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Beyond street-level shops: Characteristics of three-dimensional commercial distribution dynamics in Beijing combining *Gaode* and *Dianping* data

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ABSTRACT

This study investigates the evolving spatial patterns of urban commercial establishments in the digital era through a three-dimensional analytical framework. Using integrated data from *Gaode Map* and *Dianping*, we analyze traditional street-level businesses —retail, food and beverage (F&B), and daily service—across Beijing's Fifth Ring Road from 2012 to 2024. The results show ground-floor street-facing (street-level) establishments declined overall but proved more resilient during the pandemic with a partial rebound, while their non-street-facing counterparts grew steadily, and non-ground-floor businesses maintained overall growth despite a temporary drop during COVID, followed by partial recovery. Spatially, street-level business proportion decreased with distance from the urban core, whereas non-ground-floor establishments clustered within the 2nd–4th ring roads. Retail and F&B establishments strongly favored street-level locations, particularly after the pandemic, whereas daily service businesses showed relatively greater preference for non-street-level spaces. Notably, platform comparisons reveal distinct recording patterns: while *Gaode* captured more street-level establishments, *Dianping* registered higher proportions of horizontally/vertically expanded businesses. Vertically expanded establishments demonstrated higher online ratings and review volumes, suggesting digital platforms may help mitigate visibility limitations in physical space. National and local policies that may have facilitated commercial expansion are also discussed. These insights offer valuable implications for the operation of commercial establishments and urban policymaking in the digital era.

1. Introduction

As cities increasingly depend on their roles as centers of consumption (Glaeser et al., 2001), commercial establishments—defined as physical venues for the sale of goods or services—play a critical role in driving local economic growth, creating jobs, and enhancing urban quality of life (Holguín-Veras et al., 2021). Scholars in urban economics, urban planning, and geography have long sought to identify key factors contributing to the success of commercial establishments, highlighting the significance of prime location (Alonso, 1964), appealing design and layout (Kalantari et al., 2022), exceptional customer experience (Cornelius et al., 2010), robust operational strategies (Minazzi, 2015), and advanced technology integration (Pantano, 2016). Among these factors, location is widely regarded as paramount (Anderson et al., 1997; Brown, 1989), with shopping centers (Rao & Dovey, 2021) and street-level shops (Kickert, 2021) serving as key locations for traditional commercial establishments due to their high agglomeration, accessibility, and visibility (Xu et al., 2024). However, the proliferation of the internet, mobile payments, e-commerce platforms, and social media has reshaped consumer behavior and service delivery, transitioning from traditional offline settings to a multidimensional environment that integrates both online and offline experiences (Leung et al., 2013; Minazzi, 2015; Seghezzi et al., 2021). This transformation not only reshapes consumer habits but also exerts a profound impact on the spatial distribution of commercial establishments in urban areas (Talamini et al., 2022; Yang et al., 2019), influencing urban forms and city dynamics (Yousefi & Dadashpoor, 2020).

The impact of digitalization on commercial establishments has garnered increasing attention from economists, urban planners, and policymakers. Most studies highlight the threats posed by online

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shopping and delivery services to traditional brick-and-mortar stores, examining the vulnerability of conventional street-level shops (Kickert, 2021; Kickert et al., 2020), shopping districts (Rao & Liu, 2023), and retail centers (Dolega & Lord, 2020). In response, researchers propose traditional and digital strategies to revitalize commerce, highlighting the importance of proactive planning (Hardaker et al., 2022), enriched urban experiences (Rao & Liu, 2023), electronic marketing (e-marketing) on social media (Minazzi, 2015), and the integration of interactive technologies in physical stores (Kickert, 2021; Pantano, 2016). In parallel, some research has shifted its focus to new retail geographies, investigating how online platforms influence commercial relocation patterns (Mokhtarian et al., 2006), and revealing the decentralization (Hardaker et al., 2022; Yousefi & Dadashpoor, 2020), fragmentation (Xi et al., 2017), and hybridization (Matern et al., 2019) of commercial establishments. Recently, emerging concepts such as "location-less restaurant" (Talamini et al., 2022), "invisible/implicit spaces" (Han et al., 2021; Liang et al., 2023; Sun & Wang, 2021), and "dark kitchens/stores" (Bittermann & Hess, 2024; Da Cunha et al., 2024) have been introduced to describe commercial establishments that operate with reduced dependence on traditional commercial areas. A growing body of research employs quantitative methods to identify these less-visible commercial establishments (Liang et al., 2023; Sun & Wang, 2021), revealing vertically integrated services and restaurants within office buildings (Han et al., 2021; Talamini et al., 2022) and horizontally dispersed restaurants (Zhang et al., 2020).

Although recent studies have begun exploring the spatial restructuring of commercial establishments in the digital era, most focus on horizontal and vertical dimensions separately, leaving the integrated three-dimensional dynamics insufficiently addressed. Furthermore, while the impact of traditional factors—such as rent and building attributes—has been discussed, the role of e-marketing practices and related policy incentives remains underexplored. To contribute to this literature, our study addresses two central questions: (1) What are the characteristics of the three-dimensional distribution dynamics of commercial establishments in the context of digitalization? (2) What policies might have facilitated these spatial transformations?

To address these questions, this study introduces a novel four-quadrant micro-location typology that systematically captures both horizontal and vertical expansion of commercial establishments. Using Beijing within the Fifth Ring Road as a case study, we conduct a fine-grained analysis of commercial distribution patterns by integrating multi-year (2012–2024) datasets from *Gaode* (one of the most popular digital navigation applications in China) and *Dianping* (the leading consumer-driven business rating platform in China). Through the integration of these two datasets, this study explores the three-dimensional spatial dynamics of traditional street-level establishments, including retail, food and beverage (F&B), and daily services in the digital era. By performing a comparative analysis of overlapping and distinct distribution patterns across platforms, variations within different ring road areas and business categories, and differences in e-marketing performance—measured by online ratings and review counts at different locations—this study uncovers the relationships between platforms, digital operations, and commercial spatial distribution. Based on these analyses, we discuss how national and local policies, including consumption stimulus measures, employment facilitation initiatives, and spatial governance regulations, are linked to the relocations of commercial establishments. The findings provide valuable insights for urban planners, policymakers, and business operators, supporting the development of spatial strategies, policy frameworks, and adaptive measures in response to the rapidly evolving commercial landscape.

The remainder of this paper is structured as follows: Section 2 reviews the existing literature on the spatial distribution of commercial establishments, with a particular focus on the impact of digitalization. Section 3 outlines the analytic framework, methodology, and data sources. Section 4 presents the empirical findings, while Section 5 examines the policy context related to these transformations. Section 6 discusses academic contributions and practical implications, and Section 7 concludes the study.

2. Literature review

2.1. Critical role of accessibility and agglomeration in traditional commercial establishments

Location has long been recognized as crucial to the survival and success of commercial establishments (Anderson et al., 1997; Brown, 1989), with accessibility and agglomeration being primary locational attributes (Anguera-Torrell & Cerdan, 2021). Commercial centers have evolved from traditional formats, such as pedestrian streets, markets, plazas, and main streets, to large-scale retail formats, including big-box stores, strip malls, and shopping malls. More recently, they have transitioned to hybrid models, combining main streets, shopping malls, and power centers (Rao & Dovey, 2021; Rao & Liu, 2023). These commercial establishments tend to cluster near pedestrian and vehicular traffic, forming a multi-scale "retail hierarchy" that includes city, regional, district, and neighborhood centers.

Shopping malls, often classified as big-box establishments (Rao & Dovey, 2021), share positive spatial externalities that enhance their attractiveness (Yang et al., 2019). Street-level shops, typically located on the ground floor and facing the streets, represent another dominant commercial format (Bowlby, 2022; Sevtsuk, 2020). This format is especially crucial for small and micro businesses in retail, catering, and personal services (Kickert, 2021), as it offers superior accessibility and high storefront visibility (Cornelius et al., 2010; Kalantari et al., 2022). The design of windows maximizes interaction with the street, attracting pedestrians by revealing interior activities and products (Pantano, 2016).

In China, commercial establishments typically take the forms of shopping malls, street-level shops, and several scattered ground-floor shops within residential communities (Huang, 2008). According to the *Code for Classification of Urban and Rural Land Use and Planning Standards of Development Land* (Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2012), which guides urban planning in China, commercial facilities (B1) and ancillary service facilities in residential areas (R32) are strategically designed to meet consumer needs. These top-down planned commercial areas are typically located in well-connected, high-footfall zones, making them prime locations for traditional commercial establishments (Jia et al., 2024).

2.2. Impact of digitalization on the location choice of commercial establishments

Over the past two decades, social media (e.g., content communities, virtual communities, and social networking sites) and mobile technologies (e.g., devices, web platforms, and applications) have profoundly reshaped the relationship between customers and businesses (Leung et al., 2013; Minazzi, 2015). The substitutional role of online shopping has led to a reduction in physical travel, as tele-activities and telecommunications increasingly replace offline interactions (Andreev et al., 2010). Conversely, third-party business platforms and social media, such as Yelp, Instagram, and Twitter, can stimulate certain types of offline trips by reallocating activities through location-based services, user-generated content, reviews, and recommendations (Bou Mjahed et al., 2017; Fe, 2023; Mokhtarian et al., 2006). These transformations have prompted commercial establishments to adjust their location strategies.

