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Spatial Heterogeneity of O2H-Induced Efficiency Gains in Chain Retail Space: Evidence from Tianjin, China

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Abstract

As a key branch of online-to-offline (O2O) retail, the online-to-home (O2H) model enables goods acquisition through instant delivery, fundamentally reorienting urban retail spatial configuration from "accessibility" to "efficiency". Using Jincheng, the main urban area of Tianjin as a case study, this research formulated a Goods Acquisition Efficiency (GAE) index to quantify the time-based efficiency gain of O2H over the conventional OIS (offline in-store) mode. An integrated XGBoost-SHAP approach was utilized to examine the spatial variations in efficiency gains and their associated factors. The results reveal that: (1) Efficiency gains follow a concentric pattern, increasing from the core to the periphery (Inner: 0.18; Middle: 0.20; Outer: 0.26), suggesting that O2H provides more pronounced benefits in peripheral areas where retail provision remains limited; (2) The dominant factors vary across zones: environmental attributes in the Inner Urban Zone, transportation and economic factors in the Outer Urban Zone; (3) O2H and OIS exhibit a complementary rather than substitutive relationship—physical stores in inner-city areas can maintain their current configuration, while peripheral zones may benefit from enhanced O2H fulfillment or conversion to micro-fulfillment centers. The GAE index and zonal comparison framework offer methodological references for differentiated optimization of urban retail networks.

Keywords: O2H mode; hypermarket chain; efficiency gain; spatial heterogeneity; XGBoost-SHAP

1. Introduction

The rise of online-to-offline (O2O) retailing is reshaping urban retail systems [1–3]. As a prominent branch of O2O, the online-to-home (O2H) model centers on instant delivery: consumers place orders online and receive goods at their doorstep via rider delivery, enabling a "goods-to-consumer" acquisition mode [4–8]. This shift redirects the key constraint on daily consumption from "whether one can reach a store" to "whether fulfillment can be completed within an acceptable time." Hypermarket chains have been particularly affected—online channels continue to divert foot traffic while stores still bear fixed costs such as rent and labor, leaving limited operational flexibility. How to optimize store network configuration under O2H disruption has thus become a shared concern for retailers and urban planners alike.

Conventional hypermarket spatial configuration takes "accessibility" as its core objective [9–11]. At the site selection level, stores tend to locate in densely populated areas or near transport hubs to shorten consumer travel distance and expand service

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coverage [12]. At the network level, store layouts follow the distance-decay principle, using catchment analysis to define service radii that keep target customers within reasonable travel distance [13]. The underlying premise is straightforward: consumers must visit stores in person, and shorter travel distances with better transport access translate into stronger store competitiveness. O2H, however, upends this premise. When consumers no longer need to visit stores, goods acquisition efficiency hinges not on the "consumer-to-store" distance but on the "goods-to-consumer" fulfillment time [14,15].

Existing research offers limited guidance for such configuration adjustments. In terms of efficiency measurement, fulfillment optimization has largely adopted an operational perspective: in-store layout optimization uses association rule mining to improve customer flow efficiency [16,17]; warehouse layout optimization employs Systematic Layout Planning (SLP) and simulation modeling to reduce storage costs; delivery efficiency studies focus on order batching and route planning [18]; and micro-fulfillment center siting emphasizes shortening "last-mile" delivery distances [19,20]. These efforts operate at the micro level, addressing efficiency gains within individual stores or along specific delivery routes, without examining store networks at the urban scale or identifying how O2H differentially affects various locations within existing networks. Spatially, prior work has documented heterogeneity in O2O/O2H service distribution [21–23], yet such discussions often remain at the level of pattern description, lacking comparative analysis of efficiency differences between "consumer-to-store" and "goods-to-consumer" acquisition modes and the factors behind them. Synthesizing these gaps, two core questions emerge: How does O2H's efficiency improvement over OIS vary across urban space? And which spatial factors are associated with such variation?

To address these gaps, this study proposes the Goods Acquisition Efficiency (GAE) index. Given that time cost is a critical factor in consumer decision-making in instant retail scenarios, and that time offers greater stability and cross-mode comparability than economic costs (e.g., delivery fees) which fluctuate significantly with platform subsidies, this study adopts total time for consumers to obtain goods as a unified measure. The index captures the time efficiency of both offline-in-store (OIS) and online-to-home (O2H) modes, with the difference defined as "Efficiency Gain" to represent the efficiency improvement of O2H relative to OIS.

The remainder of this paper is organized as follows: Section 2 reviews related literature and identifies research gaps; Section 3 describes the study area, data, and methods; Section 4 presents the results; Section 5 discusses planning implications; and Section 6 concludes.

2. Literature Review

2.1. Approaches to Measuring Time Efficiency

Time constitutes a critical dimension in urban spatial efficiency research. Existing studies have developed various measurement approaches from different perspectives, which can be grouped into two categories: time-based accessibility and fulfillment timeliness (Table 1). Time-based accessibility methods originate from spatial accessibility research and aim to assess how conveniently individuals can reach specific facilities or services; they are widely applied in studies of public service facilities, healthcare resources, and employment opportunities [24–26]. Fulfillment timeliness methods stem from logistics and supply chain research and focus on evaluating the delivery efficiency of goods and services, with primary applications in e-commerce logistics, instant delivery, and urban freight [27,28].

Table 1. Summary of time efficiency measurement perspectives.

Category	Method	Measurement Focus	Application Context
Time-based Accessibility	OD shortest time [29–31], Isochrone [30,32,33]	Minimum travel time from origin to destination	Public service allocation; facility siting
	Cumulative opportunity [34–37]	Number of facilities reachable within a time threshold	Employment accessibility; retail coverage
	Gravity/Potential model [38,39]	Facility attractiveness weighted by distance decay	Commercial center catchment
	2SFCA and variants (with decay) [40,41]	Supply-demand matching efficiency	Healthcare resources; elderly care facilities
Fulfillment Timeliness	Generalized cost [42–44]	Composite cost of time, expense, and experience	Travel mode choice
	Space-Time Prism [45,46]	Feasible activity space under spatiotemporal constraints	Activity-travel behavior
	Delivery timeliness performance [47,48]	On-time rate; delay duration	E-commerce logistics; instant delivery

Each of these approaches has strengths within its respective domain, yet none directly answers the question: "How much time does O2H save compared with visiting a store in person?" Time-based accessibility methods focus on characterizing the single pathway of "consumer-to-store" and cannot directly compare time differences between the two modes. OD shortest-time and isochrone methods, for instance, calculate minimum travel time from origin to destination or delineate areas reachable within given time thresholds [49,50]. Cumulative opportunity approaches count the number of facilities accessible within a specified time window [36,51,52]. Gravity-based potential models incorporate facility attractiveness alongside distance decay [53]. The two-step floating catchment area (2SFCA) method and its variants assess service accessibility from a supply–demand matching perspective [54,55]. Fulfillment timeliness methods, by contrast, focus on the "goods-to-consumer" delivery process. Generalized cost approaches integrate time, monetary expense, and comfort into a single metric. Space-time prism methods delineate an individual's feasible activity space under joint temporal and spatial constraints [56]. Delivery timeliness performance methods evaluate logistics service quality through indicators such as on-time rates and delay duration [57]. The two categories thus serve different purposes: the former suits characterizing spatial accessibility under conventional in-store shopping, while the latter suits evaluating delivery efficiency under O2H. Because they employ different measurement units and analytical frameworks, direct cross-comparison remains infeasible.

