What We Lose, What We Gain: Spatio-temporal Patterns of Lost-and-Found Items in Qingdao Metro

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Abstract

Lost-and-found records in urban metro systems constitute an underexploited data source that reflects both passenger behavior and transit operational processes. This study analyzes 34,333 lost-and-found records from 173 stations across 8 lines of the Qingdao Metro system in China over 15 months (July 2024–September 2025). Items are reclassified into nine standardized categories, with Daily Necessities (47.3%) and Clothing & Accessories (30.6%) predominating. By normalizing item counts against station-level ridership (system annual ridership $\sim$530 million), we establish monthly loss rates ranging from 0.17 to 0.66 items per 10,000 passengers, with summer peaks driven by tourism. A calendar regression with weekday and monthly controls ($R^2 = 0.467$) reveals that national holidays significantly elevate daily counts—Labor Day by +70.8 items/day ($p < 0.001$) and Golden Week by +41.7 items/day ($p < 0.001$)—while Chinese New Year shows no significant effect. Spatially, Global Moran's I is non-significant

($I = -0.003$, $p = 0.376$), indicating that item accumulations are driven by station-specific attributes rather than spatial diffusion. A negative binomial regression identifies terminal-station status (IRR$= 9.93$, $p < 0.001$) and transfer-station status (IRR$= 11.03$, $p = 0.019$) as the strongest predictors of item counts, an effect we attribute primarily to end-of-line crew inspections rather than passenger behavior alone. PCA-based k-means clustering ($k = 4$) yields a four-type station typology that aligns with functional roles. These findings reframe lost-and-found data as an operational indicator for transit management and offer actionable insights for resource allocation in metro lost-property services.

Keywords: lost-and-found; metro operations; spatio-temporal analysis; negative binomial regression; station typology; Qingdao

Word count: 8,200 words + 14 figures + 4 tables = 8,200 + 4,500 = 12,700 equivalent

1 Introduction

Urban metro systems carry hundreds of millions of passengers annually and generate vast quantities of operational data. While smart-card tap records, automatic passenger counters, and vehicle telemetry have been extensively mined for insights into travel demand, network performance, and passenger behavior (Ma et al., 2013; Pelletier et al., 2011), one routine data stream has received almost no scholarly attention: lost-and-found records. Every day, passengers leave behind umbrellas, water bottles, bags, identity documents, and electronic devices on trains and platforms. Transit agencies log these items as part of standard operating procedures, creating longitudinal administrative datasets that encode information about when, where, and what passengers lose—and, crucially, where and how operational staff recover those items.

Lost-and-found data occupy an unusual position at the intersection of passenger behavior and transit operations. On the one hand, the act of losing an item is a behavioral event influenced by trip purpose, crowding, fatigue, distraction, and the physical design of the vehicle and station environment. On the other hand, the act of *finding and logging* an item is an operational event shaped by crew inspection protocols, cleaning schedules, and end-of-line turnback procedures. This duality means that lost-and-found records cannot be interpreted purely as a map of "where passengers lose things"; they are, more precisely, a map of where the transit system's recovery apparatus intersects with passenger forgetfulness. Failure to recognize this distinction risks misattributing operational patterns—such as the concentration of found items at terminal stations—to passenger behavior.

Despite this analytical richness, lost-and-found data have been almost entirely absent from the transportation research literature. A small number of practitioner reports and news articles have described the composition of lost items in individual transit systems, but to our knowledge, no peer-reviewed study has systematically examined the spatio-temporal patterns of logged lost-and-found entries across an entire metro network, controlled for ridership exposure, modeled station-level predictors, or developed a station typology based on item profiles. This gap is surprising given the growing interest in "non-traditional" data sources for urban analytics (Batty, 2013; Liu et al., 2015; Yuan et al., 2012) and the practical importance of lost-property management for passenger satisfaction and operational cost.

This study addresses the gap by analyzing 34,333 lost-and-found records collected across all 173 stations and 8 lines of the Qingdao Metro system in Qingdao, China, over a 15-month period from July 2024 to September 2025. Qingdao is a coastal city of approximately 10 million residents with a rapidly expanding metro network that carried roughly 530 million passenger trips during the study period. The dataset is comprehensive: it covers every item logged by station staff into the system-wide lost-and-found database, with fields for item category, station, date, and line.

We pursue three research questions:

1. **Temporal patterns:** How do lost-and-found item counts vary across months, days of the week, and national holidays, after controlling for ridership exposure and calendar effects?

2. **Spatial patterns:** How are lost-and-found items distributed across the metro network, and do item concentrations exhibit spatial autocorrelation or reflect station-specific attributes?

3. **Station-level predictors:** What station characteristics—including terminal status, transfer status, surrounding land use, and network position—best predict the volume of lost-and-found items, and can stations be classified into meaningful typologies based on their item profiles?

Methodologically, we combine ridership-normalized rates, a regression-based calendar regression with weekday and monthly controls, kernel density estimation (KDE), spatial autocorrelation analysis (Moran's I and LISA), negative binomial regression, and PCA-based k-means clustering. A key contribution is our explicit treatment of the distinction between where items are *lost* and where they are *found and logged*, which leads us to reinterpret the dominant role of terminal stations not as a behavioral phenomenon but as an operational one rooted in end-of-line crew inspections.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on metro passenger behavior, station classification, and non-traditional data sources. Section 3 describes the study area, data sources, and preprocessing. Section 4 presents the methodology.

Section 5 reports the results. Section 6 discusses implications, limitations, and the operational reinterpretation of terminal-station effects. Section 7 concludes.

2 Literature Review

2.1 Metro Passenger Behavior and Trip-End Dynamics

Understanding how passengers interact with metro systems has been a central concern of transportation research for decades. Smart-card data have enabled fine-grained analyses of travel patterns, revealing regularities in commuting behavior (Ma et al., 2013; Zhong et al., 2016), temporal rhythms of ridership (Briand et al., 2017), and the spatial structure of urban movements (González et al., 2008; Roth et al., 2011). These studies have established that passenger behavior is strongly shaped by trip purpose (commuting versus leisure), time of day, and the built environment around stations (Ewing and Cervero, 2010; Lee et al., 2012).

A recurring finding is that behavior at trip ends—boarding and alighting—differs qualitatively from behavior during the journey. Passengers are more attentive when boarding (oriented toward a goal) and more relaxed or distracted when alighting (goal achieved), which may increase the likelihood of forgetting belongings at the destination end of a trip (Sun and Axhausen, 2016). However, this behavioral hypothesis has never been tested with lost-and-found data, and it overlooks the operational reality that items left on trains are typically recovered not at the alighting station but at the terminal station where crew inspections occur.

Holiday and seasonal effects on transit ridership are well documented. Li et al. (2020) analyzed Shenzhen Metro smart card data during the Chinese Spring Festival, showing that holiday travel purposes differ fundamentally from non-holiday periods. Zhao et al. (2023) examined 3.3 million Beijing passengers across 120 days, finding that holidays significantly reduce travel regularity and shift spatial patterns. Tourism-driven ridership surges, common in Chinese cities during Golden Week and Labor Day, are expected to increase the volume of lost items both through higher passenger counts and through the presence of unfamiliar travelers who may be more prone to distraction.

2.2 Station Classification and Functional Analysis

The classification of metro stations into functional types has received considerable attention, typically using ridership data, land-use characteristics, or smart-card travel patterns as inputs. Lyu et al. (2021) developed TOD typologies across five Chinese megacities, identifying six station types with spatial patterns declining from city center to outskirts. Zhou et al. (2022) classified 278 Beijing stations into six risk categories using k-means clustering on smart card data, demonstrating that operational data can yield meaningful station typologies. Rong et al. (2025) used embedding representations of POI categories to classify Shanghai metro station areas into nine functional groups. POI (point-of-interest) data have emerged as a convenient proxy for land-use mix and intensity around stations (Tu et al., 2017; Yuan et al., 2012), enabling classification without costly field surveys.

These station typologies are typically constructed from demand-side variables (ridership, land use) rather than supply-side or operational variables. Lost-and-found item profiles offer a complementary perspective: the composition of items found at a station (e.g., a high share of transit cards versus documents versus electronics) may reveal aspects of station function—commuter hub, tourist destination, residential terminus—that are not fully captured by conventional ridership or land-use metrics. No prior study has attempted a station typology based on lost-and-found item composition.

The role of terminal stations deserves special mention. In operational practice, terminal stations are where trains reverse direction and crew members conduct interior inspections, collecting any items left by passengers along the entire preceding run. This means that terminal stations systematically accumulate items lost at *any* upstream station, creating a mechanical concentration effect that is entirely operational in origin. Kim and Choi (2008) noted functional differences between terminal and intermediate stations in terms of ridership patterns, but the operational implications for item recovery have not been examined.

2.3 Non-Traditional Data Sources in Transportation Research

The past decade has seen growing interest in leveraging non-traditional data sources to understand urban mobility and transportation systems (Batty, 2013). Taxi GPS traces have been used to infer urban spatial structure and travel demand (Li et al., 2012; Liu et al., 2015). Dockless bike-sharing trip data have revealed first- and last-mile travel patterns and station-area accessibility (Chen et al., 2020; Jiang and Zhang, 2022). Mobile phone signaling data have been employed to estimate origin–destination matrices and detect activity patterns (Tu et al., 2017). Social media geotagged posts have been used to study tourism flows and event impacts (Hasan et al., 2013).

The only academic study to directly address lost property in public transport is Mensah et al. (2024), who surveyed 603 bus passengers in Accra about willingness to return found items—a behavioral and ethical perspective entirely distinct from data-driven spatial analysis. No peer-reviewed study has used operational lost-and-found records to examine spatio-temporal patterns, station characteristics, or system-level trends in any transit network worldwide.

Lost-and-found data share several characteristics with these non-traditional sources: they are generated as a byproduct of routine operations, are available at fine spatial and temporal resolution, and encode information about human behavior that is not captured by conventional survey instruments. However, lost-and-found data also differ in important ways. Unlike smart-card or GPS data, which record *deliberate* actions (tapping a card, hailing a ride), lost-and-found records capture *unintentional* events—moments of forgetfulness or carelessness. This makes them a window into a dimension of the passenger experience that is rarely studied: the friction, inconvenience, and minor failures that accompany everyday transit use. Furthermore, as argued above, lost-and-found data encode operational processes (crew inspections, cleaning schedules) as much as passenger behavior, making them jointly informative about both sides of the transit service equation.

3 Data and Study Area

3.1 Qingdao Metro System

Qingdao is a major coastal city in Shandong Province, eastern China, with a resident population of approximately 10 million. The city is a significant tourism destination, known for its European-influenced architecture, beaches, and annual beer festival. The Qingdao Metro system, which began operations in 2015, had expanded to 8 lines and 173 stations by the study period. The network includes urban core lines (Lines 1, 2, 3), suburban connectors (Lines 4, 6, 8), and two express services—the Blue Valley Express (serving the eastern suburban Jimo district) and the West Coast Express (connecting the Huangdao development zone). During the study period (July 2024–September 2025), the system carried approximately 530 million passenger trips (annual ridership of 53,054 wan, or roughly 1.45 million trips per day), making it a mid-sized Chinese metro system comparable to Nanjing or Chengdu.