On one hand, e-shopping, combined with efficient delivery logistics, has emerged as an alternative to traditional material consumption (Xiao et al., 2018), leading to increased vacancies in brick-and-mortar retail establishments (Dolega & Lord, 2020) and necessitating a shift in restaurant distribution and management strategies (Kim & Wang, 2021; Li & Wang, 2020). Evidence suggests a significant relationship between e-commerce and rising commercial property vacancy rates (Kickert, 2021; Kickert et al., 2020), with potential consequences such as physical deterioration of buildings and reduced urban livability (Oskam, 2021; Zhang et al., 2016). Numerous studies have examined the spatial distribution of on-demand food delivery shops at the city and district scales, emphasizing their proximity to consumers, concentration in areas with limited walkable food access (Ma et al., 2024), and higher accessibility by cycling (Wang & He, 2021). These studies also highlight the decentralization and increasing spatial dispersion of food delivery establishments (Talamini et al., 2022). Meanwhile, new types of commercial establishments, such as “location-less restaurants” (Talamini et al., 2022), “dark kitchens” (Da Cunha et al., 2024), “dark stores” (Bittermann & Hess, 2024), and “ghost kitchens” (Cai et al., 2022), have emerged. These low-visibility establishments often operate without traditional storefronts and are located in independent locations, shared spaces, or even within residential communities and private homes (Da Cunha et al., 2024). Recent estimates suggest that cloud kitchens will account for 30 % of India's catering industry (John, 2023), while dark kitchens represent approximately 27 % of food delivery operations in Brazil (Hakim et al., 2023). Empirical studies indicate that platform-dependent restaurants tend to be more spatially dispersed, located farther from central business districts (Hakim et al., 2023), and less reliant on transport accessibility. These establishments exhibit both horizontal diffusion and vertical expansion (Talamini et al., 2022).

On the other hand, algorithmic recommendations and third-party platform booking provide abundant onsite choices for experiential consumption (van Nuenen & Scarles, 2021). Electronic word-of-mouth, as an extension of traditional word-of-mouth on the internet and wireless systems (King et al., 2014), significantly impacts customers' demand confirmation, information acquisition, selection comparison, purchase decisions, venue choices, and post-evaluations (Mu et al., 2019) through various peer networks (e.g., Facebook, Twitter, WeChat, and Sina Weibo) and anonymous review websites (e.g., TripAdvisor, Yelp, and *Dianping*) (Zhang et al., 2021). In this context, commercial establishments, particularly small and medium-sized enterprises, engage in e-marketing through social media and platforms (Eid & El-Gohary, 2013; Jaas, 2022) to present information, interact with customers, and cultivate positive feedback in the pre-trip, during-trip, and post-trip phases (Abebe, 2014; Minazzi, 2015). Consequently, this competitive advantage allows businesses to reduce their reliance on prominent, high-rent urban locations (Mitchell, 2000), giving rise to what has been termed “invisible spaces” (Han et al., 2021; Liang et al., 2023; Sun & Wang, 2021) or “implicit consumption space” (Jia et al., 2024). For instance, Zhang et al. (2020) identified inconspicuous yet popular catering spaces using street-view images and social media data, underscoring the critical role of word-of-mouth in supporting establishments located in less favorable areas. Sun and Wang (2021) and Liang et al. (2023) identified 1919 and 14,939 establishments located on non-ground floor areas as invisible consumption spaces, respectively, concealed within high-rise buildings in the central areas of Nanjing and Changsha, using data from *Dianping* and *Gaode Map*. They highlighted these establishments' proximity to commercial centers and transport hubs, as well as the influence of rent and building governance. Zhang, Hou, and Long (2025) revealed trends in the horizontal and vertical expansion of commercial establishments across 287 Chinese cities, using *Dianping* data from 2015, 2019, and 2023. Their findings highlight higher expansion rates for experiential shops and in high-tier cities.

In summary, the convenient delivery logistics and algorithmic recommendations jointly provide an alternative to the positive spatial externalities associated with traditional commercial agglomeration and accessibility, leading to reduced incentives for businesses to pay higher rents in conventional locations (Yang et al., 2019), thus relaxing geographical constraints on commercial establishment locations (Batty, 2018, 2022). Both on-demand delivery and in-person experiential consumption have contributed to the rise of less-visible shops. Consequently, recent studies have started to identify and examine commercial establishments beyond traditional settings, characterized by horizontal expansion within street blocks and vertical layouts in non-commercial buildings. However, empirical quantitative research remains in its infancy and has several limitations. (1) Spatially, while numerous studies have examined horizontal or vertical expansion separately, few have integrated both dimensions into a comprehensive three-dimensional framework, limiting their practical applicability for micro-scale spatial governance. (2) Temporally, existing studies are largely confined to isolated, year-specific snapshots (e.g., individual or sporadic years), failing to capture the longitudinal dynamics of commercial spatial restructuring, particularly during the COVID-19 period. (3) In terms of mechanisms, while previous research has explored the impact of locational factors and rental prices, the roles of e-marketing and related policies remain underexplored.

Therefore, this study proposes an integrated horizontal-vertical expansion matrix to analyze the three-dimensional spatial dynamics and characteristics of commercial establishments at the micro-scale, while also examining their relationships with digital marketing strategies and policy interventions.

3. Method

3.1. Study area and analytic framework

This study focuses on the area within Beijing's Fifth Ring Road, covering approximately 667 km^2 (Fig. 1a), for several reasons. First, as a major metropolis, Beijing ranks high among Chinese cities in terms of internet users and provides a diverse array of digital application scenarios, making it an ideal study area. Second, China's rapid economic development and urbanization have granted individuals greater leisure time, increased spending power, and a growing inclination toward experiential consumption, leading to the proliferation of commercial establishments in Beijing. Third, the study area is located in the city's central region, accommodating one-third of Beijing's permanent population and catering to various consumption activities. Lastly, from 2012 to 2024, the study area did not experience extensive urban sprawl or significant construction projects, ensuring a relatively stable environment (see Fig. S1 in the supplementary material (SM) for land use changes in the study area from 2012 to 2021). As illustrated in Fig. 1b, some traditional street-level commercial establishments have expanded horizontally into street blocks (e.g., a flower shop and photography studio on the ground floor in a residential community) and vertically within non-mall buildings (e.g., a cake shop on the 4th floor and a retail shop on the 16th floor in a service apartment).

This study focuses on three types of consumer-oriented commercial establishments: retail, F&B, and daily service sectors, which were traditionally located in street-level shops (Kickert, 2021), corresponding to Divisions 47, 56, 95, and 96 in the fourth version of the *International Standard Industrial Classification of All Economic Activities* (*ISIC, Rev. 4*) (United Nations, 2008). Detailed subtypes are presented in Table S1 in SM. Retail establishments, such as clothing shops, grocery stores, and chain supermarkets, rely heavily on foot traffic and are commonly found in ground-floor storefronts, aiming to attract pedestrians with visually appealing displays. Similarly, F&B establishments, including restaurants, dessert shops, coffee shops, bubble tea shops, and bars, predominantly occupy street-level shops. Daily service businesses, encompassing hair salons, repair shops, photography, and maintenance services, are typically located along the street to enhance accessibility for consumers. Subsequently, we employ a five-step framework for data cleaning, processing, and analysis (Fig. 2).

For data collection, unlike previous studies that focus exclusively on either *Gaode* or *Dianping* data, we place greater emphasis on the disparities and integration of shop distributions across both platforms. Consequently, we collect the point of interest (POI) data from *Gaode Map* (https://ditu.amap.com/) biennially from 2012 to 2024, specifically from the years 2012, 2014, 2016, 2018, 2020, 2022, and 2024.

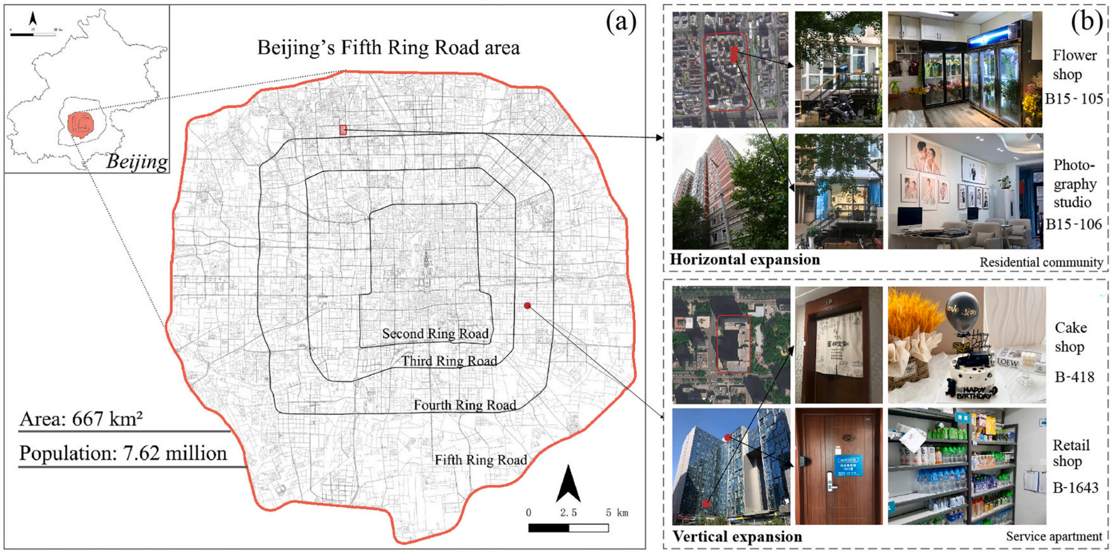

Fig. 1. The study area (a) and examples of horizontal and vertical expansion (b). Note: The population is calculated based on mobile phone data from *China Unicom* in July 2022. Map source: Baidu Maps Image. Photo source: The author's shooting and the *Dianping* platform.