2.2. Spatial Heterogeneity of O2O/O2H Effects

O2O/O2H services exhibit notable spatial variation within cities in terms of distribution patterns, influencing factors, and service efficiency. Regarding distribution patterns, O2O storefront services in Guangzhou follow a "core-periphery" structure, whereas O2O delivery services display a "horizontal, non-hierarchical, polycentric" network—revealing fundamentally different spatial logics for different service modes within the same city [58]. A study of Weifang found that communities with high store density and long online shopping duration cluster in the city center, while those with low store density but long online shopping duration are scattered across old urban districts and rural areas, suggesting a spatial mismatch between online and offline retail [59]. In Nanjing, online food delivery services show gradient distributions in density, diversity, and accessibility, with marked service-level gaps between central and peripheral areas [60]. Turning to influencing fac-

tors, O2O retail distribution in Guangzhou is significantly shaped by sociodemographic attributes such as youth share, education level, and income [61], while O2O restaurant distribution in Nanjing is tied to regional economic conditions and proximity to commercial centers [62]. Population density, road network density, distance to the city center, housing prices, and access to educational facilities jointly influence the spatial distribution of service levels [63]. In terms of service efficiency, online services in Nanjing improved retail accessibility for 96.76% of communities, yet neighborhoods with higher housing prices benefited disproportionately [64]—indicating spatial unevenness in efficiency improvements. Taken together, O2H-induced efficiency gains are not uniformly distributed; core and peripheral areas may experience structurally different levels of benefit.

These findings underscore that O2H effects are spatially heterogeneous, implying that hypermarket network strategies should not be spatially uniform but rather tailored to local conditions. Yet tailored to what? Which factors drive regional differences in efficiency gains? Although prior research has identified multiple determinants of O2O/O2H spatial distribution, how these factors shape "efficiency gains" remains unclear. To address these gaps, the present study works on two fronts: we propose a unified efficiency-gain metric to resolve the measurement issue, and we employ zonal comparison combined with machine learning to identify spatial variations in gains and their associated factors.

3. Materials and Methods

3.1. Research Design

This study aims to quantify the efficiency gains brought by the O2H model in goods acquisition and to identify how these gains correlate with spatial factors. The research framework (Figure 1) comprises five stages: (1) Mode Input. Two goods acquisition modes are compared—OIS (offline in-store) and O2H (online-to-home). Under OIS, consumers travel to stores themselves, with time consumption determined by consumer-to-store spatial accessibility; under O2H, riders handle delivery, with time consumption determined by store-to-consumer fulfillment efficiency. (2) Efficiency Measurement. A Goods Acquisition Efficiency (GAE) model is constructed using total time for consumers to obtain goods as a unified metric. Time efficiency is calculated separately for each mode, and the difference represents the efficiency gain attributable to O2H. (3) Regional Comparison. Following the city's concentric zone structure, the study area is divided into Inner Urban Zone, Middle Urban Zone, and Outer Urban Zone to compare spatial distribution patterns and regional differences in efficiency gains. (4) Factor Identification. With efficiency gain as the dependent variable and economic, transportation, and environmental attributes as independent variables, XGBoost combined with SHAP is employed to identify factors associated with efficiency gains across zones. (5) Result Analysis. Feature importance rankings and impact mechanisms are generated to reveal the key factors and their influence patterns in each zone.

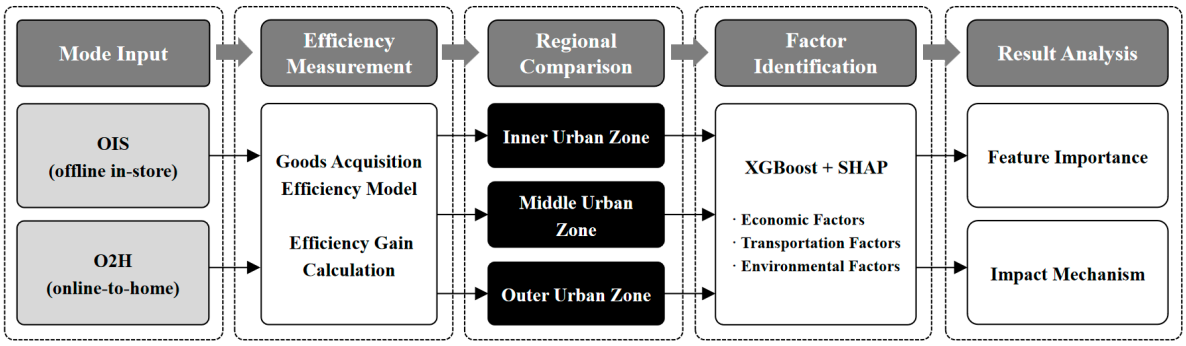


Figure 1. Research framework.

3.2. Study Area and Research Objects

This study takes Jincheng, the main urban area of Tianjin, as its empirical case. Tianjin serves as the economic hub of the Beijing-Tianjin-Hebei megalopolis in northern China. Its urban spatial structure exhibits a "core agglomeration with concentric expansion" pattern, making it an ideal setting for examining the differentiated effects of O2H across urban zones. Following the zoning scheme outlined in the *Jincheng Overall Urban Design (2021–2035)* [65], we divided the study area into three concentric zones (Figure 2): the Inner Urban Zone, located within the expressway ring, characterized by dense commercial facilities and well-developed transport networks; the Middle Urban Zone, situated between the expressway ring and the outer ring road, serving mixed residential and commercial functions as a transitional belt between core and periphery; and the Outer Urban Zone, lying beyond the outer ring road, dominated by residential land use with relatively sparse retail outlets. These three zones differ markedly in retail facility density, transport conditions, and population distribution, providing an analytical basis for comparing the heterogeneous effects of O2H.

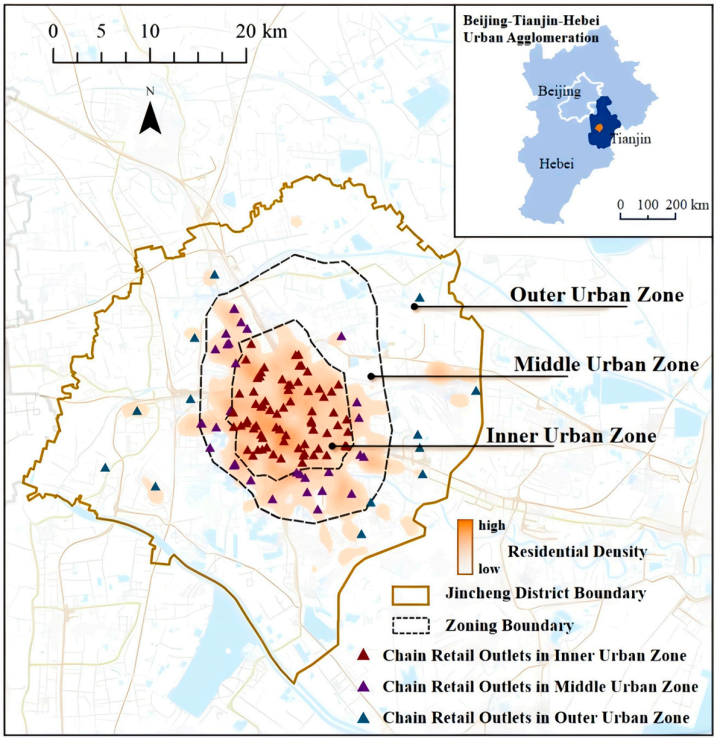


Figure 2. Study area delineation and base data.