Figure 1 shows the spatial layout of the Qingdao Metro network, with the 173 stations distributed across the urban core and extending into suburban and coastal areas. The system includes 16 terminal stations (end-of-line) and 16 transfer stations (where two or more lines intersect). Terminal stations are operationally significant because they are where trains reverse direction and crew members perform interior inspections of carriages.

3.2 Lost-and-Found Data

The primary dataset comprises 34,333 lost-and-found item records collected from the Qingdao Metro's centralized lost-property management system between July 2024 and September 2025 (15 months). Each record contains the item category, the station where the item was found and logged, the date, and the metro line. Items are logged by station staff when recovered during routine operations—including on-board crew inspections at terminal stations, platform sweeps, and passenger turn-ins at station offices.

The original item categories used by the Qingdao Metro were highly granular and inconsistent,

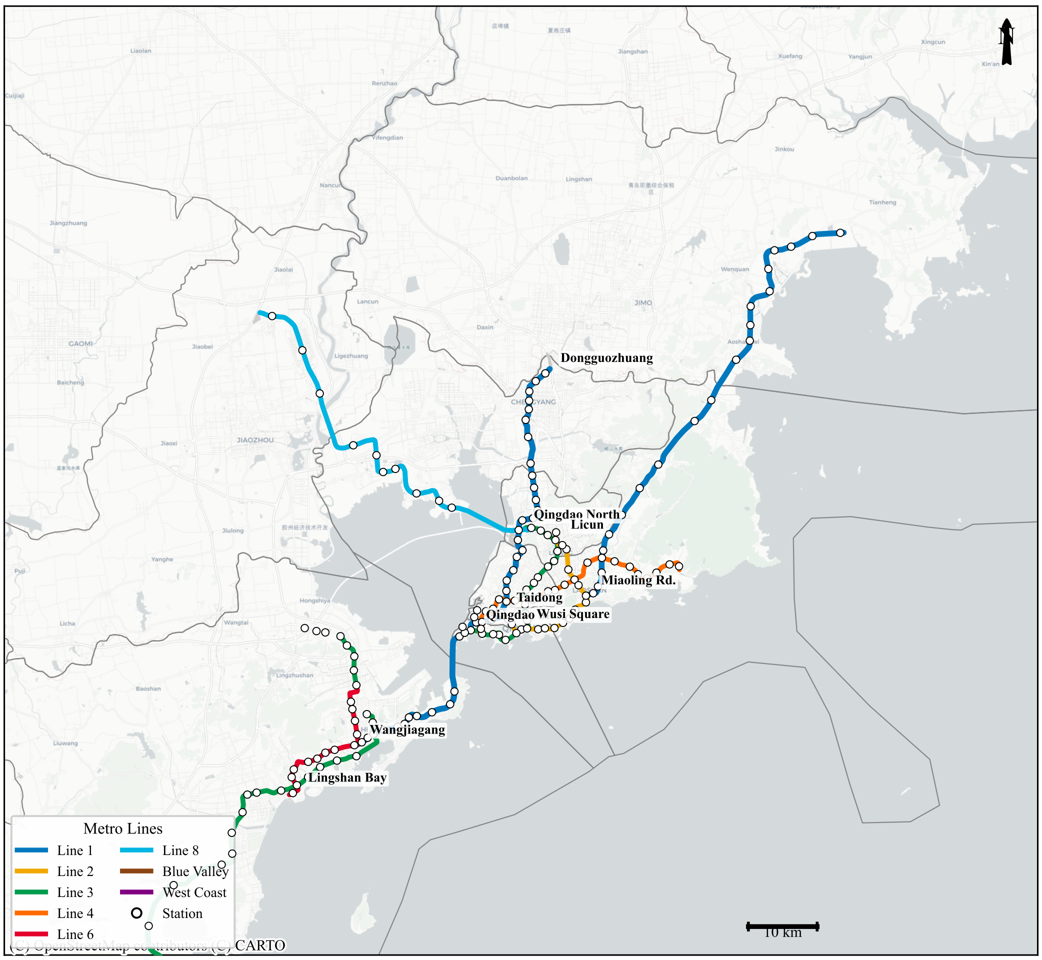

Figure 1: Study area: Qingdao Metro system with 8 lines and 173 stations. Terminal and transfer stations are highlighted.

with overlapping labels and ad-hoc descriptions. We reclassified all items into nine standardized categories based on functional similarity, as shown in Table 1. The two dominant categories—Daily Necessities (47.3%, including umbrellas, water bottles, bags, keys) and Clothing & Accessories (30.6%, including hats, scarves, gloves, eyeglasses)—together account for nearly 78% of all records. Documents & ID (8.9%) and Transit Cards (8.1%) are the next most common, followed by Electronics (2.6%), Cards (1.9%), Study & Culture (0.5%), Medical (0.1%), and Food & Delivery (0.03%).

Table 1: Reclassification of lost-and-found items into nine standardized categories.

Category	Representative items	Share (%)
Daily Necessities	Umbrellas, water bottles, bags, keys	47.3
Clothing & Accessories	Hats, scarves, gloves, eyeglasses	30.6
Documents & ID	ID cards, passports, certificates	8.9
Transit Cards	Metro cards, bus cards	8.1
Electronics	Mobile phones, chargers, earbuds	2.6
Cards	Bank cards, membership cards	1.9
Study & Culture	Books, notebooks, stationery	0.5
Medical	Medications, medical devices	0.1
Food & Delivery	Takeaway bags, food containers	0.03

Note: $N = 34{,}333$. Categories derived from functional reclassification of original Metro labels.

3.3 Supplementary Data

Three supplementary datasets were assembled to support the station-level analysis. First, monthly system-wide ridership figures were obtained from Qingdao Metro's published operational reports, enabling the computation of ridership-normalized loss rates. Annual line-level ridership estimates were also used to compute per-line rates. Second, POI data within an 800-meter buffer around each station were extracted from the Amap (Gaode) API, with POI counts and Shannon diversity indices computed for each station. Third, station-level attributes—including terminal status, transfer status, number of lines served, and Euclidean distance to the city center (defined as Qingdao Railway Station)—were compiled from official network maps and geographic coordinates. Table 2 presents descriptive statistics for the key variables.

Table 2: Descriptive statistics for station-level variables ($N = 173$).

Variable	Mean	SD	Min	Max	Median
Total lost items	198.3	554.9	0	5,630	72
POI count (800 m buffer)	353.3	463.8	0	2,819	170
POI diversity (Shannon)	2.2	0.8	0.0	3.5	2.4
Distance to center (km)	22.1	28.4	0.4	325.1	16.9
Line count	1.1	0.3	0	3	1
Terminal station (%)	9%	–	0	1	–
Transfer station (%)	9%	–	0	1	–

Note: POI diversity measured as Shannon entropy across POI categories. Distance to center measured from station centroid to Qingdao Railway Station.

4 Methodology

This section describes the five analytical approaches employed in this study, organized from temporal to spatial to multivariate. Figure 2 presents the overall research framework.

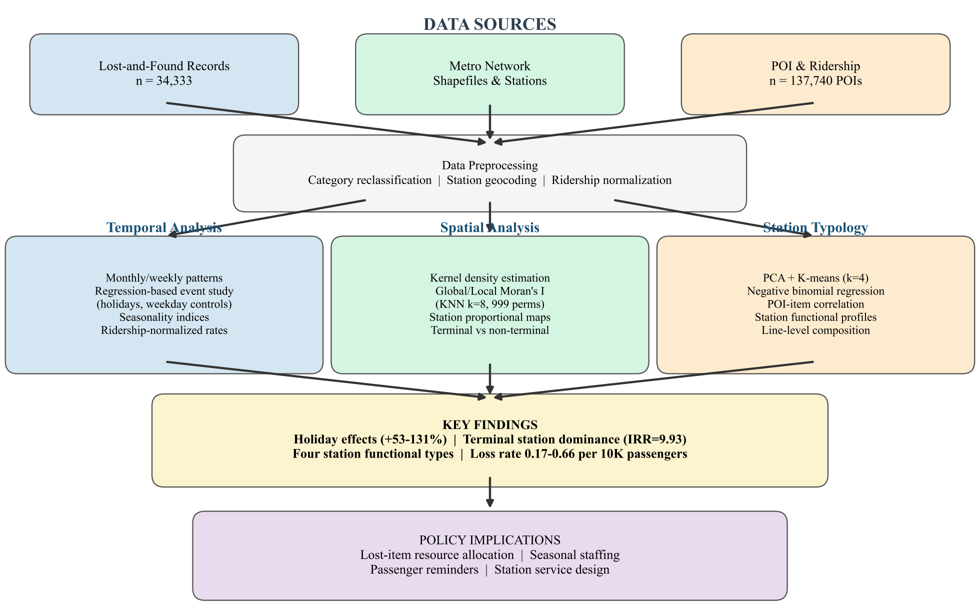

Figure 2: Research framework: from data collection through temporal, spatial, and multivariate analyses.

4.1 Ridership Normalization

Raw counts of lost-and-found items are confounded by ridership volume: stations and time periods with more passengers will mechanically produce more lost items. To address this, we normalize item counts by ridership to obtain loss rates expressed as items per 10,000 passengers. At the monthly level, the loss rate for month t is:

$$r_t = \frac{n_t}{R_t} \times 10{,}000 \tag{1}$$

where n_t is the number of items recorded in month t and R_t is the total system ridership in month t. At the line level, annual ridership figures are used because monthly line-level ridership data were not available. This normalization reveals whether temporal or cross-line variation in item counts reflects genuine differences in loss propensity or merely differences in passenger volume.

4.2 Temporal Analysis: Regression-Based Event Study

To isolate the effects of national holidays on daily lost-and-found counts while controlling for systematic calendar variation, we estimate a linear regression model of the form:

$$y_d = \alpha + \sum_{j=1}^{6} \beta_j \cdot \mathrm{DOW}_{d,j} + \sum_{m=1}^{11} \gamma_m \cdot \mathrm{Month}_{d,m} + \sum_{h=1}^{H} \delta_h \cdot \mathrm{Holiday}_{d,h} + \varepsilon_d \tag{2}$$

where y_d is the number of items recorded on day d; $\mathrm{DOW}_{d,j}$ are day-of-week fixed effects (Monday as reference); $\mathrm{Month}_{d,m}$ are month fixed effects (January as reference); and $\mathrm{Holiday}_{d,h}$ are indicator variables for H national holiday periods, including Golden Week (October 1–7), Chinese New Year (January 28–February 4), Labor Day (May 1–5), and Dragon Boat Festival (June 7–9). The coefficients δ_h estimate the holiday effect on daily item counts after removing day-of-week and seasonal trends, following the calendar-regression logic described by Angrist and Pischke (2009). This approach is preferred over simple before–after comparisons because it accounts for the confounding influence of weekday patterns and seasonal fluctuations.

4.3 Spatial Analysis

4.3.1 Kernel Density Estimation

To visualize the spatial intensity of lost-and-found item recovery, we apply kernel density estimation (KDE) using a Gaussian kernel (Silverman, 1986). Station-level item counts are treated as weighted point events in geographic space, and the density surface is estimated over a grid covering the Qingdao metropolitan area. The bandwidth is selected using Silverman's rule of thumb. The resulting map identifies hotspot areas where item recovery is concentrated, independent of the discrete station locations.