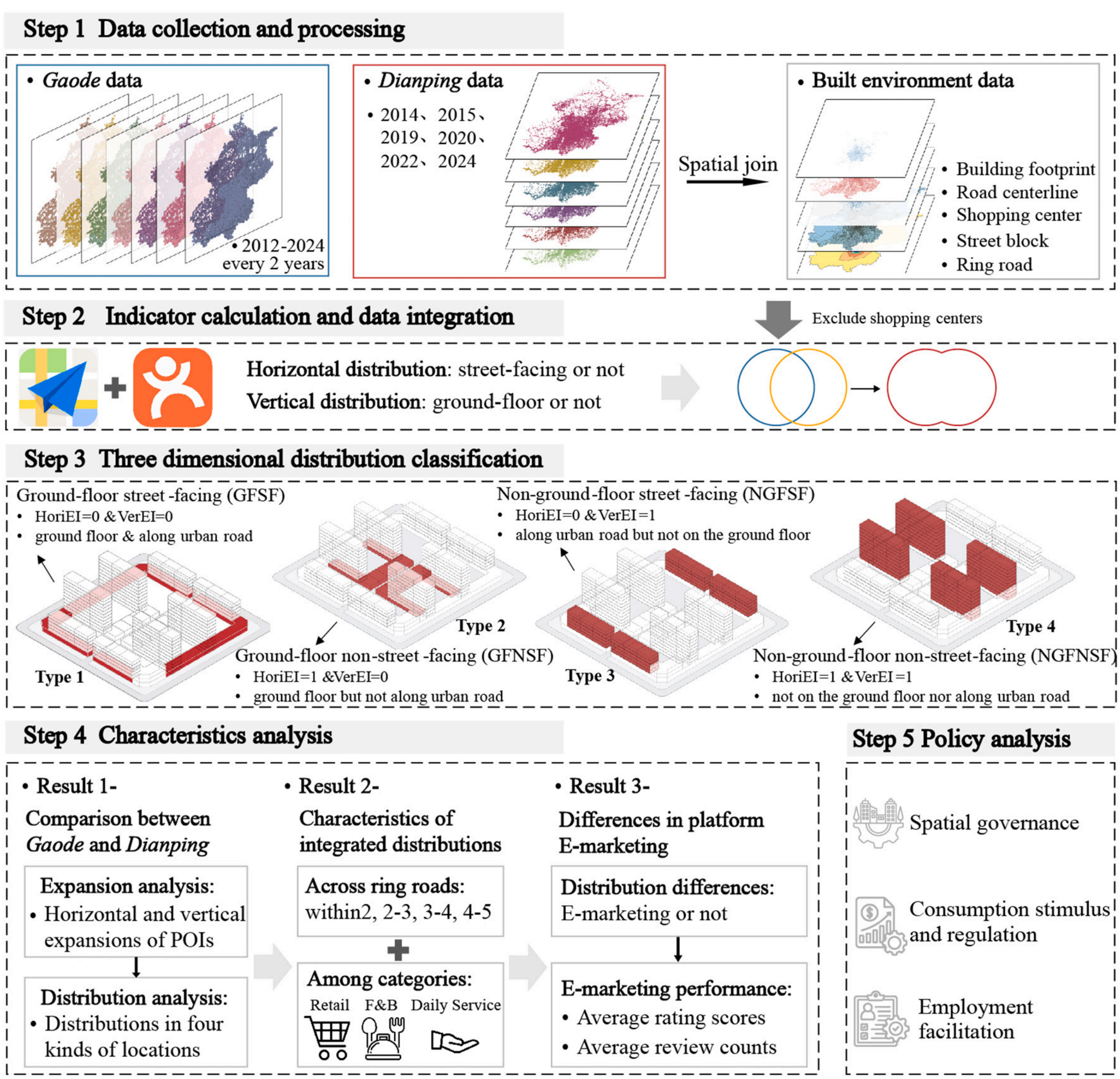

Fig. 2. Data processing and analytic framework.

Due to data availability constraints, we only obtain *Dianping* POIs (https://www.dianping.com/) for selected years (2014, 2015, 2019, 2020, 2022, and 2024), which roughly correspond to the *Gaode* dataset. Given the missing and excessive records of POIs within shopping centers in the early years of the platform's data, and considering that the consumption patterns of shopping centers differ from those of traditional fragmented street-level commerce, this study excludes commercial establishments within these areas (see Note S1 in the SM for a detailed definition of shopping centers and the method for boundary identification). Additionally, we collect built environment data to measure the micro-scale locations of POIs, including building footprints, road centerlines, street blocks, and ring roads. To ensure comparability across years, we use the same road network and building footprint data to calculate the horizontal indicators for POIs across all years. The centerlines of the urban roads and building footprints were obtained from *Gaode Map* in 2019. For data processing, we remove duplicate commercial establishments based on POI name, coordinates, and address text, and then spatially link each POI to shopping center footprints, ring roads, and street blocks.

Subsequently, this study measures the horizontal and vertical distribution of *Gaode* and *Dianping* POIs, building on previous studies that classify non-street-facing shops as horizontal expansion and non-ground-floor shops as vertical expansion or implicit locations (Jia et al., 2024; Zhang, Hou, & Long, 2025). Specifically, the Horizontal Expansion Indicator (HoriEI) determines whether a commercial establishment is street-facing (0) or not (1), while the Vertical Expansion Indicator (VerEI) assesses whether the establishment is located on the ground floor (0) or not (1). After calculating these indicators for *Gaode* and *Dianping* POIs, we categorize establishments into three groups for comparative analysis: *Gaode*-exclusive, *Dianping*-exclusive, and overlapping records. This classification facilitates the systematic integration of both platforms' data while ensuring methodological consistency.

Based on the measurement of HoriEI and VerEI, we establish a horizontal-vertical expansion matrix to classify POIs into four location types: ground-floor street-facing (GFSF, HoriEI = 0 & VerEI = 0), ground-floor non-street-facing (GFNSF, HoriEI = 1 & VerEI = 0), non-ground-floor street-facing (NGFSF, HoriEI = 0 & VerEI = 1), and non-ground-floor non-street-facing (NGFNSF, HoriEI = 1 & VerEI = 1). Within this classification framework, GFSF shops represent traditional street-level shops (Kickert, 2021), valued for their high accessibility and visibility. GFNSF establishments indicate horizontal expansion only, typically functioning as community-oriented shops (Da Cunha et al., 2024) that serve local residents. NGFSF shops (vertical expansion only) and NGFNSF shops (both horizontal and vertical expansion) are classified in recent literature as "implicit consumption spaces" (Jia et al., 2024) or "location-less" shops (Talamini et al., 2022), which are considered key beneficiaries of digitalization trends.

Next, this study examines the trends, characteristics, and e-marketing performance of commercial establishments across the four aforementioned location types, considering discrepancies and integration between *Gaode* and *Dianping* data. To identify trends, we first compare the horizontal and vertical expansion patterns of POIs on *Gaode* and *Dianping* platforms and then analyze the trends in the four location types. Regarding characteristics, we integrate the *Gaode* and *Dianping* datasets to compare POIs across different ring road areas and three business categories. To further investigate distinctions between commercial establishments with and without e-marketing, we compare the distribution of POIs only recorded on each platform and analyze the differences between e-marketing and non-e-marketing establishments, as well as e-marketing performance (measured by average online ratings and review counts) in different location types for establishments on the *Dianping* platform.

Finally, since policymakers play a crucial role in shaping economic activities by formulating policies that encourage, regulate, or restrict them, this study analyzes national and local policies related to horizontal and vertical expansion of commercial establishments from the perspectives of consumption stimulus and regulation, employment facilitation, and spatial governance.

3.2. Measurement of the three-dimensional location of commercial establishments

Given that surveys in China indicate a predominant shop depth of 9–15 m across various retail sectors (Lu, 2023), this study adopts the street-interface-based 20 m method proposed by Zhang, Hou, and Long (2025) for identifying street-facing commercial establishments, rather than the conventional road centerline-based buffer approach (e.g., 50 m) (Zhang et al., 2021) (see Note S2 in the SM for a detailed comparison of the two methods). Specifically, we first measure the distance to the nearest building façade for each urban road centerline segment (ND_j) to calculate the integrated width of the road and pedestrian pavement. Notably, the urban roads considered in this analysis exclude semi-public roads within shopping centers or private pathways within gated communities. Next, we compute the distance from each POI to its closest street centerline segment (ND_{ij}). By subtracting ND_j from ND_{ij}, we determine the distance of each POI i from the nearest street-facing façade (D_i). Finally, we apply a 20-m threshold based on the width of a street-facing building to determine whether the POI is a street-facing shop. If D_i is greater than this threshold, the POI is classified as non-street-facing, and the horizontal expansion indicator is assigned a value of 1; otherwise, it is set to 0 (Fig. 3). Although this method does not perfectly identify street-facing shops, it allows for comparisons of changes over time across different ring roads and business categories. Additionally, this study also evaluates threshold values of 15 m and 25 m to assess the robustness of the conclusions (Table S4 in SM).