The research objects are large-format hypermarket chains operating in Jincheng in 2023, comprising Carrefour (5 stores), Walmart (1), Yonghui (1), CR Vanguard (22), Renrenle (4), and Wumart (35)—68 outlets in total. Hypermarket chains represent a retail format with high O2H penetration, where both O2H and OIS acquisition modes coexist, making them well suited for capturing regional differences in efficiency gains.

3.3. Data Sources

The data used in this study comprise two components: dependent variable data and independent variable data (Table 2).

Table 2. Variables and data sources.

Variable Type	Variable Name	Calculation Method	Data Source	Processing
Environmental factors	Efficiency gain (Y)	GAE(O2H) − GAE(OIS)	-	-
Environmental factors	Economic level (X1)	Total GDP within 1 km × 1 km grid	RESDC, CAS [66,67]	Z-score
	Consumption level (X2)	Mean housing price at township/subdistrict level	Lianjia.com https://tj.lianjia.com (Accessed on 12 April 2024)	Z-score
Environmental factors	Road network density (X3)	Mean road density at township/subdistrict level	ArcGIS 10.8 extraction	-
	Bus route density (X4)	Mean bus route density at township/subdistrict level	ArcGIS 10.8 extraction	-
	Metro line density (X5)	Mean metro line density at township/subdistrict level	ArcGIS 10.8 extraction	-
	Bus stop count (X6)	Number of bus stop POIs at township/subdistrict level	Amap API	-
	Metro network density (X7)	Mean metro network density at township/subdistrict level	ArcGIS 10.8 extraction	-
	Primary road density (X8)	Mean primary road density at township/subdistrict level	ArcGIS 10.8 extraction	-
	Sidewalk density (X9)	Mean sidewalk density at township/subdistrict level	ArcGIS extraction	-
Environmental factors	Floor area ratio (X10)	Mean FAR at township/subdistrict level	ArcGIS 10.8 extraction	-
	Green space coverage (X11)	Mean green coverage at township/subdistrict level	ArcGIS 10.8 extraction	Z-score
	Healthcare facility count (X12)	Number of healthcare POIs at township/subdistrict level	Amap API	-
	Park count (X13)	Number of park POIs at township/subdistrict level	Amap API	-
	Residential community count (X14)	Number of residential community POIs at township/subdistrict level	Amap API	-
	Educational facility count (X15)	Number of school POIs at township/subdistrict level	Amap API	-
	Commercial facility count (X16)	Number of commercial center POIs at township/subdistrict level	Amap API	-
	Parking space count (X17)	Number of parking POIs at township/subdistrict level	Amap API	-

Table 2. *Cont.*

Variable Type	Variable Name	Calculation Method	Data Source	Processing
Environmental factors	Residential building count (X18)	Mean number of residential buildings at township/subdistrict level	ArcGIS 10.8 extraction	Z-score
	Household count (X19)	Mean number of households at township/subdistrict level	ArcGIS 10.8 extraction	Z-score

Note: GDP data are from 2020; road network data are from 2022; housing prices, POI data, and supermarket information are from 2023. RESDC = Resource and Environment Science and Data Center; CAS = Chinese Academy of Sciences.

Dependent variable data. Calculation of the Goods Acquisition Efficiency (GAE) relies on the following data: (1) Travel time under the OIS mode was calculated based on road network data. Mode shares were determined by travel distance following the empirical findings from [68]: walking dominates for short distances (0–2 km), walking and cycling share for medium distances (2–4 km), and car use dominates for longer distances (>4 km). Since the distribution of travel distances varies across zones, mode shares naturally differ across areas. In addition, In-store shopping time was obtained through field surveys at 1–2 representative chain supermarkets per zone. Observations were conducted over one week covering both weekdays and weekends, yielding 178 valid records. The sampled stores were all medium-to-large outlets with comparable floor areas to control for the effect of store size on shopping duration. Given the standardized operations of chain supermarkets—with similar store layouts and service processes—in-store shopping time exhibits relatively low variance across outlets of the same brand and scale. (2) O2H delivery time data were collected from Ele.me, Meituan, and brand mini-programs using a web scraping tool (Huoche Collector) between June and September 2024. Data collection spanned 7 days, covering various times during weekdays, yielding 7666 valid records (Inner Urban Zone: 4216; Middle Urban Zone: 1293; Outer Urban Zone: 2157). The data represent average delivery performance without differentiating peak and off-peak hours; instant delivery platforms employ dynamic scheduling algorithms to maintain relatively stable delivery times across periods. Online shopping time was obtained from platform statistics.

Independent variable data. Independent variables span three categories: economic, transportation, and environmental factors. Economic factors include spatially distributed GDP data from the Resource and Environment Science and Data Center, Chinese Academy of Sciences, and housing price data from Lianjia.com. Transportation factors—road network density, bus route density, metro line density, and others—were extracted from road network datasets using ArcGIS. Environmental factors include floor area ratio, green space coverage, and counts of various facilities (healthcare, parks, residential communities, educational institutions, commercial centers, and parking). Facility POI data were retrieved via the Amap API, while floor area ratio and green coverage were derived from remote sensing imagery using ArcGIS. The study area was partitioned into 1 km × 1 km grid cells using the ArcGIS Fishnet tool as the basic spatial unit; independent variables were aggregated at the township/subdistrict level and then assigned to corresponding grid cells. Selected variables underwent Z-score standardization.

3.4. Methods

3.4.1. Goods Acquisition Efficiency Model

Goods Acquisition Efficiency (GAE) measures the time efficiency from the moment a consumer decides to shop until the goods are obtained. We quantify efficiency through the

weighted sum of time required to acquire goods and express it in relative terms to enable cross-regional and cross-mode comparisons. GAE is calculated as:

$$GAE = 1 - \frac{T_{weighted}}{T_{max}} \quad (1)$$

where $T_{weighted}$ is the weighted total time for goods acquisition, and T_{max} is the maximum observed value across all samples. A GAE value closer to 1 indicates greater time savings.

Time composition. The time required to obtain goods differs by mode (Figure 3). Under OIS, consumers travel to retail outlets themselves; acquisition time comprises travel time and in-store shopping time. Under O2H, consumers place orders via online platforms and await delivery; acquisition time comprises delivery time and online shopping time.