4.3.2 Spatial Autocorrelation

To test whether stations with high (or low) item counts tend to cluster together in geographic space, we compute Global Moran's I (Moran, 1950) using a k-nearest-neighbors spatial weight matrix ($k = 8$) derived from station geographic coordinates:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{3}$$

where x_i is the item count at station i, $\bar{x}$ is the mean count, and w_{ij} are spatial weights. Significance is assessed via a permutation test with 999 permutations. To identify local clusters and outliers, we compute Local Indicators of Spatial Association (LISA) statistics (Anselin, 1995), classifying each station into one of four quadrants (HH, HL, LH, LL) or as non-significant (NS) at $p < 0.05$.

4.4 Station Typology: PCA and K-Means Clustering

To develop a data-driven station typology based on lost-and-found item profiles, we employ a two-stage approach. First, we apply Principal Component Analysis (PCA) to reduce the dimensionality of the station-level item composition matrix, where each station is described by the proportions of items in each of the nine categories (Jolliffe and Cadima, 2016). The number of retained components is determined by the Kaiser criterion (eigenvalue > 1) and cumulative variance explained.

Second, we apply *k*-means clustering to the retained principal component scores (Hartigan and Wong, 1979). The number of clusters *k* is selected using the silhouette coefficient (Rousseeuw, 1987), which measures the cohesion and separation of clusters. The resulting clusters are profiled by their mean item counts, category composition, and station attributes (terminal status, transfer status) to characterize functionally distinct station types.

4.5 Negative Binomial Regression

To model the relationship between station-level attributes and lost-and-found item counts, we estimate a negative binomial (NB) regression model. The NB model is appropriate for overdispersed count data where the variance exceeds the mean, as is the case here (mean = 198.3, variance = 307,914) (Cameron and Trivedi, 2013; Hilbe, 2011). The standard Poisson model assumes equidispersion and would produce downwardly biased standard errors, leading to spuriously significant results (Lord and Mannering, 2010). NB regression has been widely adopted for station-level count data in transit research, including ridership determinant analysis (Choi et al., 2020) and built-environment studies of the Qingdao Metro specifically (Ning et al., 2021).

Figure 3 illustrates the data-generating process underlying the lost-and-found records. Items left by passengers follow one of two recovery pathways: (A) the passenger notices the loss and reports it at the nearest station, or (B) the item remains unnoticed on the train and is recovered by crew during end-of-line terminal inspections. This dual pathway is central to interpreting station-level patterns.

An important caveat applies to all station-level analyses. The dependent variable is the number of items *logged in the lost-and-found system*, not the number of items actually lost by passengers. Logging is jointly determined by passenger forgetting, item discovery (by staff or other passengers), crew inspection protocols, and database entry practices. Because per-station ridership data were unavailable, we model raw logged counts rather than exposure-adjusted rates. The coefficients therefore estimate the association between station characteristics and *logged lost-and-found volume*, not per-passenger loss risk. We caution against interpreting the results as passenger-level

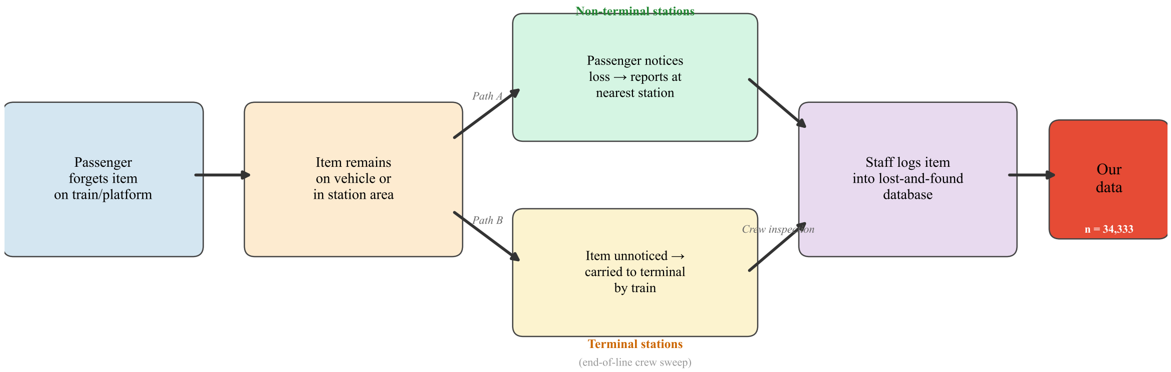

Figure 3: Data-generating process for lost-and-found records. Items follow two recovery pathways: passenger-reported (Path A, concentrated at non-terminal stations) or crew-recovered at end-of-line terminal inspections (Path B).

behavioral effects; they reflect the joint outcome of passenger behavior and operational recovery processes. The NB model specifies:

$$\ln(\mu_i) = \mathbf{x}_i'\beta \tag{4}$$

where $\mu_i = E[y_i|\mathbf{x}_i]$ is the expected count at station i, and $\mathbf{x}_i$ is a vector of predictors including POI count (log-transformed), POI diversity, terminal-station indicator, transfer-station indicator, distance to city center (log-transformed), and number of lines. The NB model adds an overdispersion parameter α such that $\text{Var}(y_i) = \mu_i + \alpha\mu_i^2$. Model fit is assessed using the Akaike Information Criterion (AIC) and the estimated α. Results are reported as both coefficients and incidence rate ratios (IRR $= e^{\beta}$), which represent the multiplicative change in the expected count for a one-unit change in the predictor.

5 Results

5.1 Temporal Patterns and Holiday Effects

5.1.1 Monthly Trends and Ridership-Normalized Rates

Figure 4 displays the monthly item counts and ridership-normalized loss rates over the 15-month study period. The raw monthly counts range from 873 items in July 2024 (the first month of data collection, likely reflecting a ramp-up effect) to 3,694 items in August 2025. The ridership-normalized loss rate, expressed as items per 10,000 passengers, ranges from 0.17 (July 2024) to 0.66 (August 2025).

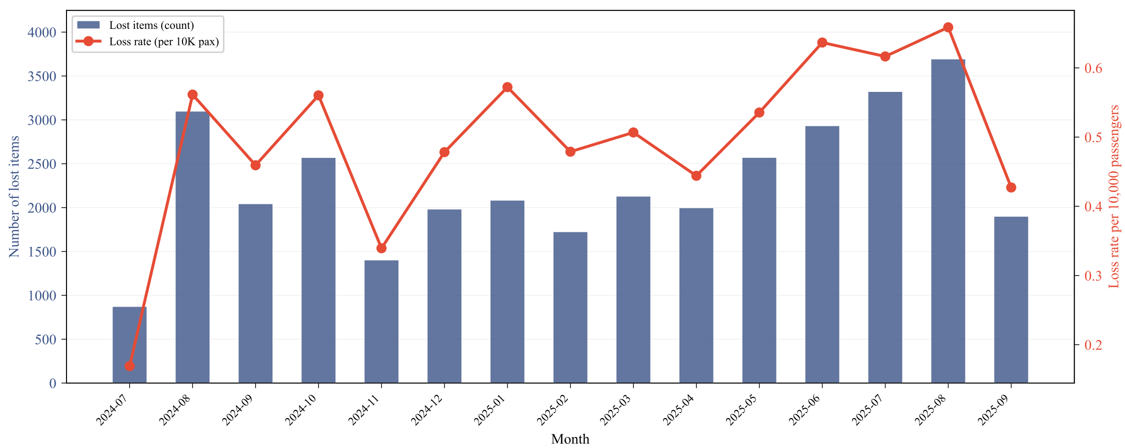

Figure 4: Monthly lost-and-found item counts (bars) and ridership-normalized loss rates (line, items per 10,000 passengers), July 2024–September 2025.

A clear seasonal pattern emerges: loss rates peak during the summer months (June–August), when rates reach 0.62–0.66 items per 10,000 passengers. This summer peak is consistent with two reinforcing mechanisms: (1) Qingdao's status as a major summer tourism destination, which brings unfamiliar travelers into the metro system; and (2) seasonal items such as umbrellas, water bottles, and sunglasses that are easily set down and forgotten. The October rate (0.56) remains elevated due to Golden Week holiday travel. Winter months show moderate rates (0.48–0.57), while the lowest rate outside the initial ramp-up month is observed in April (0.44).

At the line level, normalization reveals a different ranking than raw counts. Line 1 has both the highest absolute count (13,644 items) and a high normalized rate (0.95 items per 10,000 passengers). However, the Blue Valley Express, which ranks only fifth in absolute count (3,547 items), has the highest normalized rate of any line at 1.11 items per 10,000 passengers. This suburban/tourist express line serves the Jimo district and has a lower ridership denominator, but its elevated rate also reflects its role as a connector to tourist attractions along the eastern coastline. Lines 2 and 3, which serve the densest urban core, have the lowest rates (0.33 and 0.36, respectively), suggesting that these heavily commuter-oriented lines generate fewer logged items per passenger, consistent with the hypothesis that routine trips on familiar routes produce fewer recovery events.

5.1.2 Holiday Effects: Event Study Results

Figure 5 shows the daily time series of lost-and-found item counts with national holiday periods highlighted. Visual inspection reveals pronounced spikes during Labor Day and Golden Week, modest elevation during Dragon Boat Festival, and a dip during Chinese New Year.

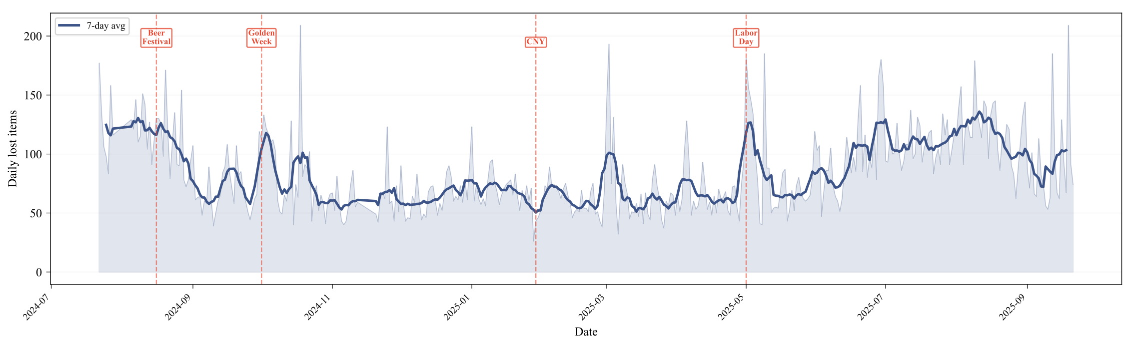

Figure 5: Daily lost-and-found item counts, July 2024–September 2025, with national holiday periods highlighted.

Table 3 reports the results of the regression-based calendar regression (Equation 2). The model achieves an R^2 of 0.467, indicating that calendar effects and holidays explain nearly half of the daily variation in item counts. The weekend effect is positive and highly significant: Saturdays and Sundays are associated with approximately 14.2 more items per day relative to weekdays ($p < 0.001$), consistent with the hypothesis that leisure and tourist travel generates more lost items than routine commuting.

Table 3: Event study regression results: effects of holidays on daily lost-and-found counts, with day-of-week and month controls ($N = 457$ days, $R^2 = 0.467$).