For vertical distribution, we employ address text mining techniques to automatically extract POI floor information, a method commonly used in previous studies (Jia et al., 2024; Talamini et al., 2022). Since most studies do not provide detailed methods for floor identification, this study outlines the process in detail (Fig. 4). First, we remove duplicate POIs with the same name and address, and convert Chinese numerals to Arabic numerals using the cn2an library in Python (e.g., "二层" to "2层"). Next, we apply specific rules to decode POI addresses (see Note S3 in the SM for standard Chinese address formats). Rule 1 identifies ground-floor commercial establishments using distinct keywords, such as "底商 (ground floor)", to mark the floor as "1". Rule 2 extracts floor number information before apparent floor-related words such as "楼 (floor)" and "层 (layer)". Rule 3 extracts floor information from room numbers. For example, "312室 (room 312)" is inferred to be on the 3rd floor. Rule 4 identifies POIs in underground levels based on keywords such as "B (abbreviation for basement)", "负 (lower level)", and "地下 (underground)". POI addresses are processed using these rules to extract floor information, and the applied rule is recorded for validation. Since some POIs may have conflicting floor information identified by multiple rules, we refine the extracted floor data through a series of cleaning steps (see Note S4 in the SM for the details). For multi-floor POIs, we select the floor closest to the ground floor (e.g., assigning the 1st floor to floors 1–3). For POIs without explicit floor information, we classify them as ground-floor establishments based on Chinese address naming conventions. Finally, POIs identified as ground-floor establishments are assigned a value of 0 for VerEI, while others are assigned as 1. Given that some commercial podiums extend from the 1st to the 3rd floor, we also treated floors 1–2 and 1–3 as thresholds to identify NGF shops to test the robustness of the results (Table S4 in SM).

3.3. Integration of Gaode and Dianping data

To validate the accuracy of the identification method, compare address discrepancies, and integrate POIs from both platforms, we match POI data from *Gaode* and *Dianping*. Initial manual observations reveal inconsistencies in shop names, addresses, and coordinates between the two datasets. To improve matching precision, we standardize

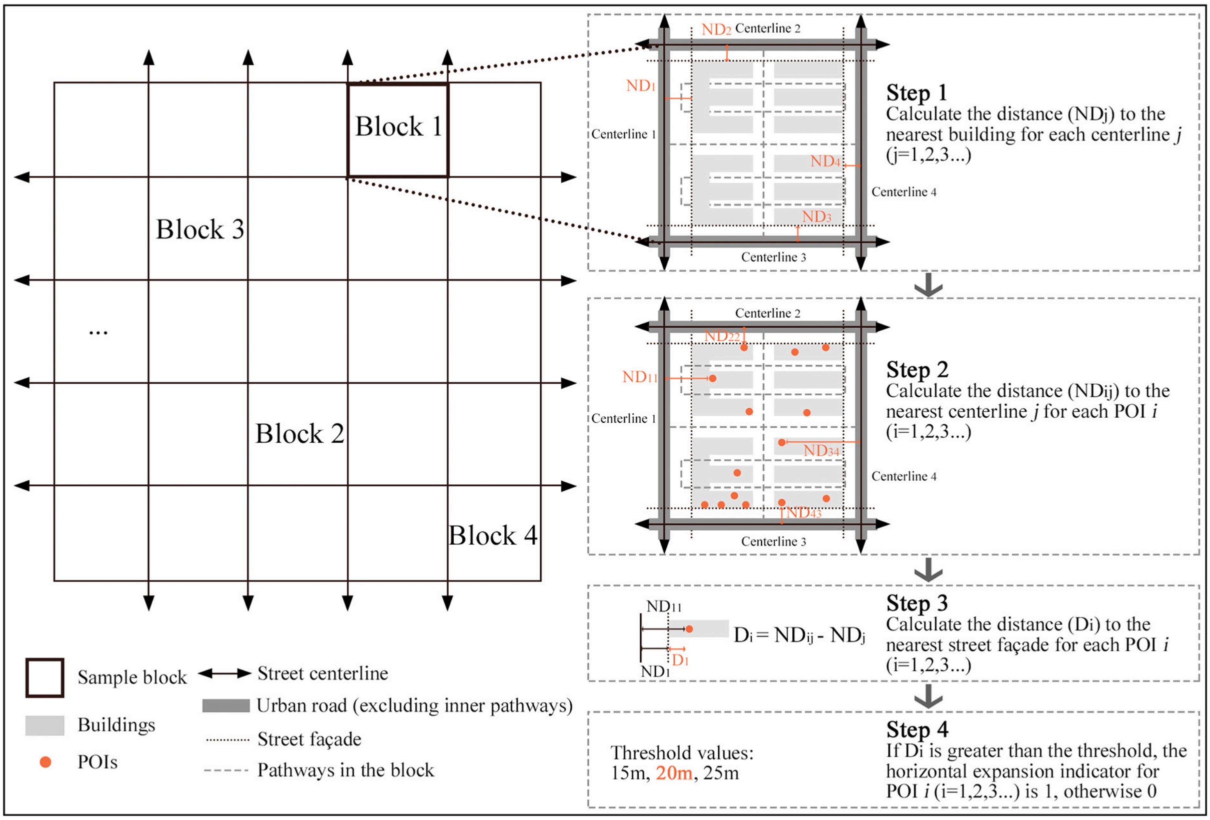

Fig. 3. The process and illustration of calculating the HoriEI.

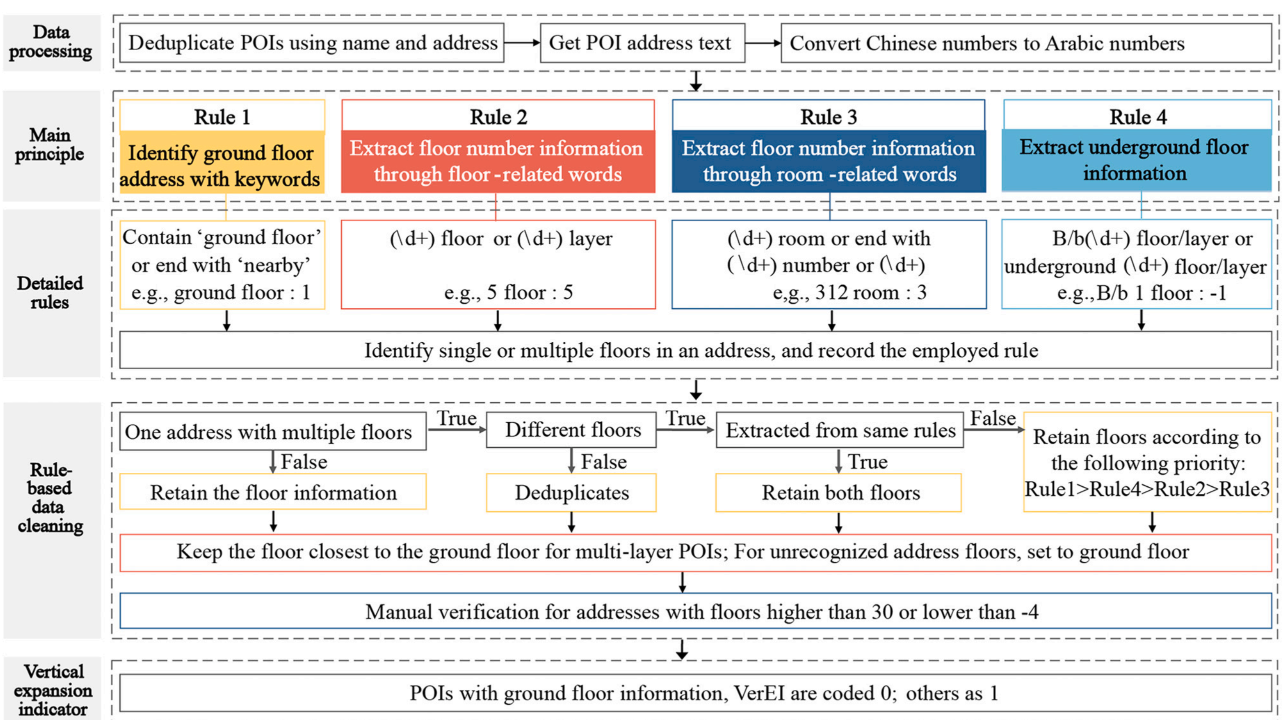

Fig. 4. The process of identifying the floor information and calculating the VerEI. Note: In the Chinese floor naming system, the numbering starts from "1F" for the ground floor. The regular expression (\d+) captures a sequence of numerical digits (a number).

shop names by removing text within parentheses (typically containing branch information of chain stores) and then link the datasets based on standardized names and previously joined street block IDs. Given the differing classification systems between the platforms, we use *Gaode*'s categories (F&B, retail, and life services) as the reference to filter corresponding major and subcategories in *Dianping* data based on the overlapping records. We extract all available years of relevant subcategories from both datasets and manually exclude POIs related to leisure, exercise, or education, retaining only those associated with F&B, retail, and daily services. The datasets are then categorized into three groups: *Gaode*-exclusive, *Dianping*-exclusive, and overlapping records.