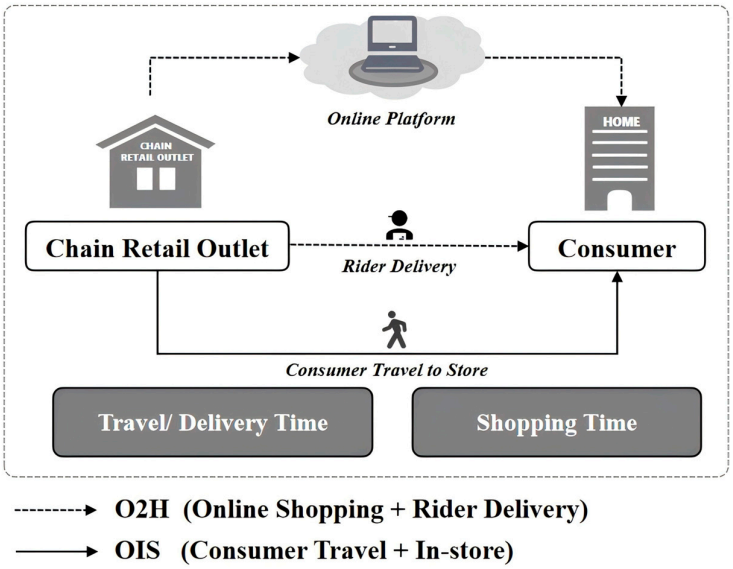


Figure 3. Time composition of OIS and O2H modes.

Entropy weighting. Because each time component contributes differently to overall efficiency, we applied the entropy weight method to determine weights objectively. This approach assigns higher weights to components with greater dispersion, as they explain more of the inter-regional variation in efficiency. Weighted times for the two modes are calculated as follows:

$$T_{OIS} = \omega_1 \cdot T_{Travel} + \omega_2 \cdot T_{shopping_offline} \quad (2)$$

$$T_{O2H} = \omega_3 \cdot T_{delivery} + \omega_4 \cdot T_{shopping_online} \quad (3)$$

where ω_i denotes the entropy weight for each component, derived from time data across 68 retail outlets (Table 3). T_{max} is set to the maximum weighted total time observed across both modes, ensuring comparability under a unified benchmark.

Table 3. Entropy weights of time components.

Mode	Travel	Shopping (Offline)	Delivery	Shopping (Online)
OIS	0.370	0.63	-	-
O2H	-	-	0.381	0.619

Efficiency gain calculation. The dependent variable in this study is the efficiency gain of O2H over OIS:

$$Efficiency\ Gain = GAE_{O2O} - GAE_{OIS} \quad (4)$$

Efficiency gain represents the extent to which O2H reduces the time consumers spend acquiring goods compared with OIS.

Sensitivity analysis. To test the robustness of the efficiency measurement, we also calculated the time saving ratio as an alternative measure:

$$\text{Time Saving Ratio} = \frac{T_{OIS} - T_{O2H}}{T_{OIS}} \quad (5)$$

where T_{OIS} and T_{O2H} represent the total acquisition time (travel/delivery time + shopping time) under OIS and O2H modes, respectively. This measure directly compares the raw time difference without entropy weighting, providing a robustness check for the main analysis.

3.4.2. XGBoost Model

To identify key factors influencing efficiency gains, we employed XGBoost (Extreme Gradient Boosting) to establish quantitative relationships between efficiency gains and spatial factors [69]. XGBoost is a gradient-boosting ensemble algorithm that iteratively constructs multiple decision trees and combines them through weighted aggregation, offering advantages in handling high-dimensional features and capturing nonlinear relationships [70].

The dataset was split into training and test sets at an 8:2 ratio. Given the distinct data characteristics across urban zones, model parameters were adjusted accordingly (Table 4). For the Middle Urban Zone, a transitional area with higher spatial heterogeneity, stronger regularization (max_depth = 6, reg_lambda = 1.0) was applied to mitigate overfitting. Additionally, Moran's I test was conducted to assess the spatial independence of model residuals and verify the appropriateness of random splitting for spatial data.

Table 4. XGBoost Model Parameters.

Urban Zone	n_estimators	learning_rate	max_depth	subsample	colsample_bytree	reg_lambda (L2)
Inner Urban Zone	1000	0.01	10	0.8	0.8	0.2
Middle Urban Zone	500	0.02	6	0.3	0.3	1.0
Outer Urban Zone	1000	0.01	10	0.5	0.5	0.2

3.4.3. SHAP Analysis

The "black-box" nature of XGBoost makes it difficult to interpret relationships between input variables and outputs. To address this, we introduced SHAP (SHapley Additive exPlanations) to quantify each factor's contribution to efficiency gains. Rooted in the Shapley value from cooperative game theory, SHAP calculates the marginal contribution of each feature to model predictions, providing both global feature importance rankings and local single-sample explanations [71].

4. Results

4.1. Efficiency Comparison Across Regions

Using the Goods Acquisition Efficiency model, we calculated efficiency values for the three urban zones under both OIS and O2H modes. The results reveal significant differences between the two modes ($p < 0.001$).

In the Inner Urban Zone (Figure 4a), median efficiency values for OIS and O2H are 0.69 and 0.87, respectively, yielding an efficiency gain of 0.18. Retail outlets are densely distributed and transport is convenient in this zone; OIS already performs well, leaving limited room for O2H to add value. In the Middle Urban Zone (Figure 4b), median efficiency values are 0.60 for OIS and 0.80 for O2H, with an efficiency gain of 0.20. Retail service provision is relatively weaker here, and O2H effectively enhances goods acquisition efficiency through instant delivery. The Outer Urban Zone (Figure 4c) exhibits median efficiency values of 0.56 for OIS and 0.82 for O2H, producing an efficiency gain of 0.26—the highest among the three zones. Retail outlets are sparse in this area, and consumers face lengthy travel times under OIS; O2H substantially reduces the time needed to obtain goods.

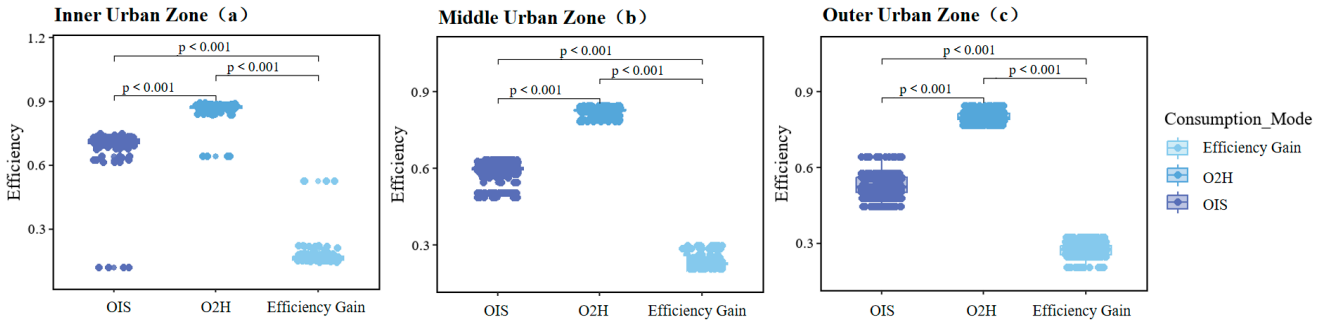


Figure 4. Efficiency gains across urban zones.