Variable	Coefficient	SE	t-value	p-value
Weekend (Sat–Sun)	+14.2	3.1	4.58	<0.001***
Golden Week	+41.7	10.6	3.93	<0.001***
Chinese New Year	−8.5	9.4	−0.91	0.365
Labor Day	+70.8	12.1	5.87	<0.001***
Dragon Boat Festival	+16.3	14.7	1.11	0.268
Month fixed effects	Included (11 indicators)			
Day-of-week effects	Included (6 indicators)			

Note: Dependent variable is daily item count. Reference categories: Monday, January. Holiday indicator equals 1 during the official holiday period. Standard errors are heteroskedasticity-consistent (HC1). *** $p < 0.001$.

Figure 6 presents the weekday–month interaction heatmap, revealing that Saturdays and Sundays in peak tourism months (July–August) produce the highest daily item counts, exceeding 100 items per day. The interaction between weekend leisure travel and seasonal tourism creates compounding effects that are not visible in marginal temporal analyses alone.

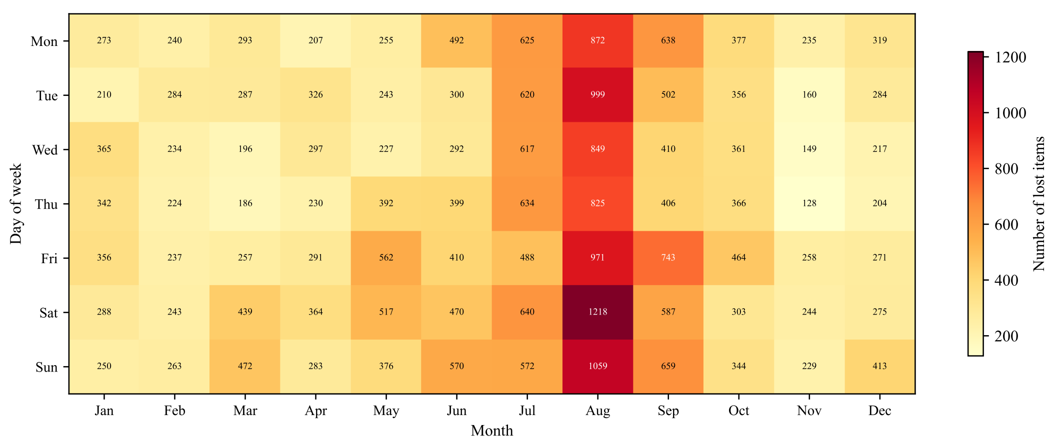

Figure 6: Weekday–month heatmap of daily lost-and-found item counts. The interaction between weekends and summer months produces the highest accumulations.

Among the holidays, Labor Day has the largest effect: +70.8 items per day ($p < 0.001$), representing a 109.5% increase over the baseline. Golden Week adds +41.7 items per day ($p < 0.001$,

+64.4% over baseline). Both holidays are major travel periods in China, characterized by high volumes of tourism and leisure trips. The Labor Day effect is larger partly because the 2025 Labor Day period coincided with exceptionally warm weather that amplified tourist flows to coastal Qingdao.

Chinese New Year shows a non-significant negative coefficient (-8.5, $p = 0.365$), consistent with the fact that CNY is a home-bound holiday during which urban metro ridership typically declines as residents travel to family homes outside the city. Dragon Boat Festival shows a positive but non-significant effect (+16.3, $p = 0.268$), suggesting a modest boost that is within the range of normal weekend variation after applying controls.

5.2 Spatial Distribution

5.2.1 Station-Level Distribution

Figure 8 displays the proportional circle map of lost-and-found item counts across the 173 stations. The distribution is highly skewed (Gini coefficient = 0.697): the top 5 stations account for 39.7% of all logged items, the top 10 for 50.7%, and the top 20 for 64.7% (Figure 7).

The distribution is also highly right-skewed in terms of individual stations: the top 5 stations account for a disproportionate share of all items. Wangjiagang (5,630 items) and Dongguozhuang (3,929 items) dominate the distribution, each recording more than twice the count of the third-ranked station, Miaoling Road (1,710 items). The fourth and fifth stations, Lingshan Bay (1,190) and Qingdao Railway Station (1,166), are also prominent.

Notably, the two highest-count stations—Wangjiagang and Dongguozhuang—are both terminal stations. This pattern is a key finding that we return to in the Discussion: their dominance likely reflects crew inspection protocols at end-of-line turnbacks rather than (or in addition to) high rates of passenger item loss at those specific locations. Items left on trains at any point along the line accumulate at the terminal, where they are collected by staff.

A comparison of category profiles between terminal and non-terminal stations further supports this operational interpretation (Figure 9). Terminal stations have a higher share of Daily Necessities

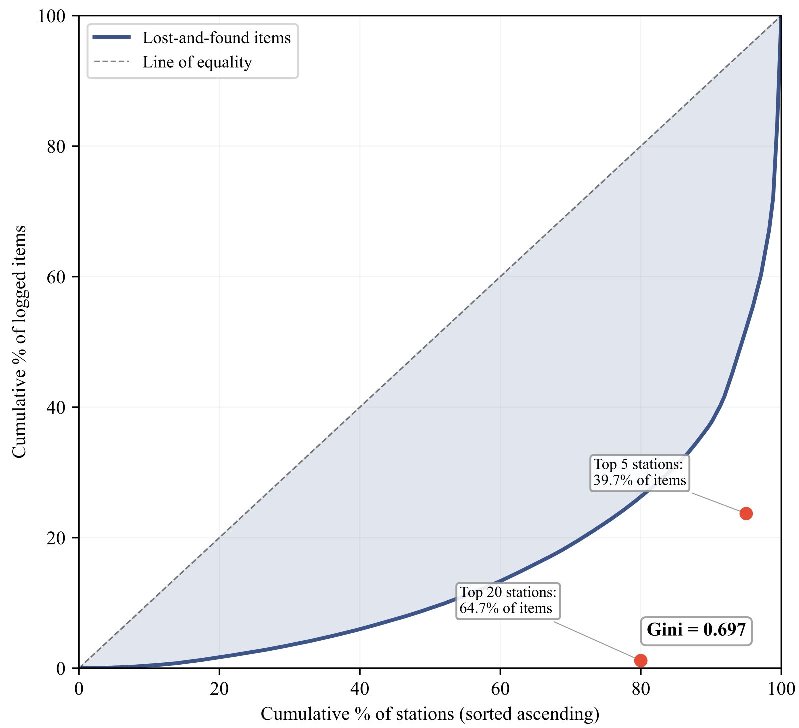

Figure 7: Lorenz curve of logged lost-and-found items across 173 stations. The Gini coefficient of 0.697 indicates high concentration, with the top 5 stations accounting for nearly 40% of all items.

(50.0% vs. 44.4%) and Clothing & Accessories (33.2% vs. 27.8%)—common, low-value items that passengers are unlikely to report and that accumulate through crew inspections. Conversely, non-terminal stations have a disproportionately high share of Transit Cards (11.5% vs. 5.0%) and Documents & ID (10.0% vs. 7.8%), consistent with the hypothesis that passengers who notice the loss of a high-value or high-urgency item report it immediately at the nearest station rather than waiting for crew recovery at the terminal. A chi-square test confirms that the category distribution differs significantly between terminal and non-terminal stations ($\chi^2 = 746.8$, $df = 8$, $p < 0.001$).

5.2.2 Kernel Density Estimation

Figure 10 shows the KDE hotspot surface of lost-and-found item intensity. The highest-density areas are concentrated around the terminal stations of Lines 1, 4, and 6, with secondary hotspots near the central business district stations along Lines 2 and 3 (around Wusi Square and Miaoling Road). The suburban terminals of the Blue Valley Express and West Coast Express also show

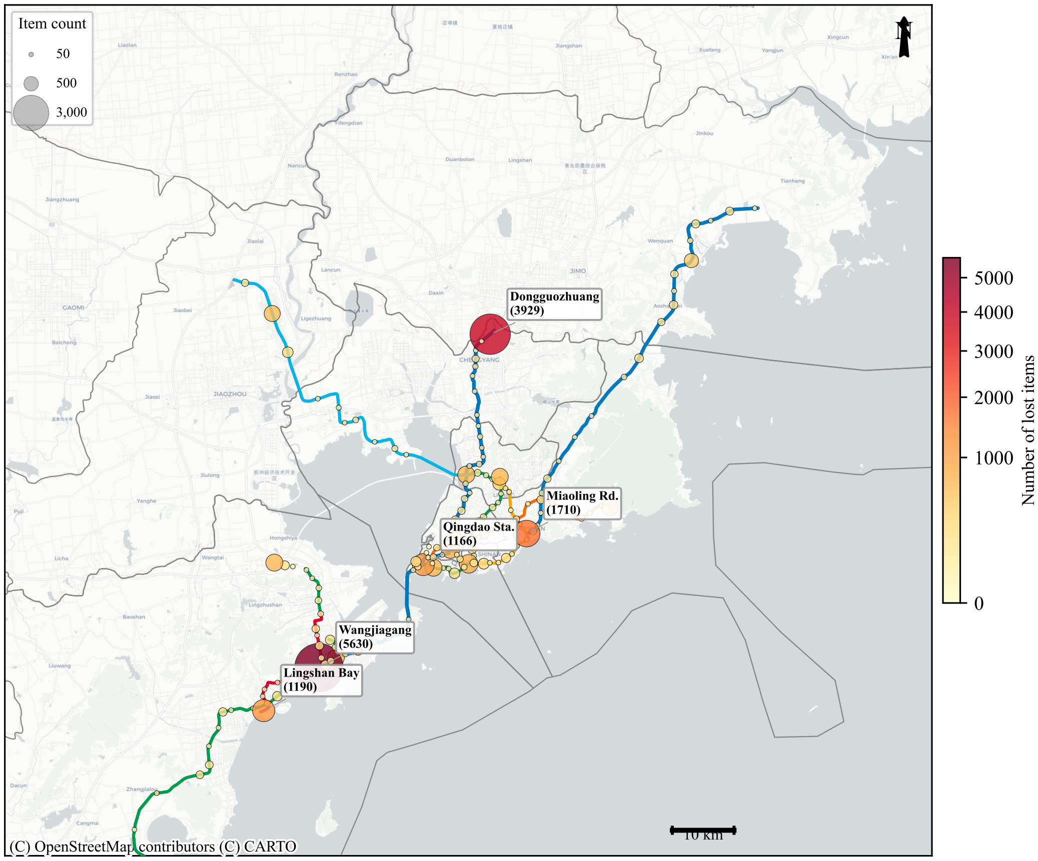

Figure 8: Proportional circle map of lost-and-found item counts across 173 Qingdao Metro stations.