For the overlapping data, we compare discrepancies in horizontal and vertical expansion indicators between the two platforms to better integrate the data. For data spanning from 2014 to 2024, the overall horizontal consistency rate (HoriEI, using a 20 m threshold) is 90.9 %, while the vertical consistency (VerEI) is 96.81 %. Additionally, differences in address text and coordinate accuracy are evaluated through manual checks and a field survey (refer to Note S5 in the SM). Further analysis of mismatched cases reveals that horizontal discrepancies primarily occurred when non-street-facing establishments, such as shops located at residential compound entrances, inward-facing units in street-side high-rises, or deep-set offices, were geotagged closer to roads in one platform's dataset. Vertical inconsistencies typically arose when one platform provided more detailed records (including floor/room numbers), while the other only specified building-level information (defaulting to ground-floor locations in this study). This indicates that inconsistencies between the two platforms often occur when one platform inaccurately records an address, incorrectly identifying it as a street-facing or ground-floor property. Meanwhile, the other provides a more precise record, correctly classifying it as non-street-facing or non-ground-floor commercial.

To construct the final integrated dataset, inconsistencies in overlapping records are resolved by retaining the NSF and NGF records from the *Gaode* and *Dianping* platforms where discrepancies existed, and then merging these with platform-exclusive data. Specifically, for entries with inconsistent Hori EI and Ver EI values, we retain the results from NSF and NGF based on our prior manual review judgement, as these typically yield more precise geolocations. For entries with consistent values, we retain any one of them. Finally, the modified overlapping data, *Gaode*-exclusive data, and *Dianping*-exclusive data are combined into a single integrated dataset. Due to data availability constraints, *Dianping*'s 2015 and 2019 data are paired with *Gaode*'s 2016 and 2018 data, respectively, while other years were matched chronologically (Note S5 in the SM). The resulting integrated biennial dataset covers the period from 2014 to 2024 and contains a total of 1,590,469 samples (Fig. 5).

To evaluate the accuracy of the method, 100 samples are randomly selected each year from the final dataset (600 in total), with 25 samples drawn from each of the four integrated location types. This ensures that both HoriEI and VerEI are evaluated on 50 samples each annually. The address information of these samples is manually verified based on address texts, building numbers from *Gaode Map*, and remote sensing imagery. The results indicate that HoriEI achieves a precision of 86.67 % and a recall of 87.84 %, while VerEI attains a precision of 96.67 % and a recall of 96.03 %. Together, these metrics demonstrate the relative reliability of the approach.

3.4. Data description

This study utilizes core datasets obtained from the *Gaode* Map and *Dianping* platform. Python-based web scraping techniques systematically collect establishment information, including names, categories, address texts, and geographic coordinates from both sources, with *Dianping* data also incorporating online review counts and ratings. Online ratings can be regarded as electronic word-of-mouth, reflecting consumers' evaluations of product/service quality, while the number of online reviews is generally considered to correlate with consumption frequency, suggesting consumer visiting preferences.

The summary statistics are presented in Table 1. The compiled dataset contains 2,378,961 entries from *Gaode* spanning seven annual observations and 2,751,409 entries from *Dianping* across six temporal periods, all representing three primary POI categories within Beijing. To ensure data reliability, we examine potential reasons for fluctuations between 2014 and 2018 (see Note S6 in the SM for details). Given this study's focus on the proportion of establishments in four location types outside shopping centers each year rather than the absolute quantity, the data are considered relatively comparable. Among these observed years, POIs located within Beijing's Fifth Ring Road account for 44.7 %–58.9 % of *Gaode*'s records and 46.7 %–70 % of *Dianping*'s records. Both datasets exhibit a consistent decline in the proportion of Fifth Ring Road POIs over time, with the differential narrowing.

The subset of non-mall POIs within the Fifth Ring Road shows similar temporal patterns on both platforms: the proportion decreases during 2012–2020 before reversing to an increasing trend post-2020. Among these, *Gaode* data shows a higher proportion of retail establishments compared to daily service and F&B establishments, though these

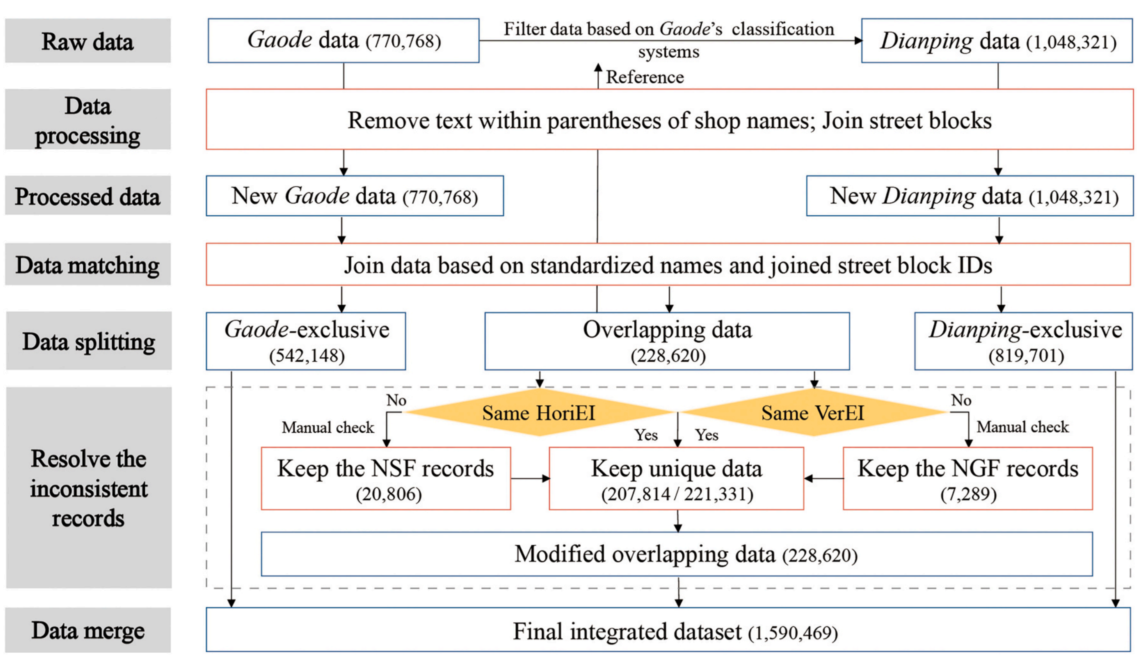

Fig. 5. The process of integrating *Gaode* (2014, 2016, 2018, 2020, 2022, 2024) and *Dianping* (2014, 2015, 2019, 2020, 2022, 2024) data.

Table 1
Summary statistics of sampled POIs for *Gaode* and *Dianping* data.

Year	POI count in Beijing filtered by types	Percentage of POIs in R5 (%)	Percentage of non-mall POIs in R5 (%)	Percentage of POIs in different categories (%)			Percentage of POIs in different ring road areas (%)				Percentage of e-marketing (%)
				Retail	F&B	Daily service	With 2nd	2nd-3rd	3rd-4th	4th–5th	
Gaode											
2012	119,248	58.5	84.1	38.4	31.2	30.4	19.3	23.9	25.2	31.6	–
2014	164,273	58.9	80.2	32.7	37.8	29.5	18.8	23.9	27.5	29.8	–
2016	477,728	53.6	71.6	35.1	37.1	27.8	17.3	22.3	28.0	32.4	–
2018	375,943	52.2	68.8	39.4	26.8	33.8	15.3	21.5	28.4	34.8	–
2020	422,905	50.8	62.8	39.2	27.4	33.4	14.7	23.0	28.9	33.4	–
2022	454,375	44.9	64.1	36.4	33.0	30.7	14.3	22.0	28.6	35.1	–
2024	364,489	44.7	65.3	33.2	33.6	33.2	14.7	22.0	28.4	34.9	–
Dianping											
2014	335,481	69.8	80.0	25.9	46.1	28.0	19.8	26.6	28.2	25.4	11.8
2015	421,196	70.0	77.1	25.5	46.0	28.5	19.1	26.4	28.8	25.7	14.0
2019	599,782	50.4	63.5	31.1	36.9	32.0	14.3	21.8	28.7	35.2	19.0
2020	571,560	49.1	65.9	28.6	38.0	33.4	13.6	21.7	28.7	35.9	20.1
2022	475,661	47.6	66.4	28.8	43.3	27.9	14.2	21.9	28.0	35.8	25.2
2024	347,729	46.7	67.2	25.0	48.4	26.6	15.8	22.0	28.2	34.0	41.1

Note: Percentages for POI categories, ring road areas, and e-marketing (with more than 10 online reviews) are calculated specifically for non-mall POIs within Beijing's Fifth Ring Road.

proportions gradually converge. Conversely, *Dianping* data shows an F&B sector dominance over daily services and retail, with diverging trends that intensify by 2024. The distribution of POIs across ring roads remains consistent between platforms, showing a gradual increase with greater distance from the urban core. For *Gaode* data, POI proportions within the Third Ring Road show a consistent decrease during the 2012–2020 period, followed by an increase in subsequent years, while areas beyond this boundary demonstrate the inverse trend. For *Dianping* data, the Fourth Ring Road serves as the critical boundary. For the e-marketing analysis, we define POIs on *Dianping* with more than 10 online reviews as e-marketing shops and others as non-e-marketing shops. The proportion of e-marketing shops gradually increases from 2014 to 2024, reaching 41.1 % by 2024.