4.2. Efficiency Gain Spatial Distribution

4.2.1. Spatial Pattern of Efficiency Gains

Comparing the spatial distributions of GAE under OIS, O2H, and the resulting efficiency gains reveals contrasting concentric patterns: GAE under both OIS and O2H exhibits a "low-center, high-periphery" gradient, whereas efficiency gains show the opposite trend (Figure 5). These results indicate that O2H's efficiency benefits vary markedly across zones, with the most pronounced improvements occurring in peripheral areas where conventional retail coverage falls short.

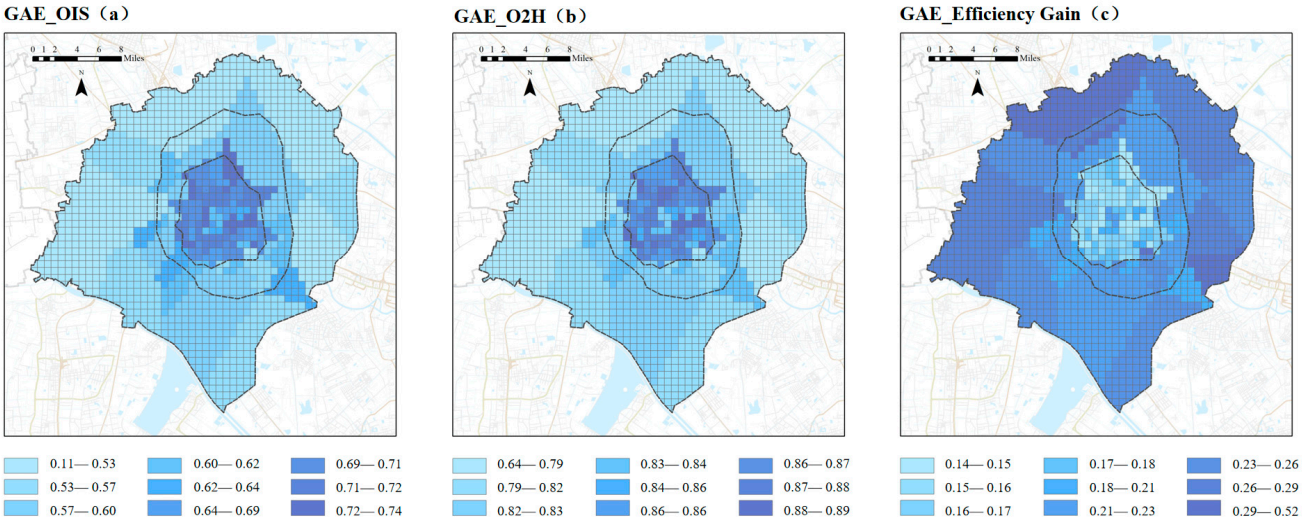


Figure 5. Spatial distribution of efficiency gains across urban zones.

Under OIS (Figure 5a), GAE displays a clear concentric gradient: higher in the Inner Urban Zone (0.64–0.74), declining in the Middle Urban Zone (0.53–0.64), and lowest in the Outer Urban Zone (0.11–0.57)—a pattern closely tied to denser retail networks and better transport infrastructure in the core. Under O2H (Figure 5b), GAE rises across all

zones: 0.72–0.74 in the Inner Urban Zone, 0.64–0.80 in the Middle Urban Zone, and the largest gains in the Outer Urban Zone (0.64–0.83). Instant delivery under O2H compensates for sparse retail provision in peripheral areas. The spatial distribution of efficiency gains (Figure 5c) confirms that the Outer Urban Zone benefits most (0.23–0.52), the Inner Urban Zone least (0.05–0.15), with the Middle Urban Zone falling in between (0.10–0.30).

The results reveal a low in core, high in periphery spatial pattern of efficiency gains. The Inner Urban Zone has dense retail outlets and high accessibility, making OIS already efficient with limited marginal contribution from O2H. The Outer Urban Zone has sparse retail networks and longer travel distances, where O2H significantly reduces goods acquisition time, yielding the highest efficiency gains. The Middle Urban Zone exhibits transitional characteristics. Therefore, retail network optimization should consider regional differences: enhancing delivery networks in peripheral areas while focusing on integrating offline retail with O2H services in the urban core.

4.2.2. Robustness Check

To verify the robustness of the concentric pattern, we calculated the time saving ratio as an alternative measure. As shown in Table 5, the concentric pattern persists: the time saving ratio increases from 56.8% in the Inner Urban Zone to 69.6% in the Outer Urban Zone, confirming that the low in core, high in periphery pattern is robust to the choice of efficiency measurement approach.

Table 5. Sensitivity analysis of efficiency gains.

Urban Zone	Efficiency Gain (Entropy Weight)	Time Saving Ratio/%
Inner Urban Zone	0.18	56.8
Middle Urban Zone	0.2	62.6
Outer Urban Zone	0.26	69.6

4.3. Feature Importance Analysis

4.3.1. XGBoost Model Fitting Result

Table 6 presents the XGBoost model fitting results for the three urban zones.

Table 6. XGBoost model performance by urban zone.

	Inner Urban Zone				Middle Urban Zone				Outer Urban Zone			
Metric	**MAE**	**RMSE**	**MAPE**	**R^2**	**MAE**	**RMSE**	**MAPE**	**R^2**	**MAE**	**RMSE**	**MAPE**	**R^2**
Training	0.000	0.001	0.003	1.000	0.003	0.005	0.051	0.923	0.002	0.003	0.041	0.988
Test set	0.014	0.023	0.028	0.864	0.009	0.013	0.034	0.509	0.007	0.012	0.045	0.719

The XGBoost model performs well in the Inner and Outer Urban Zones, with training/test R^2 values of 1.000/0.864 and 0.988/0.719, respectively. These results indicate that the model not only fits the training data closely but also generalizes reasonably well, effectively capturing efficiency gains and their associated factors in these two zones. However, the Middle Urban Zone shows lower explanatory power, with training R^2 of 0.923 and test R^2 of 0.509. This is consistent with its transitional location, mixed functions, and higher spatial heterogeneity. Accordingly, the analysis for the Middle Urban Zone should be considered exploratory.

To assess the spatial independence of model residuals, Moran's I tests were conducted for each zone (Table 7).

Table 7. Moran's I test for model residuals.

Zone	Moran's I	*p*-Value	Spatial Autocorrelation
Inner Urban Zone	0.002	0.281	Not significant
Middle Urban Zone	0.398	<0.001	Significant
Outer Urban Zone	0.141	<0.001	Significant

The Inner Urban Zone shows no significant spatial autocorrelation in residuals, indicating adequate model specification. The Middle and Outer Urban Zones exhibit significant positive spatial autocorrelation in residuals, suggesting that the model may not fully capture all spatial factors influencing efficiency gains in these areas. Future research could employ spatial regression techniques or geographically weighted methods to address this spatial dependence.