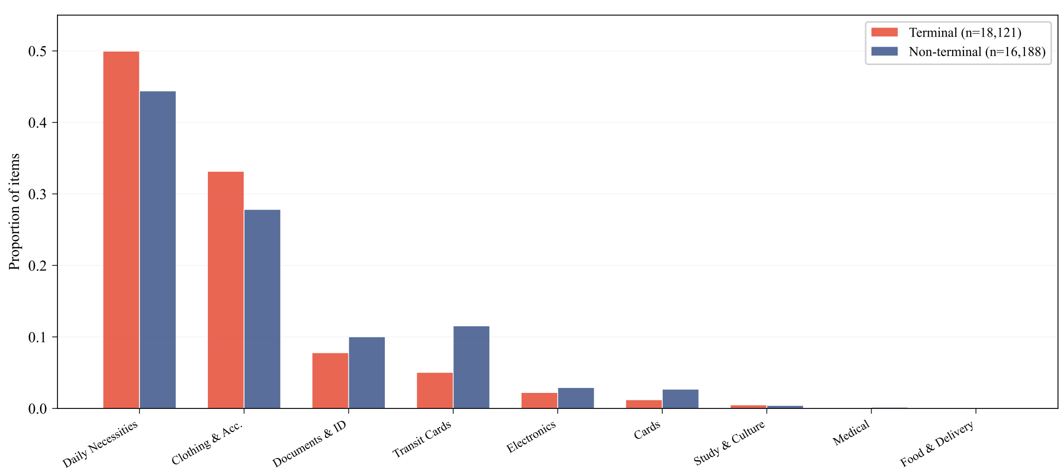

Figure 9: Category composition of lost-and-found items at terminal vs. non-terminal stations. Terminal stations accumulate more common items via crew inspections, while non-terminal stations receive more passenger-reported high-value items.

elevated density, though at lower absolute levels due to fewer surrounding stations.

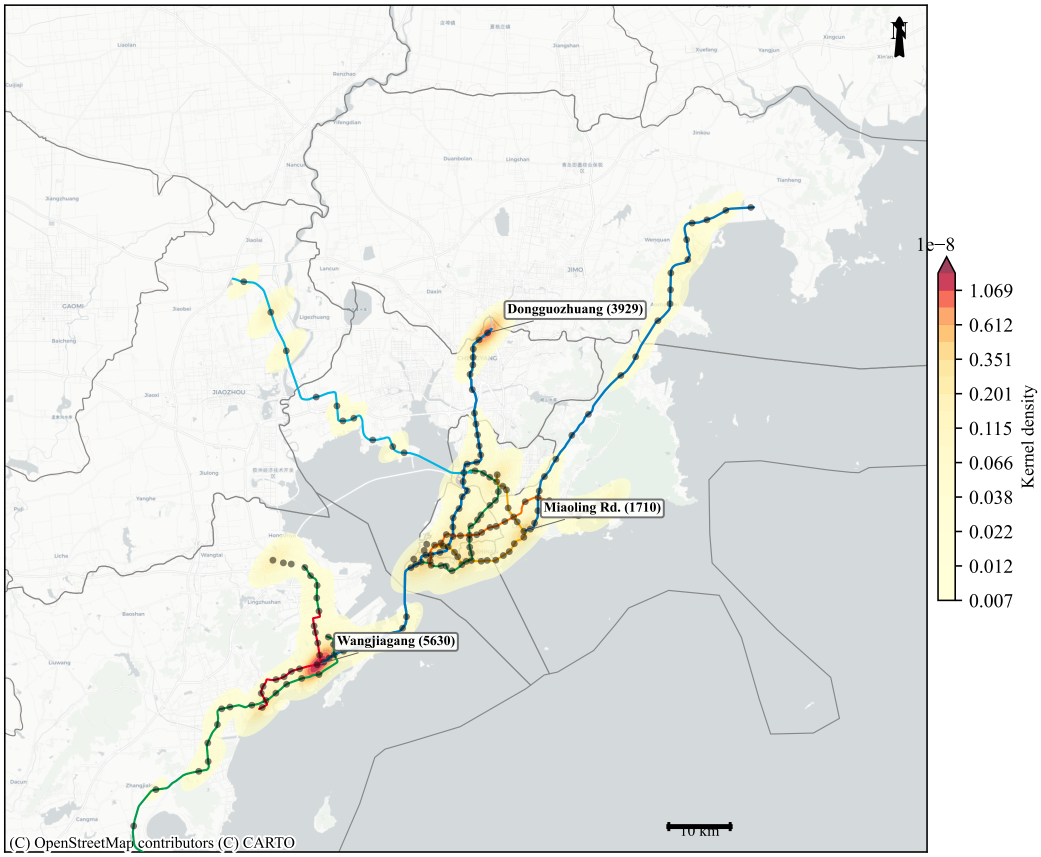

Figure 10: Kernel density estimation of lost-and-found item intensity across the Qingdao Metro network.

At the line level, category composition varies meaningfully (Figure 11). The Blue Valley Express shows the highest proportion of Clothing & Accessories (38.2%), consistent with its role as a suburban–tourist corridor where leisure travelers carry more seasonal clothing items. Lines 2 and 3, which serve the urban core, have elevated shares of Transit Cards (12–14%) and Documents & ID, reflecting their commuter-dominated passenger base. Line 1, the longest and busiest line, closely mirrors the system-wide average, serving as a representative backbone.

5.2.3 Spatial Autocorrelation

The Global Moran's I statistic is -0.003 ($p = 0.376$) under a k-nearest-neighbors weight matrix ($k = 8$). Robustness checks with $k = 4$ ($I = -0.009$, $p = 0.289$), $k = 6$ ($I = -0.005$, $p = 0.269$),

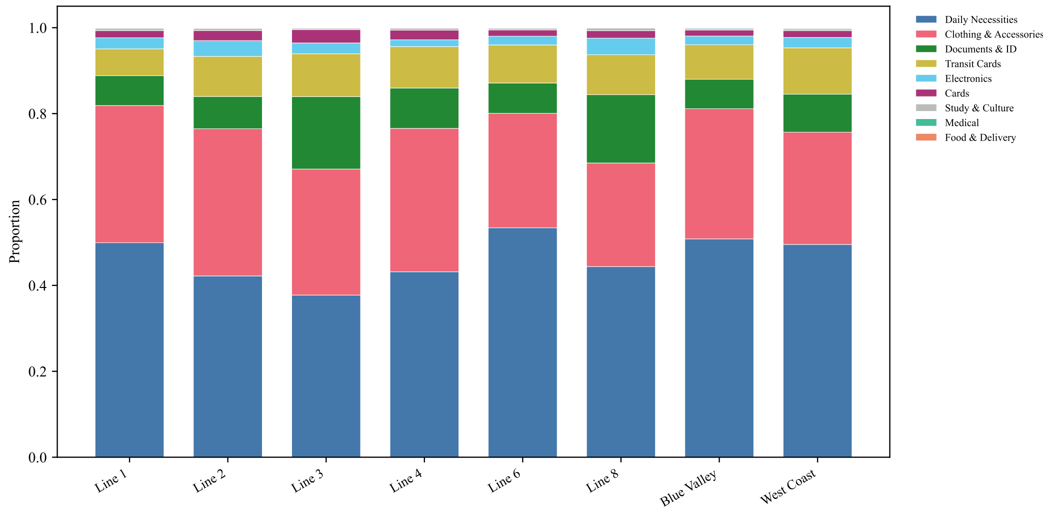

Figure 11: Category composition of lost-and-found items by metro line, revealing functional differentiation across lines.

and $k = 12$ ($I = -0.003$, $p = 0.148$) consistently yield non-significant results, indicating no evidence of spatial autocorrelation in logged lost-and-found item counts across the network under any tested specification. This finding is noteworthy: unlike ridership or land-use variables, which typically show strong positive spatial autocorrelation (nearby stations tend to have similar values), lost-and-found item counts are effectively spatially random after accounting for station-specific effects. High-count stations are not systematically adjacent to other high-count stations; instead, their elevated counts are driven by station-specific attributes—particularly terminal status—rather than by neighborhood-level processes.

The LISA analysis confirms this picture: of 173 stations, 164 are classified as non-significant (NS), 7 as Low-High (LH, low-count stations adjacent to high-count ones), and 2 as High-High (HH). The HH stations are a pair of adjacent terminal stations that share a high-count neighborhood by virtue of being on the same line terminus. The near-complete absence of spatial clustering reinforces the interpretation that lost-and-found patterns are station-specific rather than spatially diffuse.

5.3 Station Typology

5.3.1 PCA Results

PCA on the nine-category item composition matrix yields five components with eigenvalues exceeding 1, collectively explaining 73% of the total variance. The first component (23% of variance) loads most heavily on Daily Necessities (positive) versus Documents & ID (negative), distinguishing stations where common everyday items predominate from those where identity documents and formal paperwork are disproportionately represented. The second component (17%) contrasts Clothing & Accessories (positive) with Transit Cards (negative), separating stations with a tourist/leisure profile from those with a commuter profile.

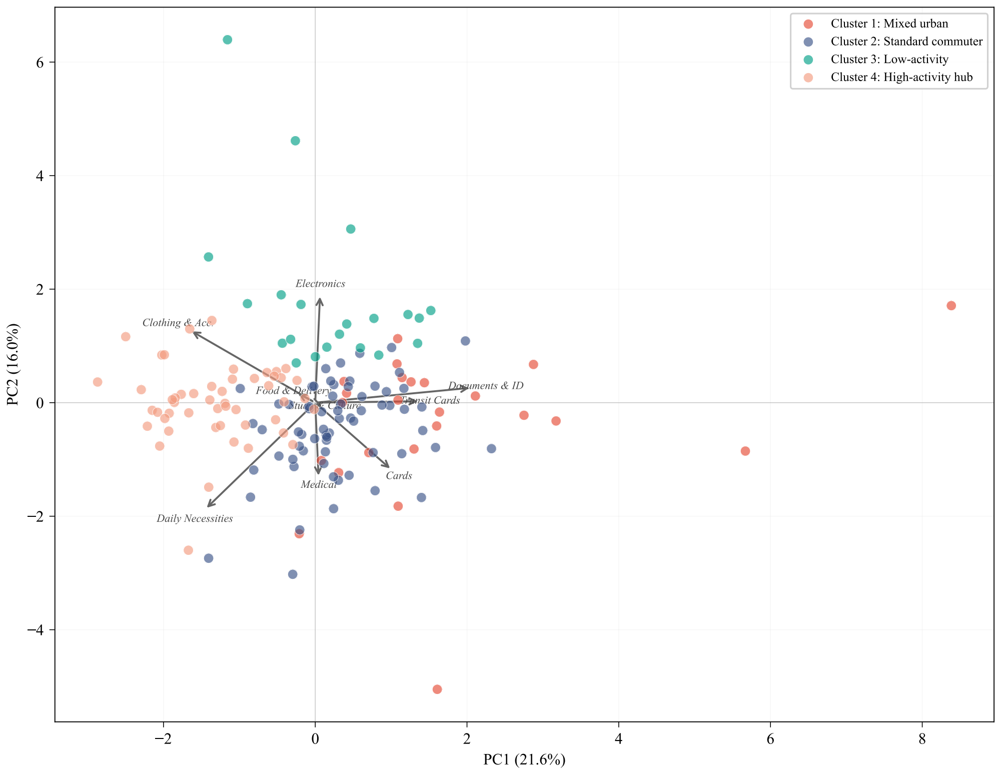

Figure 12: PCA biplot of station-level lost-and-found item composition, with k-means cluster assignments ($k = 4$) shown by color.