In terms of policy analysis, this study examines national and local (Beijing) policies issued between 2012 and 2024, with particular attention to three key dimensions: consumption stimulus and regulation, employment facilitation, and spatial governance—selected because they collectively shape urban commercial dynamics. Through a

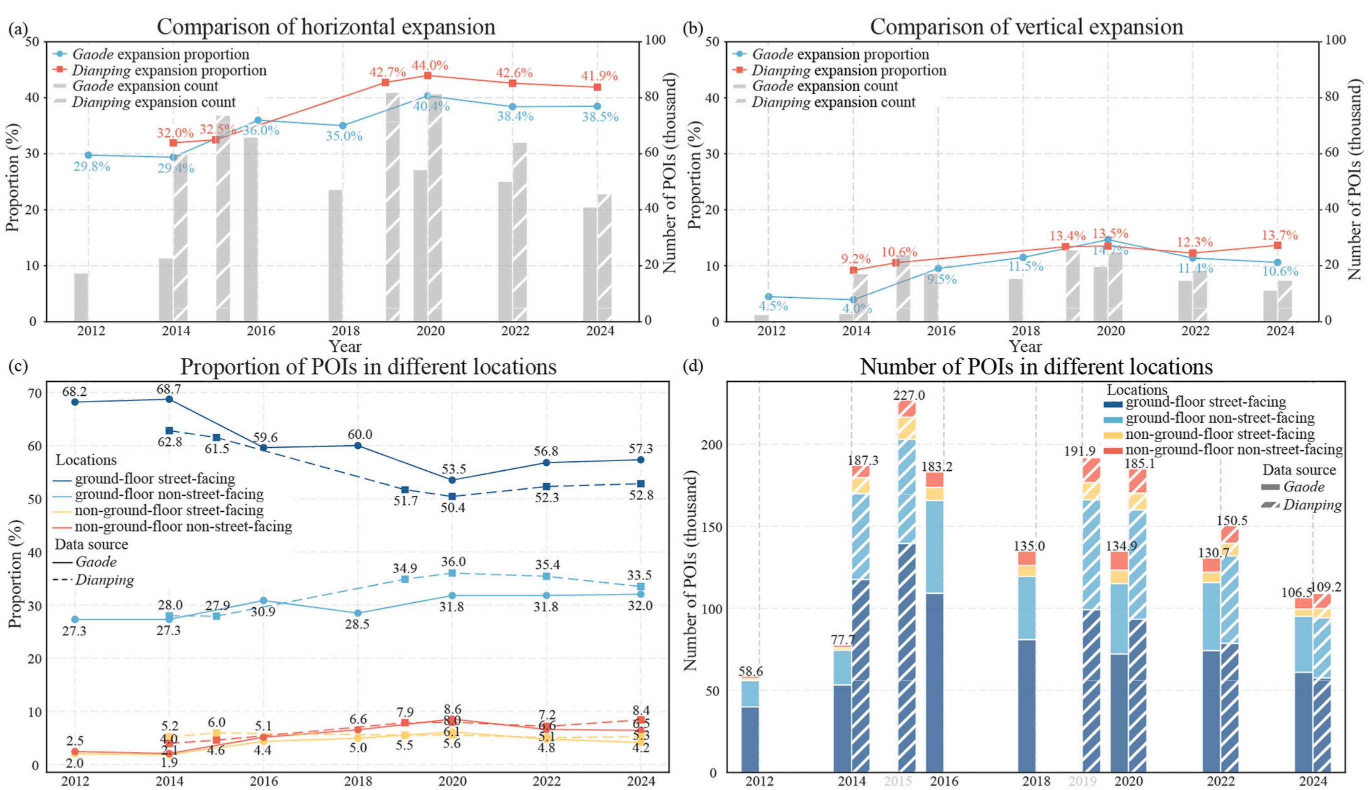

Fig. 6. Three-dimensional distribution of commercial establishments on *Gaode* and *Dianping* platforms from 2012 to 2024: (a) counts and proportions of horizontal expansion; (b) counts and proportions of vertical expansion; (c) proportions of commercial establishments in four location types; (d) counts of commercial establishments in four location types.

comprehensive review of policy documents, we identify those containing keywords such as "street-level commerce", "spatial utilization", and "mixed-use development". This analysis evaluates how these policies may positively or negatively influence the horizontal and vertical expansion of commercial establishments. Additionally, the implementation intensity of these measures is assessed based on the annual volume of relevant policies enacted. Finally, our policy review identifies 21 regulations directly relevant to commercial spatial development (for detailed policy contents, please refer to Table S9 in the SM).

4. Results

4.1. The three-dimensional distribution of commercial establishments on Gaode and Dianping

This study separately calculates the quantity and proportion of horizontal and vertical expansion of commercial establishments on *Gaode* and *Dianping* (Fig. 6a, b). The results reveal that, despite varying degrees, both platforms exhibited similar overall trends: continuous growth from 2012 to 2020, a decline from 2020 to 2022, and stabilization or partial recovery from 2022 to 2024. Notably, the quantity and proportion of horizontal expansion were nearly three times those of vertical expansion, with *Dianping* generally reporting higher values than *Gaode*. The findings indicate that for commercial establishments traditionally reliant on street-level storefronts, there was a significant pre-COVID trend of horizontal expansion into inner street blocks and vertical expansion into NGF spaces within buildings. During COVID, street-level commercial spaces demonstrated greater resilience, while in the post-COVID period, inner-block and NGF areas began regaining their appeal.

Synthesizing these two indicators, we analyze the distribution of commercial establishments across four location types (Fig. 6c, d). The results from the *Gaode* platform reveal a fluctuating decline in the proportion of GFSF shops from 2012 to 2020, followed by an increase from 2020 to 2024. GFNSF shops showed a gradual upward trend from 2012 to 2024, though with fluctuations. Non-ground-floor establishments, including both NGFSF and NGFNSF shops, exhibited similar patterns: an increase from 2014 to 2020, a decline from 2020 to 2022, and a slight rise from 2022 to 2024. *Dianping*'s results show similar overall trends, but with several differences. The proportion of GFSF shops on *Dianping* followed trends largely parallel to those on *Gaode*, though at consistently lower levels. In contrast, the proportions in the other three location types were higher on *Dianping*. Furthermore, post-2022 results diverged significantly between the platforms: while *Gaode* showed an increase in the proportion of GFNSF shops and a decrease in NGF establishments, *Dianping* exhibited the opposite trends. These findings suggest that, while both platforms indicate the enhanced role of street-level commerce post-COVID, their recording differences result in varying recovery patterns for non-street-level shops. *Gaode* captures more neighborhood ground-floor establishments, while *Dianping* shows stronger representation of non-ground-floor businesses. This divergence highlights platform-specific trends in the post-COVID revival of non-street-level commercial spaces.

4.2. Characteristics of three-dimensional distributions of integrated commercial establishments

Given that *Gaode* and *Dianping* exhibit consistent overall trends but demonstrate certain divergences during the post-COVID recovery phase, this study integrates both datasets to analyze differential patterns in the three-dimensional distribution of commercial establishments across various ring road areas and categories. Since the two platforms share partial overlaps in data coverage, we separately extract *Gaode*-exclusive, *Dianping*-exclusive, and overlapping records from both platforms. The overlapping dataset is then used to validate and refine our analytical methodology, ultimately enabling the creation of an integrated composite dataset. Table 2 shows that, in the integrated dataset, the proportion of *Gaode*-exclusive records gradually increases, *Dianping*-exclusive records exhibit a declining trend—though *Dianping* still maintains a higher overall share, the proportion of overlapping records steadily rises. Regarding the overlapping data, the consistency of HoriEI exceeds 90 % across all years except 2016, while the consistency of VerEI remains above 95 % throughout. This suggests that the 20-meter threshold for identifying street-facing shops and the ground-floor detection method demonstrate cross-platform robustness. To mitigate these issues, corrections shown in Fig. 5 are applied to the mismatched dataset to build the modified overlapping data and integrated data.

A comparative analysis of the integrated dataset and platform-specific records reveals distinct patterns (Fig. 7a). *Gaode* shows a stronger tendency to record street-facing establishments, while *Dianping* covers a greater proportion of non-street-facing businesses. In the post-COVID period, the increased visibility of street-facing locations led to their simultaneous recording on both platforms, resulting in the lowest proportion of horizontally expanded establishments in the overlapping data. The integrated dataset exhibits trends consistent with those in Fig. 6, characterized by rapid pre-COVID growth in non-street-facing establishment proportions, followed by a temporary decline and subsequent stabilization. Regarding vertical expansion, ground-floor commercial spaces (Fig. 7b), owing to their higher visibility, are more likely to be recorded by both platforms, leading to the lowest proportion of vertically expanded establishments in the overlapping data. However, temporal discrepancies emerge between *Dianping* and *Gaode* in the recording of non-ground-floor establishments. The integrated vertical expansion metrics demonstrate sustained growth before 2020, decline during 2020–2022, and recovery thereafter. The findings emphasize the importance of multi-platform data integration for comprehensive urban commercial analyses, particularly when examining three-dimensional distributions across different time periods. Sensitivity analysis employing alternative thresholds for horizontal (15 m, 25 m) and vertical (Floors 1–2, 1–3) expansion measurements using the integrated data revealed that the directions of proportion changes are almost consistent with those obtained from our primary thresholds (20 m for horizontal, Floor 1 for vertical). This consistency confirms the robustness of our findings to threshold selection (Table S4).