4.3.2. Feature Importance Results

Analysis of key factors associated with efficiency gains reveals that different zones are dominated by different variables (Figure 6).

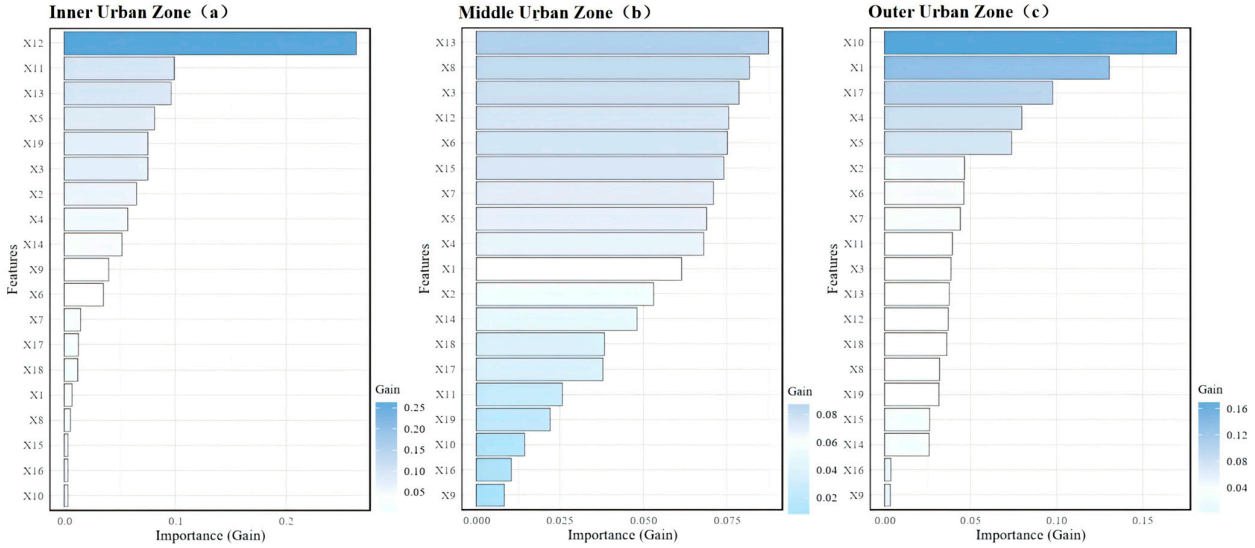


Figure 6. Feature importance rankings for efficiency gains by urban zone.

The key factors associated with efficiency gain differ notably across zones. In the Inner Urban Zone, efficiency gain is closely linked to healthcare facility count (X12), green space coverage (X11), park count (X13), and metro line density (X5), with public services and environmental factors as the primary drivers. In the Middle Urban Zone, park count (X13), primary road density (X8), road network density (X3), and healthcare facility count (X12) are the leading factors, reflecting a balance between environmental and transportation elements. In the Outer Urban Zone, floor area ratio (X10), economic level (X1), parking space count (X17), and bus route density (X4) dominate, indicating the combined influence of development intensity, economic conditions, and transportation accessibility. Regarding feature distribution, the Inner Urban Zone (Figure 6a) and Outer Urban Zone (Figure 6c) show concentrated feature importance, with a few key factors explaining most of the variance in efficiency gain. By contrast, the Middle Urban Zone (Figure 6b) exhibits a more dispersed pattern with no clearly dominant factor, consistent with its mixed-use character and higher spatial heterogeneity.

4.4. SHAP Dependence Analysis

4.4.1. Overall Distribution of Feature Contributions

SHAP summary plots further reveal the direction and magnitude of each feature's contribution to efficiency gain predictions (Figure 7).

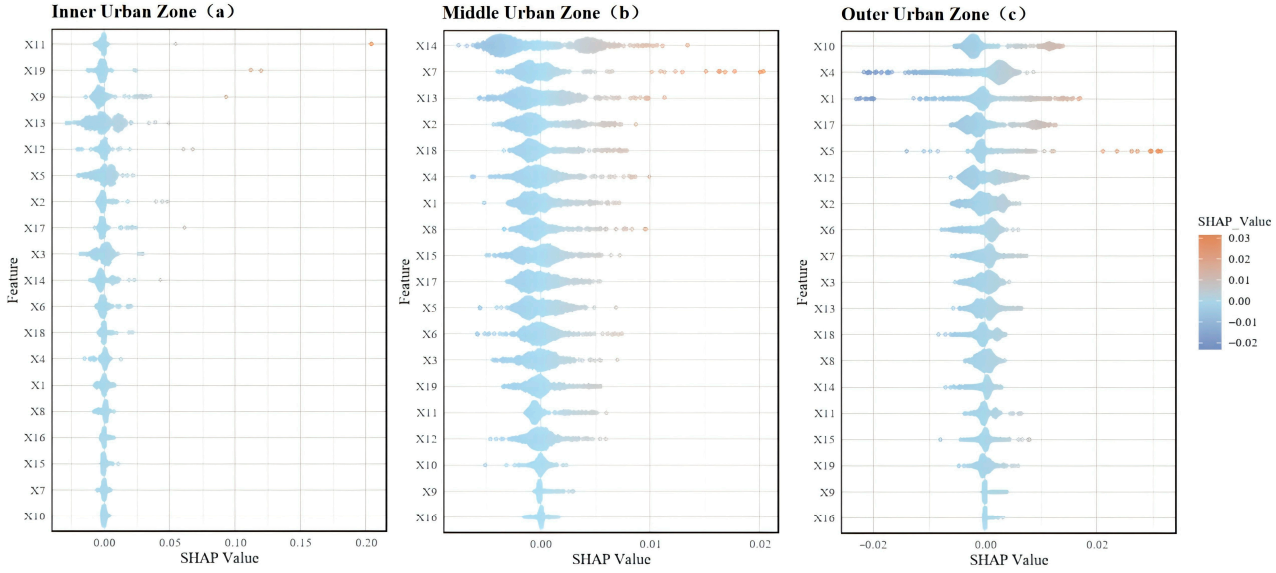


Figure 7. SHAP summary plots by urban zone.

In the Inner Urban Zone (Figure 7a), SHAP values for all features span a narrow range, indicating stable efficiency gain predictions. In terms of contribution direction, green space coverage (X11) and household count (X19) show positive associations—high feature values correspond to positive SHAP values. Sidewalk density (X9) and park count (X13) also exhibit consistent contribution directions, suggesting that the relationships between spatial factors and efficiency gains are relatively clear-cut in this zone. In the Middle Urban Zone (Figure 7b), SHAP values span a wider range and contribution directions diverge. For residential community count (X14), metro network density (X7), park count (X13), and consumption level (X2), the same feature value may yield either positive or negative contributions, reflecting more complex mechanisms underlying efficiency gains—a pattern that echoes the overfitting observed in Section 4.3.1. In the Outer Urban Zone (Figure 7c), a few features display SHAP value ranges substantially larger than the rest, with pronounced differences in contribution magnitude. Floor area ratio (X10) and bus route density (X4) exert far stronger influence than other variables, and their feature values align consistently with positive contributions, indicating that infrastructure conditions are the key drivers of efficiency gains in peripheral areas.