5.3.2 K-Means Clustering

K-means clustering on the five retained PCA scores yields an optimal $k = 4$ with a silhouette coefficient of 0.251. While this silhouette value is moderate—reflecting the inherent overlap among station profiles rather than discrete types—the four clusters are interpretable and align with known functional differences among stations. Robustness checks with $k = 3$ and $k = 5$ yield qualitatively similar groupings, with the terminal/hub cluster consistently emerging as the most distinct group. We treat this typology as exploratory rather than definitive. Table 4 profiles the four clusters, and Figure 13 maps their spatial distribution.

Table 4: Profiles of four station clusters based on lost-and-found item composition (k-means, $k = 4$, silhouette = 0.251).

Cluster	N stations	Mean items	Daily Necess. (%)	Clothing & Access. (%)	Docs & ID (%)	% Terminal stations
1: Mixed urban	24	109	37.7	20.8	20.2	8%
2: Standard commuter	66	99	48.4	21.2	10.4	0%
3: Low-activity suburban	21	55	34.9	31.5	12.9	0%
4: High-activity hub	50	480	48.4	33.3	5.8	26%

Note: Mean items are per station over the 15-month study period. Category shares are cluster means of station-level proportions. Representative stations—Cluster 1: Qingdao North Railway, Yan'erdao Road; Cluster 2: Jinggangshan Road, Haibo Bridge; Cluster 3: Zhengyang Middle Road, Taihangshan Road; Cluster 4: Wangjiagang, Dongguozhuang, Miaoling Road.

Figure 14 presents the category composition heatmap for the top 20 stations, revealing clear visual patterns: terminal stations (Wangjiagang, Dongguozhuang) show uniformly high proportions of Daily Necessities and Clothing, while non-terminal hubs (Qingdao Station, Wusi Square) exhibit more diverse profiles with elevated Documents and Transit Card shares.

Cluster 1: Mixed urban stations (24 stations, mean 109 items). These stations have the highest share of Documents & ID (20.2%) and the lowest share of Clothing & Accessories, suggesting a business/institutional function. Representative stations include Qingdao North Railway Station and stations near hospitals and government offices.

Cluster 2: Standard commuter stations (66 stations, mean 99 items). The largest cluster, characterized by a typical item profile dominated by Daily Necessities (48.4%) and moderate

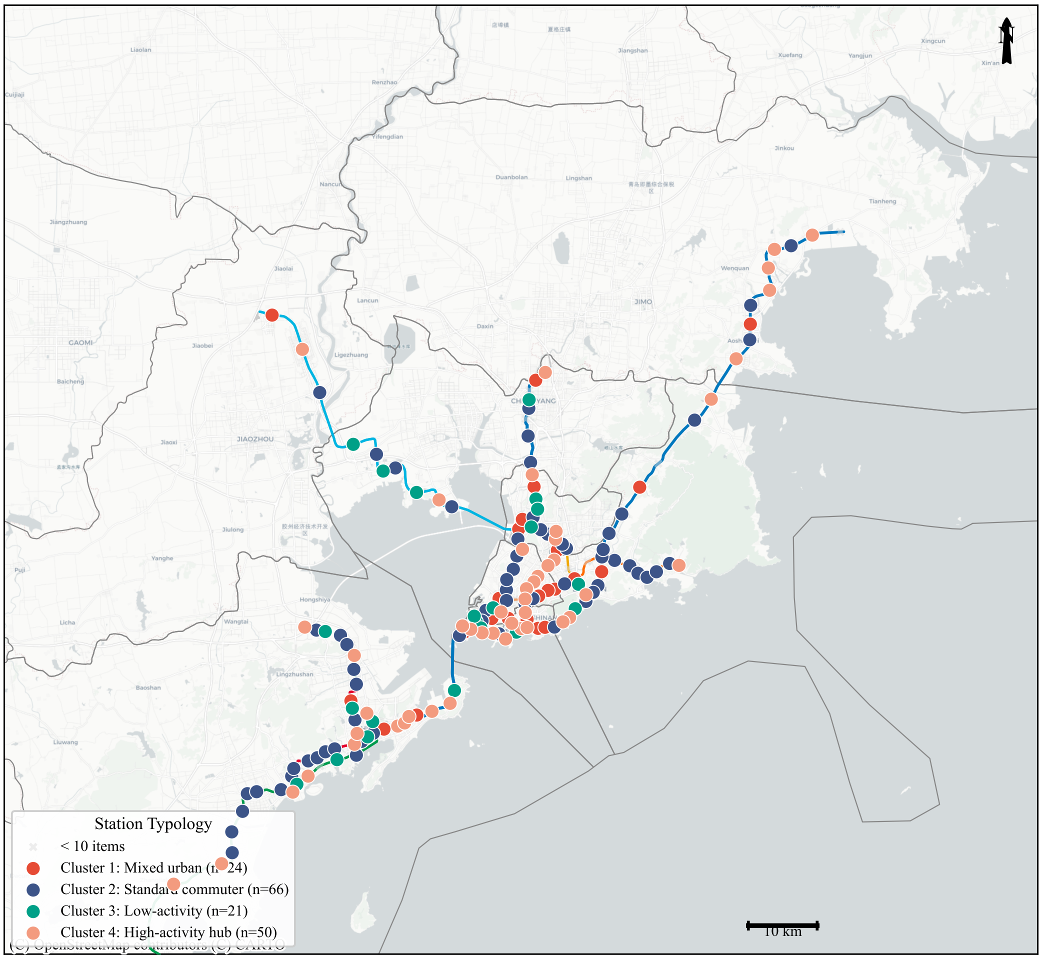

Figure 13: Spatial distribution of four station typology clusters across the Qingdao Metro network.

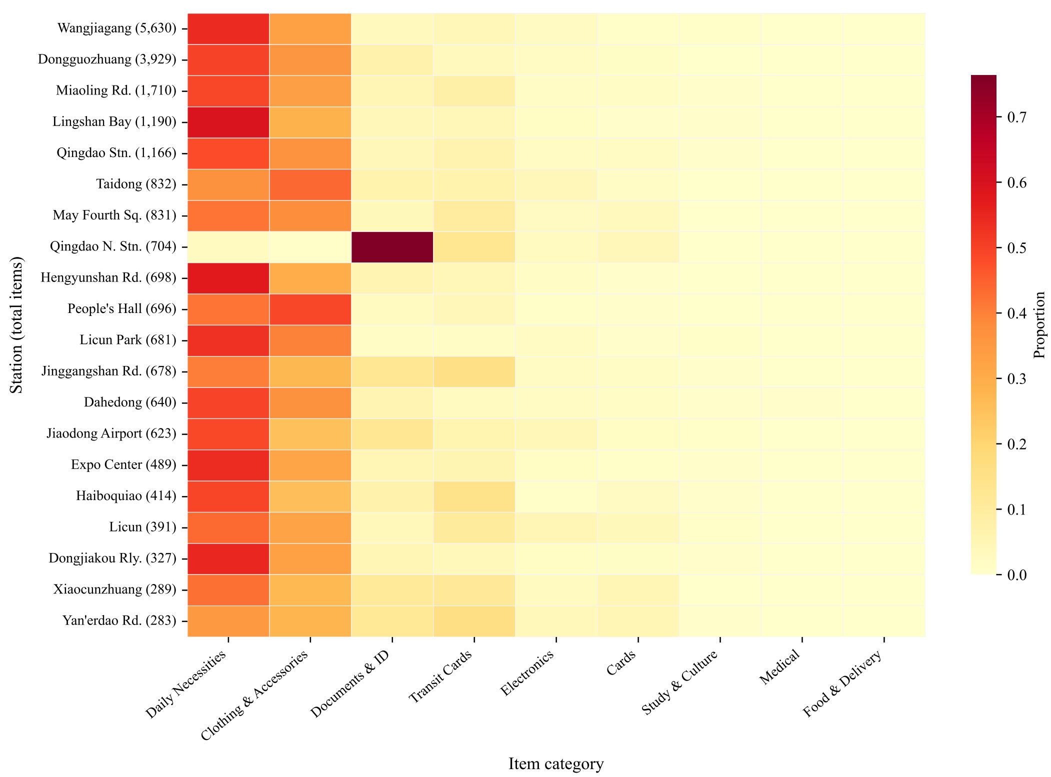

Figure 14: Category composition heatmap for the top 20 stations by total lost-and-found items. Row labels include total item counts in parentheses.

Transit Card shares (14.7%). No terminal stations are in this cluster, and transfer station share is low (8%). These are the workday backbone of the network.

Cluster 3: Low-activity suburban stations (21 stations, mean 55 items). These stations have the lowest mean item counts and the highest share of Clothing & Accessories (31.5%) and Electronics (7.6%). They are located predominantly in suburban areas with lower ridership and fewer surrounding POIs.

Cluster 4: High-activity terminal/transfer hubs (50 stations, mean 480 items). This cluster has by far the highest mean item count—nearly five times the next cluster—and contains 26% of the system's terminal stations and 16% of its transfer stations. The high share of Daily Necessities (48.4%) and Clothing & Accessories (33.3%) reflects the accumulation of common items through crew inspections at end-of-line turnbacks. The low share of Documents & ID (5.8%) is consistent with the hypothesis that passengers who lose important documents are more likely to report and reclaim them before the train reaches the terminal.

5.4 Station-Level Predictors: Negative Binomial Regression

Figure 15 shows the Pearson correlation matrix among station-level variables. Total item count is most strongly correlated with terminal-station status ($r = 0.58$) and transfer-station status ($r = 0.21$), with weaker positive associations with POI count and line count. POI diversity and distance to center show modest negative correlations with item counts.

The negative binomial regression results are summarized below (see also Figure 16). The model has an overdispersion parameter $\alpha = 0.743$, confirming substantial overdispersion in the data that would violate Poisson assumptions. The AIC is 1,985, based on $N = 172$ stations (one station with zero items excluded).

The strongest predictor is terminal-station status, with a coefficient of 2.296 ($p < 0.001$) corresponding to an incidence rate ratio (IRR) of 9.93. A sensitivity check excluding the two highest-volume terminals (Wangjiagang and Dongguozhuang) yields a reduced but still substantial terminal IRR of 5.25, confirming that the terminal effect is not driven solely by two outlier stations. In

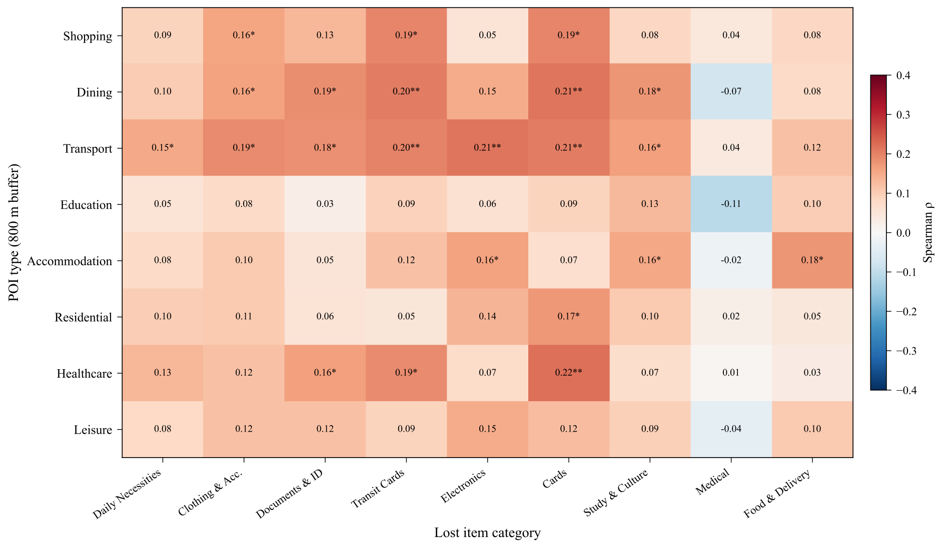

Figure 15: Pearson correlation matrix of station-level variables. Stronger colors indicate stronger correlations.

practical terms, being a terminal station is associated with nearly a tenfold increase in expected lost-and-found item counts, all else equal. This is the single most important finding of the regression analysis and warrants careful interpretation (see Discussion). Transfer-station status is also significant, with a coefficient of 2.400 ($p = 0.019$) and an IRR of 11.03. Transfer stations see elevated counts likely because of higher passenger volumes, more complex wayfinding, and the presence of multiple crew teams performing inspections.