Using the integrated dataset, we reveal distinct variations across different ring road areas and business categories. The analysis of commercial distribution across different ring road areas shows that (Fig. 7c) as distance from the urban core increases, the proportion of GFSF establishments gradually decreases, while GFNSF businesses increase correspondingly. Non-ground-floor establishments exhibit higher concentrations within the 2nd to 4th ring roads, lower proportions in the 4th to 5th ring road areas, and minimal presence within the 2nd ring road. Temporally, while all four location types demonstrated consistent trends before 2020, their post-COVID trajectories diverged. NGFNSF establishments experienced a decline followed by recovery across all ring roads. Within the 3rd ring road, both GFSF and NGFSF establishments showed post-COVID growth, whereas beyond the 3rd ring road, these categories experienced initial declines before rebounding. GFNSF establishments exhibited fluctuating patterns across all ring roads.

Category-specific analysis also reveals variations (Fig. 7d): Daily services exhibit substantially lower proportions of GFSF establishments compared to F&B and retail sectors, while showing higher proportions in other location types. F&B establishments are more prevalent in both non-ground-floor location types compared to retail counterparts. Temporally, while all three sectors followed fundamentally similar trends before 2020, they showed different post-COVID trajectories. The retail sector exhibited sustained growth in GFSF shops, alongside continuous declines in other location types. The F&B sector maintained persistent growth in GFSF establishments, with GFNSF and NGFNSF shops experiencing initial declines followed by recovery, while NGFSF proportions showed delayed reductions. Daily services experienced fluctuations across all location types during 2020–2022 before gradually

Table 2
The descriptions and cross-platform consistency of commercial establishments.

Year (*Gaode-Dianping*)	Integrated data	*Gaode*-exclusive (%)	*Dianping*-exclusive (%)	Overlapping	Overlapping data	
					Same HoriEI (%)	Same VerEI (%)
2014–2014	245,255	23.8	67.9	8.3	91.5	96.7
2016–2015	372,276	39.5	50.2	10.3	85.6	96.7
2018–2019	282,494	32.0	52.3	15.7	93.0	97.9
2020–2020	273,447	32.6	50.7	16.7	91.1	96.9
2022–2022	236,786	36.5	45.0	18.6	92.3	96.7
2024–2024	180,211	39.3	40.8	19.9	91.7	95.7

reverting to pre-COVID trends.

4.3. E-marketing performance for commercial establishments in different locations

The above findings suggest that *Dianping*'s operational model may influence both horizontal and vertical expansion patterns of commercial establishments. To further explore the role of digital platform operations, we conduct several analyses. The cross-platform comparison (Fig. 8a) reveals that overlapping establishments show a higher concentration in GFSF locations, and *Dianping*-exclusive establishments exhibit lower proportions of GFSF establishments and correspondingly higher representation in other location types compared to *Gaode*, with these distributional patterns stabilizing post-2018. This result suggests that *Dianping* may offer greater viability opportunities for non-street-level businesses compared to *Gaode*'s records.

Focusing specifically on *Dianping* data, we conduct a comparative analysis of e-marketing (>10 reviews) and non-e-marketing (≤10 reviews) shops (Fig. 8b). The results indicate that e-marketing businesses have higher proportions in NGFSF and NGFNSF locations but lower proportions in GFNSF spaces compared to non-e-marketing shops. These patterns are reasonable: GFNSF establishments benefit from visibility within residential communities and lower rental costs, reducing their reliance on digital marketing. Conversely, non-ground-floor establishments depend more heavily on digital operations to compensate for limited physical visibility, while GFSF businesses—despite their natural visibility—still engage in e-marketing due to competitive pressures from high rent burdens.

An analysis of digital performance metrics for e-marketing establishments on *Dianping* reveals consistent annual growth in both online ratings and review counts. The rating data demonstrates a clear spatial hierarchy since 2019, with GFSF establishments exhibiting the lowest scores, followed by GFNSF, NGFSF, and finally NGFNSF shops, which show the highest ratings. This suggests an inverse relationship between physical visibility/accessibility (measured by rent, with details in Note S7 in the SM) and dependence on electronic word-of-mouth management (Fig. 8c). However, review count distribution follows a different spatial pattern, with NGFSF establishments generating the highest volume, followed by GFSF, NGFNSF, and GFNSF shops (Fig. 8d). This divergence suggests that while reduced horizontal accessibility (non-street-facing locations) corresponds with decreased online consumption activity (as reflected in lower review counts), vertical expansion into non-ground-floor spaces appears to drive greater digital engagement and online consumption, likely due to these establishments' stronger reliance on e-marketing channels. These findings collectively highlight how digital platform metrics reflect distinct compensatory mechanisms adopted by commercial establishments operating in different spatial contexts: less visible locations compensate through enhanced digital reputation management (higher ratings), and vertically expanded businesses leverage digital tools to overcome physical accessibility limitations (higher review counts).

5. Policy analysis

We situate key policy implementation events (Fig. 9b) alongside the distribution evolution of commercial establishments across different business categories (Fig. 9a) and ring road areas (Fig. 9c). Fig. 9b shows that innovation and entrepreneurship policies aimed at relaxing spatial regulations on shops were particularly prominent in 2015. The year 2017 saw more vigorous implementation of the “Opening Walls and Creating Openings” remediation initiative. In contrast, economic policies supporting the daily life service sector remained relatively stable and were sustained from 2015 to 2022. Since 2022, spatial governance policies have increasingly emphasized revitalizing underutilized land and vacant properties. We compare variations in the proportion of shops across four location types within different business categories and ring road areas, against the timing and nature of policy interventions.

Across business categories, proportional trends over location types show broadly consistent patterns, suggesting that policies may have influenced sectors similarly. However, changes in the proportion of NGFSF shops in the daily service sector appear to align with consumption stimulus policies targeting daily life services. Notable increases were observed following service-sector policy efforts in 2015, 2018, 2019, and 2022. These policies also corresponded with a widening gap between the proportion of GFNSF daily service stores and those in other categories. In comparison, the “Opening Walls and Creating Openings” remediation initiative shows a stronger association with increases in NGFNSF commercial properties—especially in the retail sector.

Across the ring road areas, GFNSF shops within the 2nd ring road appear less responsive to policy changes. In contrast, differences in GFSF properties between the 2nd ring road and other areas tend to coincide with innovation and entrepreneurship policies. The gap between the 2nd ring road and the outer areas narrowed when these policies were active, but stabilized afterward, implying that consumption stimulus and spatial governance measures may have exerted stronger effects outside the 2nd ring road. Between 2016 and 2018, the growth of NGFNSF shop proportions along the 2nd and 4th ring roads became more pronounced—a trend that may be related to the intensified remediation policy in 2017. Furthermore, under consumption stimulus policies in 2018 and 2019, the proportion of NGFSF shops between the 2nd and 3rd ring roads increased more remarkably compared to other ring roads.

Overall, spatial governance policies—especially the “Opening Walls and Creating Openings” remediation initiative—may have contributed to the growth of NGFNSF businesses, especially in retail within the 2nd–4th ring roads. Consumption stimulus policies targeting daily life services were accompanied by an increase in NGFSF proportions, particularly in daily service businesses between the 2nd and 3rd ring roads. Employment facilitation and spatial remediation policies together appear to have supported GFNSF shops before 2019, though their influence was weaker inside the 2nd ring road. The 2024 F&B Industry Pollution Regulations, however, impose spatial constraints on food and beverage establishments, which could potentially inhibit vertical expansion in this sector afterward.