4.4.2. Influence Patterns of Key Features

SHAP dependence plots illustrate how individual features affect efficiency gains across zones (Figure 8). The relationships between features and efficiency gains are nonlinear: some features exhibit saturation effects, while others display clearer patterns of diminishing or increasing marginal returns.

In the Inner Urban Zone (Figure 8a), the SHAP value for green space coverage (X11, standardized value) reaches its peak SHAP value at approximately 1.5 standard deviations above the mean. Household count (X19) maintains a persistent positive association with efficiency gains, suggesting that densely populated areas benefit from greater service coverage. Sidewalk density (X9) shows diminishing marginal effects beyond a density of 5.5. Park count (X13) stabilizes once density exceeds 0.75 per km^2.

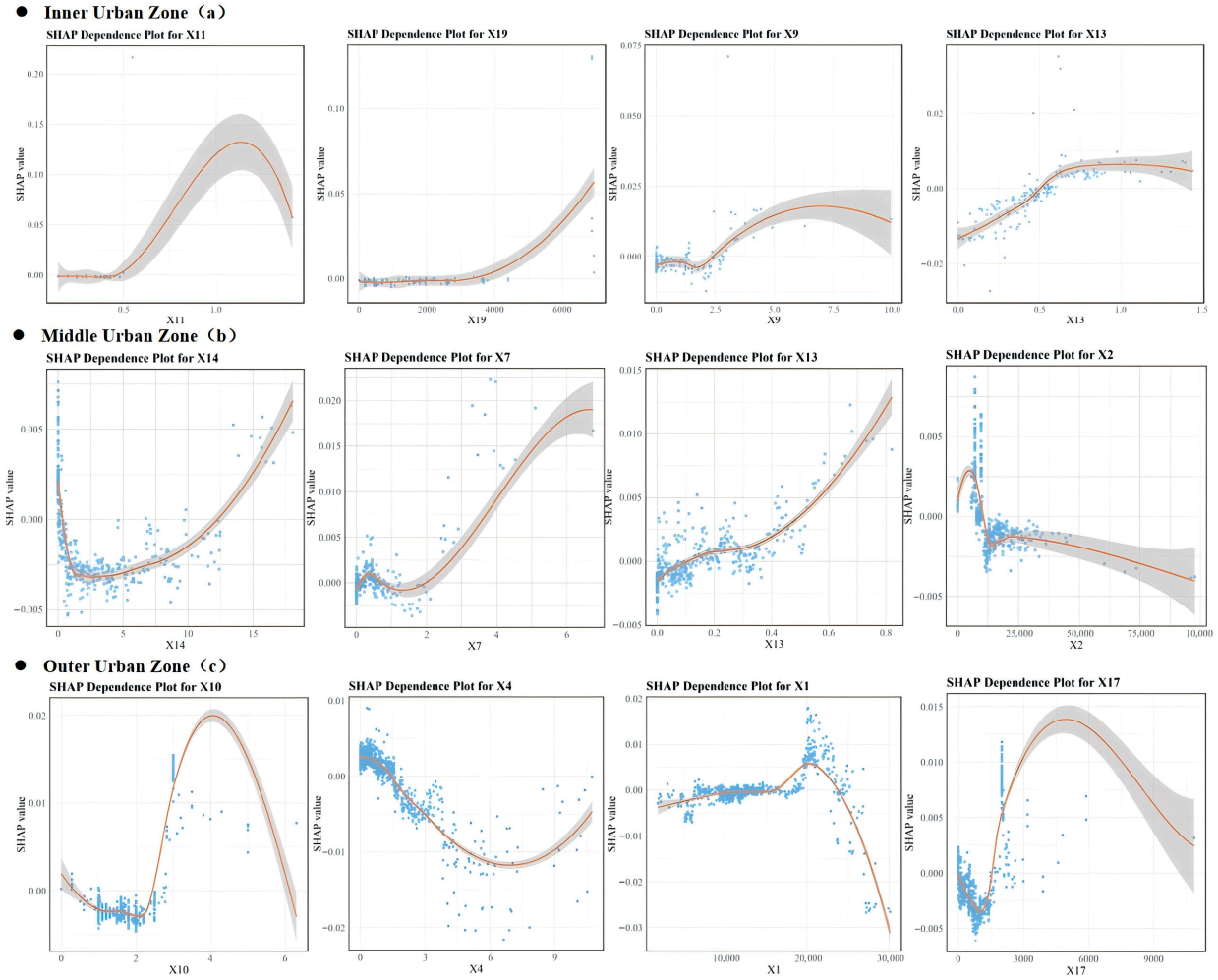


Figure 8. SHAP dependence plots for the top four features by urban zone. Blue dots represent individual observations; the orange line indicates the fitted trend (LOESS smoothing); the grey shaded area represents the 95% confidence interval.

In the Middle Urban Zone (Figure 8b), residential community count (X14) turns positively associated with efficiency gains once it exceeds 2.5 per km^2. Metro network density (X7) likewise shifts to a positive association beyond 0.75, indicating that a well-connected rail network can substantially improve goods acquisition efficiency in this zone. Park count (X13) stabilizes after exceeding 0.2 per km^2. Consumption level (X2) exhibits an inverted-U relationship, rising initially before declining. Given the model's limited explanatory power for this zone, these patterns warrant further verification in future research.

In the Outer Urban Zone (Figure 8c), floor area ratio (X10) traces an N-shaped curve, with the strongest positive association occurring in the 2–4 range—suggesting that moderately dense development facilitates efficiency gains. Bus route density (X4) is initially negatively associated with gains but turns positive once density exceeds 7, reflecting that bus systems deliver convenience benefits only after reaching a threshold coverage level. Economic level (X1) sees declining SHAP values once GDP surpasses 20,000 yuan. Parking space count (X17) is positively associated with efficiency gains within the 1300–4500 spaces per km^2 range, indicating that adequate parking provision effectively reduces consumer travel costs.

5. Discussion

5.1. Explaining Regional Differences in Efficiency Gains

The rise of O2H is shifting the configuration objective of urban retail space from "accessibility" to "efficiency." From this perspective, efficiency gains reflect the degree to which O2H improves upon OIS in the time dimension, and the magnitude of such improvement depends on how well-developed existing retail provision already is.

Our findings reveal a concentric pattern of efficiency gains—low in the core (0.18) and high in the periphery (0.26). This result aligns with existing research on the spatial distribution of online shopping. A substantial body of literature indicates that urbanization level, retail facility density, and transport conditions significantly influence residents' online consumption behavior: areas close to commercial centers with high road density and convenient transport exhibit lower e-shopping participation [71–73], whereas rural and suburban residents are more inclined to rely on online channels [74]. Meanwhile, the spatial evolution of retail formats reinforces this pattern—large-format chain retailers have expanded into suburban areas, while central districts have developed more competitive retail clusters driven by the "retail revolution" and logistics innovation [75–77]. By adopting an efficiency-gain lens, this study provides fresh empirical evidence for understanding how O2H performs across different urban zones.

