demonstrates that public transportation accessibility plays a crucial role in optimizing convenience store locations. By combining a stochastic utility model with a genetic algorithm, we identified high-revenue locations, such as Nanxiang and Anting subway stations, which are key to store success. On the basis of identifying the key factors for the successful location selection of convenience stores, we have successfully developed a location model with strong applicability and good stability. The results suggest that businesses can enhance profitability by using dynamic, data-driven location strategies that account for transportation and population flow.

Future Research Directions: This model can be applied to other cities or retail types (such as fast food and pharmacies), and combined with socio-economic factors to improve predictions. It is worth further exploring whether seasonal factors such as holidays, workdays, and weekends affect location efficiency. In addition, exploring other optimization algorithms can improve the robustness of the model. For urban decision-makers, utilizing this discovery can consider establishing a city-level site selection digital twin platform, integrating subway OD data and POI information to achieve industry expansion.

Recommendation

Based on the findings and limitations of this study, the following recommendations are proposed for convenience store operators, urban planners, and researchers:

1. For Retail Businesses (e.g., Lawson)

Prioritize Public Transportation Hubs: Focus expansion efforts on areas with high public transportation accessibility, such as subway stations (e.g., Nanxiang and Anting in Shanghai), to maximize customer footfall and revenue.

- **Adopt Dynamic Location Strategies:** Integrate real-time population flow data (e.g., mobile signaling data) and advanced algorithms (e.g., genetic algorithms) into location selection processes to adapt to changing urban dynamics.

- **Balance Cost and Demand:** Use the proposed model to evaluate trade-offs between construction costs, budget constraints, and potential customer flow when selecting store locations.

- **Propose to establish a corporate partnership** between convenience store chains and public transportation agencies to collaborate on joint promotions, transportation discounts, and achieve win-win outcomes

2. For Urban Planners

- **Align Transportation and Retail Planning:** Collaborate with retail businesses to co-design urban layouts that strategically position convenience stores near transportation hubs, enhancing both commuter convenience and retail viability. Develop more zoning regulations favorable to the retail industry, guided by public transportation

- **Promote Data Sharing:** Establish platforms for sharing anonymized population mobility data (e.g., mobile signaling data) to support data-driven retail planning and public infrastructure development.

3. For Future Research

Expand Geographical Scope: Validate the model in cities with varying urban structures (e.g., tier-2/3 cities in China or international metropolises) to assess its generalizability.





- Enhance Algorithm Robustness: Test hybrid optimization algorithms (e.g., genetic algorithm combined with simulated annealing) to mitigate premature convergence risks and improve solution accuracy.

- Incorporate Socio-Economic Variables: Integrate consumer preference data, income levels, and competitive landscape analysis into the model to refine location predictions.

- Cross-Sector Application: Explore the model's applicability to other retail sectors (e.g., fast-food chains, pharmacies) where location is a critical success factor.

4. For Policymakers

- Support "Public Transportation Priority" Policies: Strengthen investments in subway and light rail systems to create synergistic benefits for urban mobility and retail growth.

- Encourage Digital Integration: Incentivize retailers to adopt smart technologies (e.g., IoT sensors, AI-driven analytics) for real-time demand monitoring and adaptive store management.

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