POI count within 800 meters shows a marginally significant positive effect (coefficient = 0.147, $p = 0.070$, IRR = 1.16), suggesting that stations in areas with more diverse commercial activity tend to have slightly higher item counts, potentially because such areas attract more diverse trip purposes and passenger profiles. POI diversity (Shannon entropy), distance to center, and number of lines served are not statistically significant after controlling for terminal and transfer status, indicating that the operational attributes of stations dominate over land-use characteristics in predicting lost-and-found item accumulation.

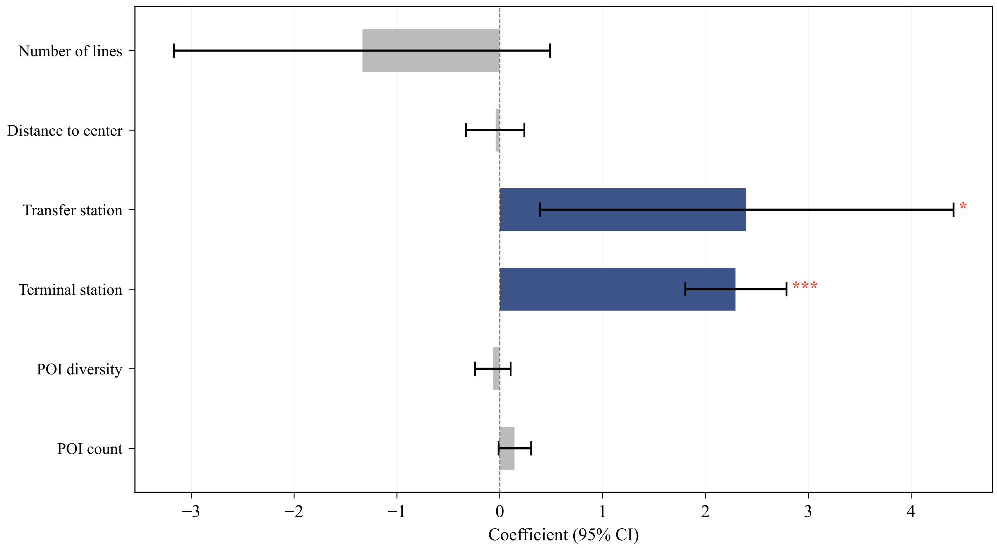

Figure 16: Negative binomial regression coefficient plot with 95% confidence intervals. Coefficients are in log scale; exponentiation gives incidence rate ratios (IRR).

6 Discussion

6.1 Reinterpreting the Terminal Station Effect

The most striking result of this study is the overwhelming dominance of terminal-station status as a predictor of lost-and-found item counts. Terminal stations record nearly ten times more items than non-terminal stations (IRR = 9.93), and the two highest-count stations in the entire network—Wangjiagang (5,630 items) and Dongguozhuang (3,929 items)—are both terminals. This finding demands careful interpretation.

The conventional behavioral interpretation would be that passengers are more likely to lose items at terminal stations—perhaps because they are distracted by the need to exit, are less familiar with the station, or are carrying more belongings at the start or end of a long trip. While these behavioral factors may contribute, they are likely secondary to an operational explanation, consistent with the observation that terminal stations are where train crews conduct systematic interior inspections of carriages during the end-of-line turnback process. Items left by passengers at *any* station along the line are carried to the terminal, where they are discovered and logged by staff. The terminal station is therefore not the location where items are *lost* but the location where they are *found and recorded*.

This distinction between the geography of loss and the geography of recovery is fundamental. Lost-and-found data do not map passenger forgetfulness; they map the intersection of passenger forgetfulness with operational recovery processes. Analyses that treat found-item locations as proxies for loss locations will systematically overestimate the role of terminal stations and underestimate the role of intermediate stations where items were actually left behind.

The category-composition analysis provides further evidence for this interpretation. Terminal stations show higher proportions of Daily Necessities (50.0% vs. 44.4%) and Clothing (33.2% vs. 27.8%)—common items that passengers rarely report and that accumulate passively through crew sweeps. Non-terminal stations, by contrast, have disproportionately more Transit Cards (11.5% vs. 5.0%) and Documents & ID (10.0% vs. 7.8%)—items whose loss passengers notice immediately and report at the nearest station. This asymmetry strongly suggests that the geography of recovery (operational) differs systematically from the geography of loss (behavioral), and that lost-and-found data should be interpreted as a composite signal from both processes.

The same logic applies, to a lesser degree, to transfer stations (IRR = 11.03, $p = 0.019$). Transfer stations may genuinely experience higher rates of item loss due to the complexity of wayfinding and the need to change platforms. However, some transfer stations also serve as intermediate inspection points or have larger staff contingents that are more likely to recover and log items. The large standard error on the transfer coefficient (SE = 1.026) suggests heterogeneity within the transfer-station category.

6.2 Temporal Patterns: Tourism, Leisure, and Seasonal Items

The strong summer peak in loss rates (0.62–0.66 items per 10,000 passengers in June–August) and the large holiday effects (Labor Day +70.8 items/day, Golden Week +41.7 items/day) point to tourism and leisure travel as key drivers of item loss. Several mechanisms may be at work. First, tourist travelers are less familiar with the metro system and may be more prone to distraction. Second, summer and holiday travel involves carrying more incidental items (water bottles, umbrellas, sunglasses, hats) that are easily set down and forgotten. Third, the sheer volume of passenger flow during peak tourism periods increases the probability of items being displaced or left behind in crowded carriages.

Item-level analysis reinforces the seasonal story. Umbrellas—the single most common identifiable item type, with 2,551 records—peak sharply in August (764 items) and are concentrated entirely in the June–September rainy season, demonstrating how weather-sensitive personal items drive the seasonal component of loss rates. Year-over-year comparison for overlapping months shows a 19.2% increase in August (from 3,099 to 3,694 items between 2024 and 2025), consistent with the system's growing ridership.

The non-significance of Chinese New Year (-8.5, $p = 0.365$) provides a useful contrast: CNY is a holiday during which urban metro ridership declines as residents leave the city, reducing both the population at risk and the operational intensity of the system. The Dragon Boat Festival shows a positive but non-significant effect (+16.3, $p = 0.268$), possibly because it is a shorter holiday (3 days) with a smaller tourism component than Golden Week or Labor Day.

The finding that weekends are associated with +14.2 items per day ($p < 0.001$) reinforces the leisure-travel mechanism. Weekend riders are more likely to be engaged in shopping, dining, and recreational activities that involve carrying bags and accessories—items that are easily misplaced.

6.3 Spatial Randomness and Station-Specific Effects

The non-significant Global Moran's I (-0.003, $p = 0.376$) is an important negative finding. In most urban transportation analyses, spatial autocorrelation is the norm: ridership, traffic volume, accident counts, and land-use intensity all exhibit strong positive spatial dependence. The absence of spatial autocorrelation in lost-and-found counts indicates that item accumulation is driven by station-specific attributes (primarily terminal and transfer status) rather than by neighborhood-level processes or spatial spillovers.

This finding has methodological implications: spatial lag or spatial error models, which are commonly applied in transportation research, are not warranted for this outcome variable. Instead, station-level models that incorporate station-specific operational attributes are more appropriate.

6.4 Practical Implications

The results suggest several actionable recommendations for transit agencies:

1. **Resource allocation:** Lost-property staffing and storage facilities should be concentrated at terminal stations, which accumulate the vast majority of items. Dedicated lost-property counters at high-volume terminals could improve passenger retrieval rates.

2. **Seasonal preparedness:** Agencies should anticipate elevated lost-item volumes during summer months and major holidays, adjusting staffing and communication efforts accordingly.

3. **Passenger communication:** Targeted announcements reminding passengers to check belongings before alighting could be deployed during peak tourism periods, especially on tourist-oriented lines such as the Blue Valley Express.

4. **Data integration:** Lost-and-found data, when combined with ridership and POI data, can serve as a supplementary indicator of station function and passenger behavior, complementing traditional metrics.

6.5 Limitations

This study has several limitations. First, the data lack time-of-day information, precluding analysis of within-day patterns (e.g., morning versus evening peaks). Second, per-station ridership data were not available; only system-wide monthly and annual line-level ridership could be used for normalization. Station-level normalization would enable a more precise assessment of which stations have genuinely elevated loss rates. Third, the study covers a single city (Qingdao) over 15 months. Generalizability to other metro systems with different operational protocols, passenger demographics, or network structures should be tested. Fourth, we cannot distinguish between items lost on trains (which are recovered at terminals) and items lost on platforms or in station areas (which are recovered on-site). This distinction is central to the behavioral-versus-operational interpretation and would require more detailed records. Finally, the moderate silhouette coefficient (0.251) for the k-means clustering indicates that the station typology, while interpretable, has limited separability, and alternative clustering methods or additional features might improve classification.

7 Conclusions

This study presents the first systematic analysis of lost-and-found items in an urban metro system, using 34,333 records from 173 stations across 8 lines of the Qingdao Metro over 15 months. We demonstrate that lost-and-found data are a rich, underexploited source of information about both passenger behavior and transit operations, with spatio-temporal patterns that reflect the interplay between human forgetfulness and organizational recovery processes.

Three principal findings emerge. First, loss rates exhibit strong seasonal and holiday patterns, peaking in summer tourist months (0.62–0.66 items per 10,000 passengers) and during major national holidays (Labor Day +70.8 items/day, Golden Week +41.7 items/day after controls), consistent with the hypothesis that unfamiliar and leisure-oriented travelers are more prone to losing items. Second, the spatial distribution of found items shows no significant spatial autocorrelation (Moran's $I = -0.003$, $p = 0.376$), indicating that item accumulation is driven by station-specific attributes rather than neighborhood-level processes. Third, terminal-station status is the dominant predictor of item counts (IRR = 9.93, $p < 0.001$), an effect we attribute primarily to end-of-line crew inspections rather than elevated rates of passenger item loss at those locations.

The critical methodological contribution of this work is the explicit recognition that lost-and-found data encode operational processes—particularly crew inspections at terminal stations—as much as passenger behavior. Treating found-item locations as proxies for loss locations, without accounting for the recovery apparatus, would lead to fundamentally misleading conclusions. Future research should develop methods to disentangle the behavioral and operational components of lost-and-found patterns, potentially by incorporating train-level tracking, time-stamped item recovery logs, and natural experiments based on changes in inspection protocols.