The concentric pattern of efficiency gains can be interpreted through the "Accessibility Hypothesis." Accessibility research suggests that when public transport and retail facilities are inadequate, consumers tend to rely on online channels to compensate for gaps in physical retail access [78–80]. Our results reflect a similar mechanism: in the Inner Urban Zone, dense retail networks and convenient transport mean that OIS already achieves high GAE (median 0.69), leaving limited room for O2H to add value. In the Outer Urban Zone, by contrast, sparse retail outlets and high travel costs result in markedly lower OIS efficiency (median 0.56); instant delivery effectively compresses goods acquisition time, yielding greater efficiency gains. Prior literature characterizes this phenomenon as "compensatory distribution" [58]—the time-efficiency advantage of online instant delivery is most pronounced in areas with weak retail infrastructure [81,82].

Regarding the relationship between O2H and OIS, our efficiency-gain results reveal differentiated functional roles across urban zones. High efficiency gains in the Outer Urban Zone suggest that O2H primarily serves a supplementary function where time costs are elevated. International research on multichannel retailing likewise indicates that online and offline channels are more often complementary than substitutive, particularly for suburban consumers who rely on online channels to enhance overall acquisition efficiency [83]. Empirical studies in Chinese cities similarly show that digital technology has fostered synergistic development of online and physical retail, with the two coexisting widely in large cities [84,85]. Moreover, channel relationships are notably dynamic: prior work demonstrates that complementarity and substitution evolve with income, city size, and technology adoption [86–89]. The complementary pattern observed here should therefore be understood as a structural feature of a particular period, subject to adjustment as O2H penetration and consumer habits evolve.

5.2. Implications for Retail Network Configuration

Our findings offer zone-differentiated guidance for configuring hypermarket chain store networks.

(1) Inner Urban Zone: Stabilize store layout and reinforce "experience + instant acquisition"

With relatively low O2H efficiency gains (0.18), OIS remains competitive in the Inner Urban Zone. Store networks can be kept stable, prioritizing locations with high population

density and good environmental quality to strengthen the experiential attributes and instant-access advantages of physical stores. Prior research offers useful guidance: digital technology has not diminished the value of physical stores but has instead fostered online-offline synergy, with brick-and-mortar outlets serving as "offline perception venues" that enhance overall consumer experience [90,91]. Inner-city stores may thus further emphasize a differentiated positioning of "experiential retail + instant fulfillment."

(2) Outer Urban Zone: Build a hybrid fulfillment system of "stores + micro-fulfillment centers"

The Outer Urban Zone registers the highest O2H efficiency gains (0.26), with instant delivery playing a pronounced gap-filling role. Store networks can be optimized in two ways: (i) in areas with better infrastructure (bus route density >7, floor area ratio 2–4), strengthen stores' O2H fulfillment capacity; (ii) in areas with weaker infrastructure, convert selected stores into micro-fulfillment centers to shorten delivery distances and boost fulfillment efficiency. Research has shown that micro-fulfillment models can significantly reduce delivery times, making them particularly suitable for low-density areas [16,92].

(3) Middle Urban Zone: Adopt a "flexible store strategy" tailored to local characteristics

Efficiency gains in the Middle Urban Zone are moderate (0.20), but influencing factors are dispersed and spatial heterogeneity is strong. Store configuration should be adjusted according to local conditions: where a subarea resembles the Inner Urban Zone (high density, good environmental quality), physical store stability can be maintained; where it resembles the Outer Urban Zone (high transport dependence, moderate development intensity), O2H fulfillment capacity should be strengthened.

(4) Implications for urban planning: O2H may accelerate spatial decentralization

The spatial adaptability of retail networks not only affects firm location decisions but may also reshape urban spatial structure in return. Farag noted that the spread of e-shopping may weaken the traditional accessibility-oriented logic of residential location choice, inclining households toward suburban areas [71]. Our finding that O2H improves goods acquisition efficiency for suburban residents potentially reinforces metropolitan decentralization trends. Urban planners formulating land-use policies should give full consideration to how O2H may alter conventional retail patterns and urban structure.

6. Conclusions

Taking Jincheng, the main urban area of Tianjin, as a case study, this research developed a Goods Acquisition Efficiency (GAE) index to quantify the efficiency gains of O2H over OIS and employed XGBoost combined with SHAP to identify spatial variations in gains and their associated factors. The main findings are as follows:

(1) O2H-induced efficiency gains exhibit a concentric pattern—low in the core and high in the periphery. The Inner Urban Zone records an efficiency gain of 0.18, the Middle Urban Zone 0.20, and the Outer Urban Zone 0.26. Well-developed retail provision in the inner city leaves limited room for O2H to improve efficiency; weaker provision in peripheral areas allows instant delivery to fill a substantial time-efficiency gap.

(2) Key factors associated with efficiency gains differ markedly across zones. Environmental attributes (green space coverage, park count, sidewalk density) predominate in the Inner Urban Zone, while transportation and economic factors (bus route density, floor area ratio, economic level) dominate in the Outer Urban Zone. These findings provide quantitative references for zone-specific store network configuration.

(3) O2H and OIS exhibit a complementary relationship across zones. In the Inner Urban Zone, OIS remains time-competitive, and physical stores can maintain relative

stability. In the Outer Urban Zone, O2H's supplementary role is pronounced; stores may strengthen delivery fulfillment capacity or transition toward micro-fulfillment functions.

This study has the following limitations. First, the study used time as the sole efficiency measure without considering economic costs, service quality, or consumer preferences; additionally, the in-store observation sample was limited in scale. Future research could incorporate multi-dimensional indicators and expand the sample size. Second, the Middle Urban Zone model showed limited explanatory power (test $R^2 = 0.509$), and residuals in the Middle and Outer Urban Zones exhibited spatial autocorrelation, indicating that the current variables and tri-zone classification may not fully capture the complex spatial mechanisms. Future research could explore spatial regression methods or finer spatial zoning approaches. Additionally, the implementation of micro-fulfillment strategies in the Outer Urban Zone faces practical constraints including limited courier capacity, underdeveloped logistics infrastructure, and zoning regulations. Future planning should consider these local conditions. Third, this study uses Tianjin as the empirical case. As a typical city with concentric development patterns, Tianjin's "core agglomeration–peripheral expansion" spatial structure is representative of many large and medium-sized Chinese cities. Nevertheless, cities vary in retail network density and delivery system maturity, and future research could extend the applicability of these findings through multi-city comparative studies.

This study makes the following contributions: first, it proposes the Goods Acquisition Efficiency (GAE) index, providing a quantifiable and replicable framework for comparing efficiency between O2H and OIS modes; second, it reveals the concentric pattern of efficiency gains, extending the research perspective on spatial heterogeneity in O2O retail; third, it identifies the key factors associated with efficiency gains in different zones, offering empirical evidence for differentiated retail network planning. Overall, the efficiency advantage of O2H mode is most significant in the Outer Urban Zone where retail coverage is weak. This compensatory effect provides a new perspective for understanding the spatial relationship between O2H and traditional retail, and the GAE index and zonal comparison framework proposed in this study can serve as methodological references for retail network optimization in other cities.

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