For transit agencies, the practical implication is clear: lost-and-found management resources should be concentrated at terminal and transfer stations, with seasonal augmentation during summer and holiday periods. The four-type station typology developed here provides a framework for tailoring lost-property services to station function. More broadly, this study demonstrates that routine operational data—even something as mundane as a lost-umbrella log—can yield valuable insights when subjected to rigorous analytical methods.

Author Contribution Statement

The authors confirm their contributions to the paper as follows: study conception and design—K. Tan, C. Guan; data collection and preprocessing—K. Tan; analysis and interpretation of results—K. Tan, C. Guan; manuscript drafting—K. Tan; critical revision and supervision—C. Guan. Both authors reviewed the results and approved the final version of the manuscript.

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Appendix

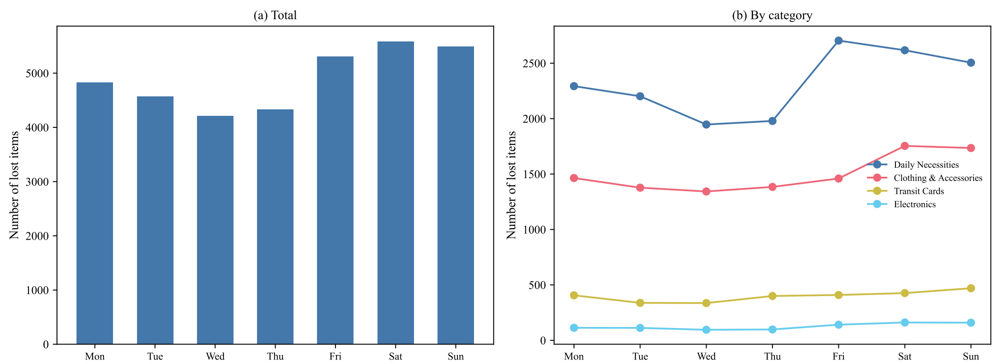

Figure A1: Distribution of lost-and-found item counts by day of week.

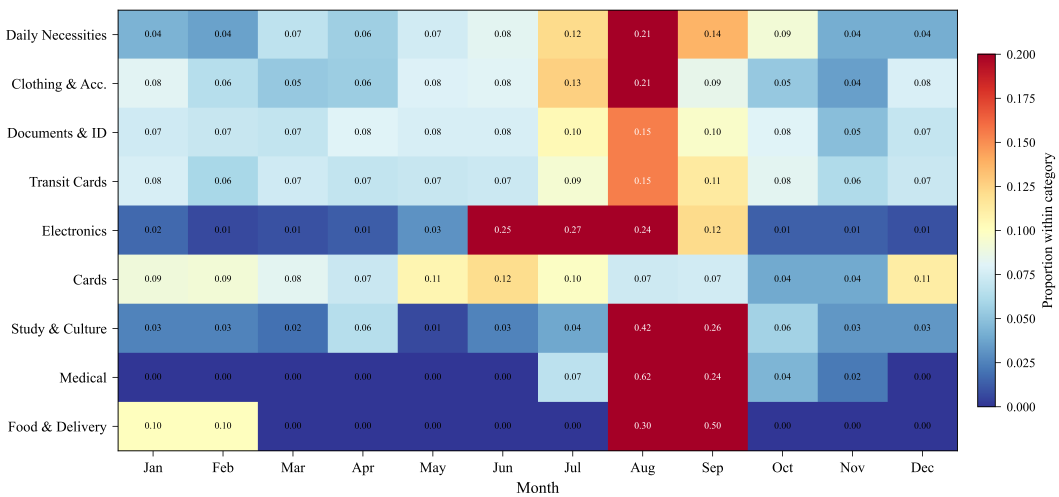

Figure A2: Heatmap of lost-and-found item counts by category and month, showing seasonal variation across item types.

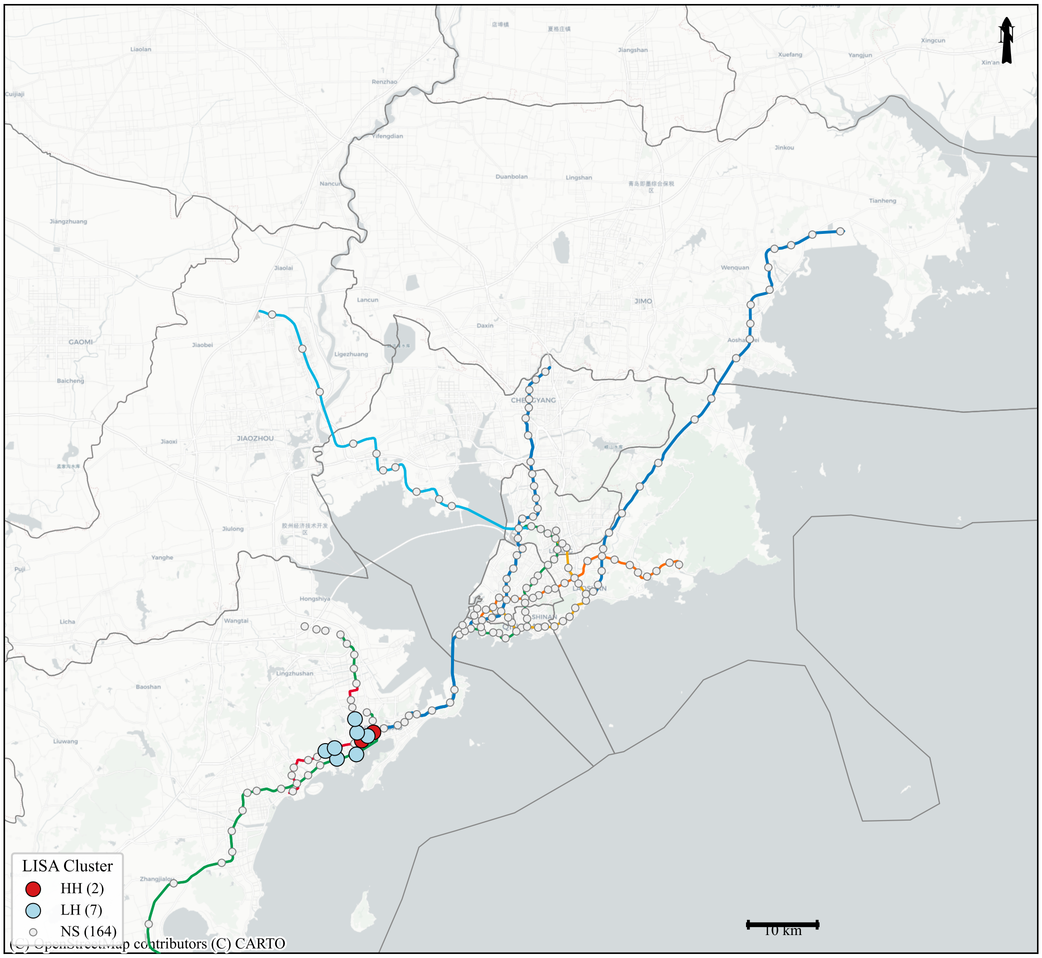

Figure A3: LISA cluster map of lost-and-found item counts. The near-complete absence of significant clusters (164 of 173 stations are NS) confirms the lack of spatial autocorrelation.

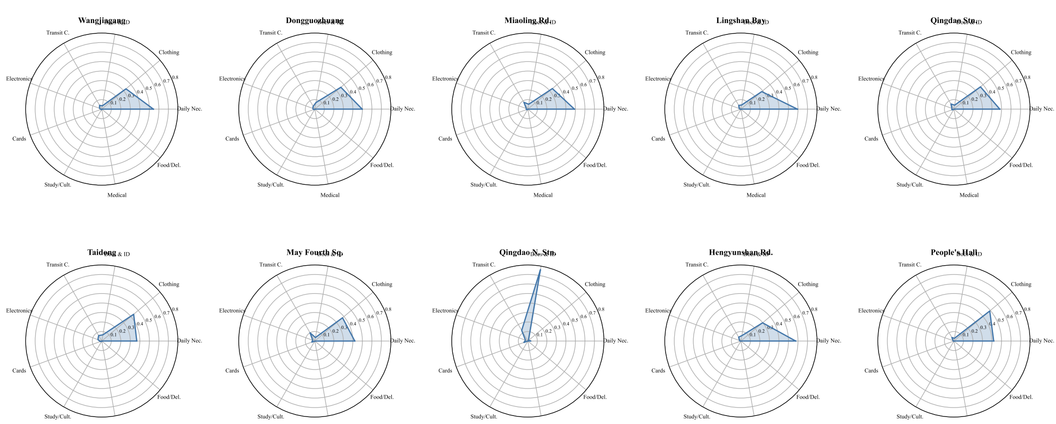

Figure A4: Radar charts showing the item category composition of the top 10 stations by total lost-and-found count.

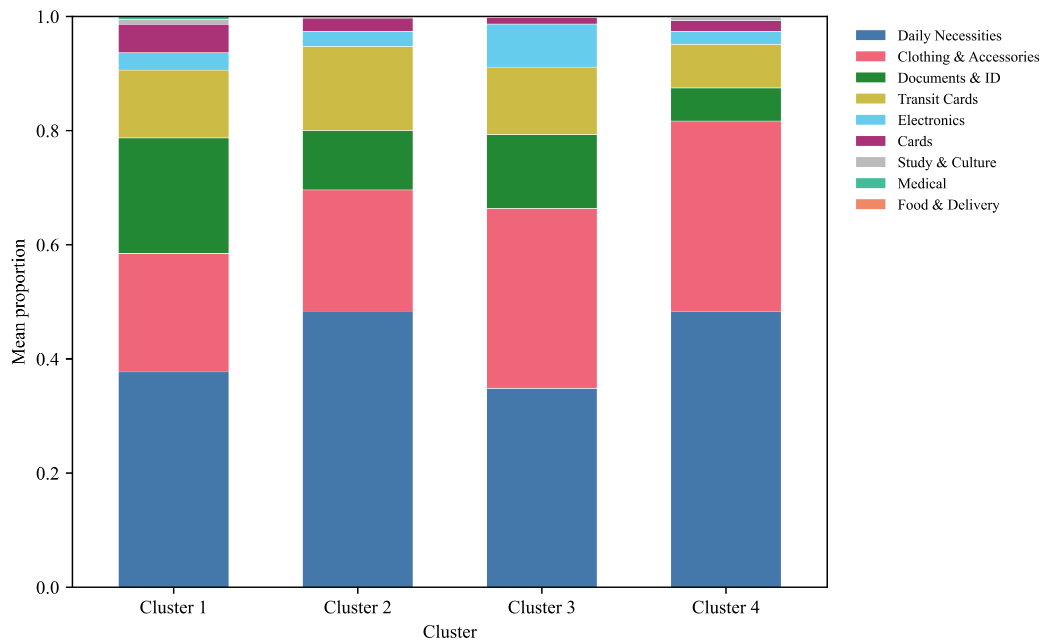

Figure A5: Item category composition across the four station typology clusters, showing percentage breakdown by cluster.