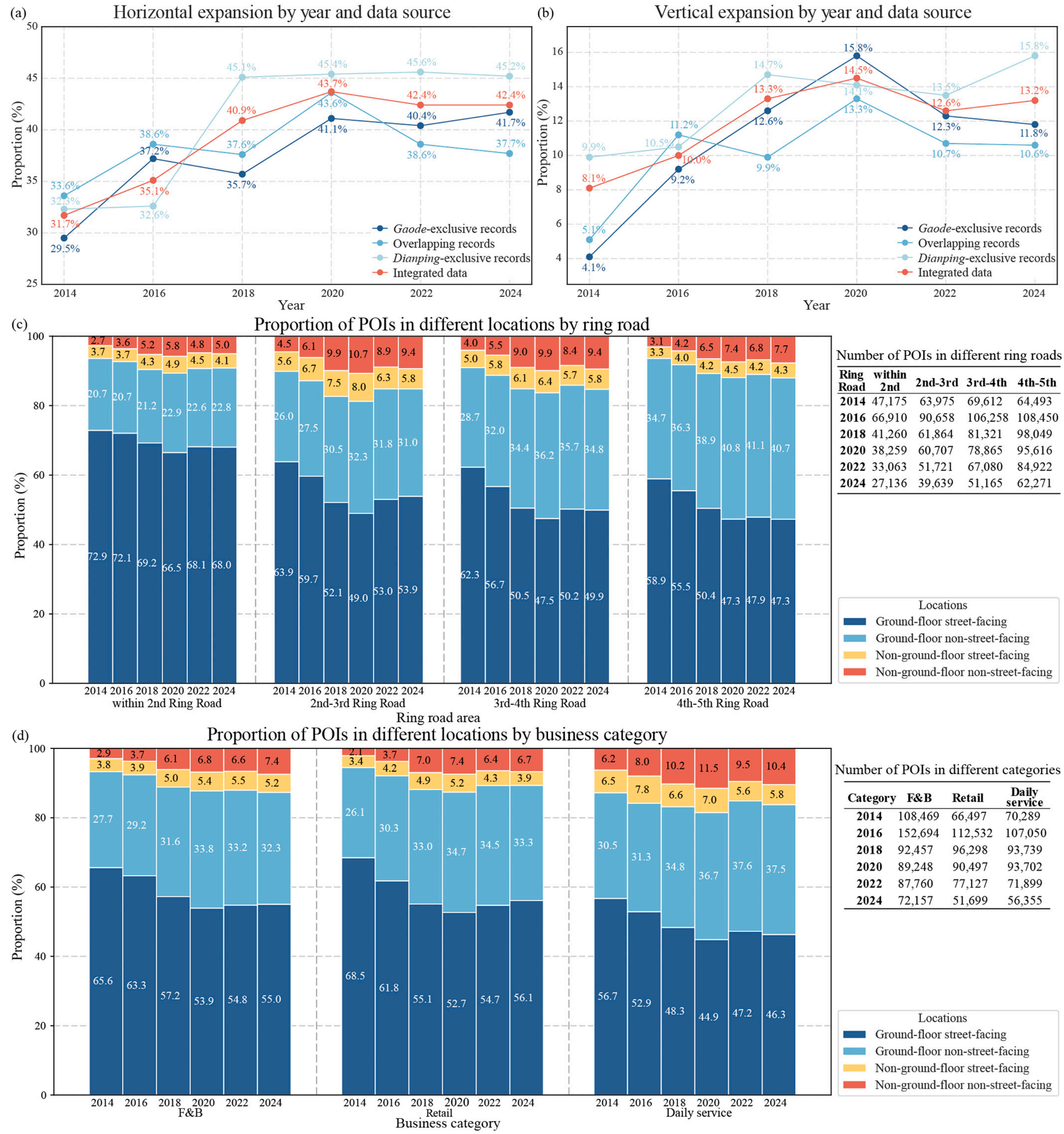

Fig. 7. Data integration and characteristics of the three-dimensional distributions of commercial establishments: (a) horizontal expansion of integrated data and its composition; (b) vertical expansion of integrated data and its composition; (c) three-dimensional distributions of commercial establishments in different ring road areas (integrated data); (d) three-dimensional distributions of commercial establishments across different business categories (integrated data).
Note: The sample sizes (a, b) for the integrated data and its composition are detailed in Table 2.

6. Discussion

6.1. Academic contribution and implications

Building upon existing research on the horizontal and vertical expansion of commercial establishments, this study explores the continuous dynamic changes from an integrated three-dimensional spatial layout perspective and examines their relationship with e-marketing and policies, thereby contributing to both academic knowledge and practical applications.

This study forms a horizontal-vertical expansion matrix to identify four types of commercial establishment locations, extending previous single-dimension analysis. From a temporal perspective, this study supplements existing research that focuses on single years or a few years

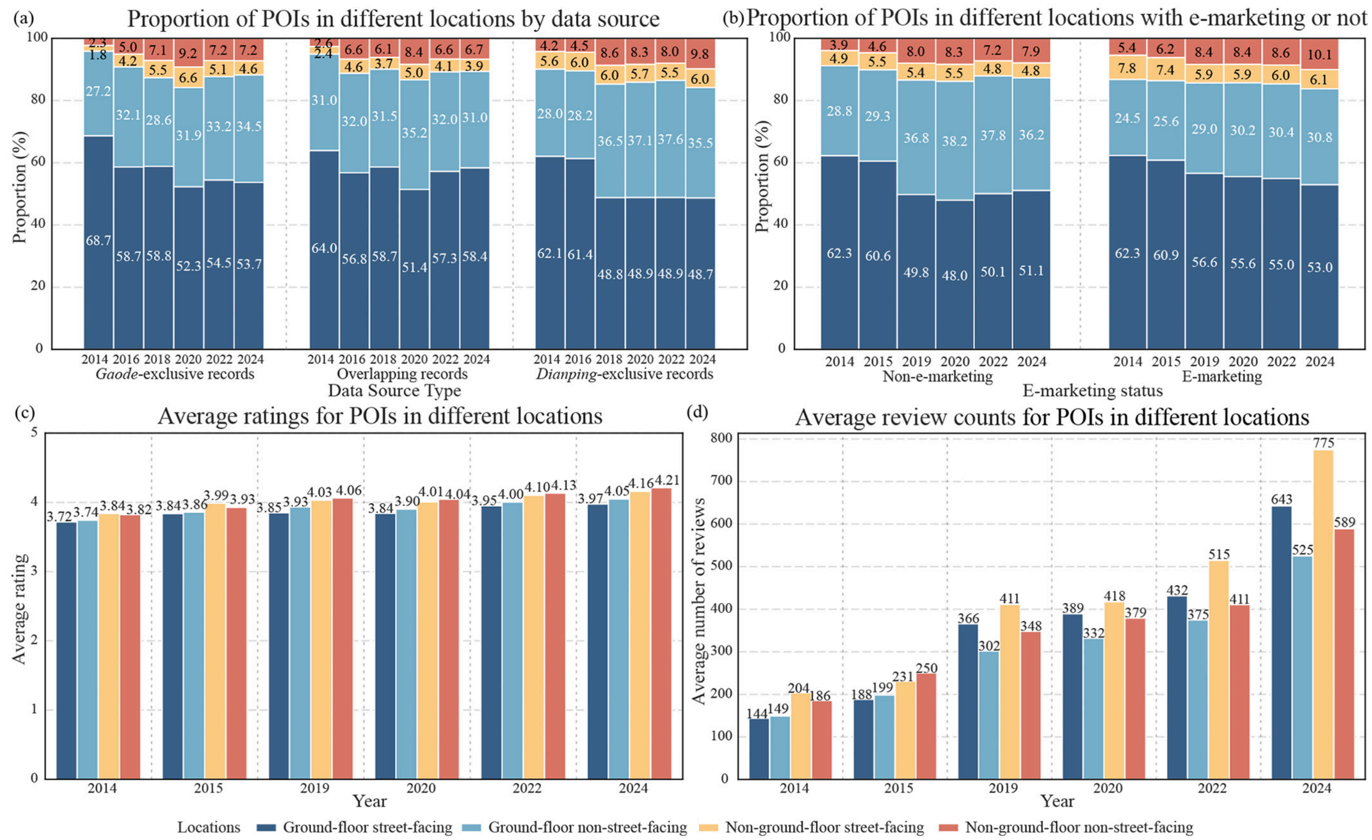

Fig. 8. E-marketing performance of commercial establishments in different locations: (a) three-dimensional distributions of establishments on different platforms; (b) three-dimensional distributions of e-marketing and non-e-marketing shops; (c) average online ratings for e-marketing shops in four location types; (d) average online review counts for e-marketing shops in four location types.
Note: The sample sizes for the different datasets (a) are shown in Table 2, with counts for the e-marketing dataset (b, c, d) provided in Table 1.

by revealing the sustained increase in the proportion of non-street-level shops before 2020, a brief decline during COVID, and a gradual recovery afterward. This reflects the higher resilience of street-level shops during COVID, particularly in the retail sector, aligning with previous studies that show the revival of street-level storefronts in central areas (Rao et al., 2024; Rao & Liu, 2023). And the faster recovery of the daily service industry after the pandemic is also consistent with existing research (Zhang, Li, & Long, 2025). From a spatial perspective, this study reveals that the proportion of GFSF establishments is higher within the Second Ring Road, while areas between the Second and Fourth Rings have a higher proportion of NGFNSF establishments. Beyond the Fourth Ring, GFNSF establishments show higher proportions. This pattern is likely related to urban morphology and function, suggesting that existing studies focusing on phenomena around the CBD (Han et al., 2021; Jia et al., 2024) are also present in more general urban areas but with different performances. Moreover, this study analyzes these phenomena from different platforms and a digitalization perspective. In contrast to existing research that primarily uses data from one platform with another as a supplementary source (Jia et al., 2024; Zhang, Li, & Long, 2025), this study compares the spatial differences in data collected by the two platforms, thus providing an additional contribution to related research. This study reveals consistent trends between the two platforms while also showing that *Gaode* tends to record more GFSF shops, whereas *Dianping* is more likely to record shops located in non-street-facing and non-ground-floor areas. GFNSF establishments show relatively lower reliance on digital operations, while other locations, due to visibility demands or rent pressures, have a higher need for digital operations (Fe, 2023; Mitchell, 2000). Areas with lower accessibility and visibility are more inclined to enhance their digital reputation. Although NGFSF shops represent the smallest proportion, their higher accessibility and digital reputation result in the highest average online consumer engagement. Overall, this study examines the potential impacts of digitalization on urban morphology and spatial structure from a consumption perspective (Yousefi & Dadashpoor, 2020), revealing that the decoupling of spatial form and function (Batty, 2018) creates development opportunities for less-visible spaces.

This study also offers important policy implications concerning the potential role of policymakers in stimulating consumption, promoting economic activity, and regulating commercial establishments. This study outlines the potential policies, including consumption stimulus and regulation, employment facilitation, and spatial governance, that may have contributed to the expansion of commercial facilities across different business sectors and ring road areas. The findings indicate that while these policies were primarily oriented toward stimulating commercial activity, more recent measures—such as the 2024 regulations targeting underground spaces for F&B establishments—reflect a shift toward stricter spatial oversight. Looking forward, it will be essential to balance economic development with social impacts and to avoid potential negative consequences similar to those observed in other contexts, such as gentrification, blurred regulatory boundaries, and environmental and safety concerns linked to platforms like Airbnb (Da Cunha et al., 2024). Therefore, given the increasing prevalence of horizontal and vertical expansion of commercial establishments in Beijing and similar dark kitchens in other countries and cities, there is an urgent need for policymakers and researchers in China and other countries to address these emerging challenges through appropriate regulatory responses and strategic guidance.

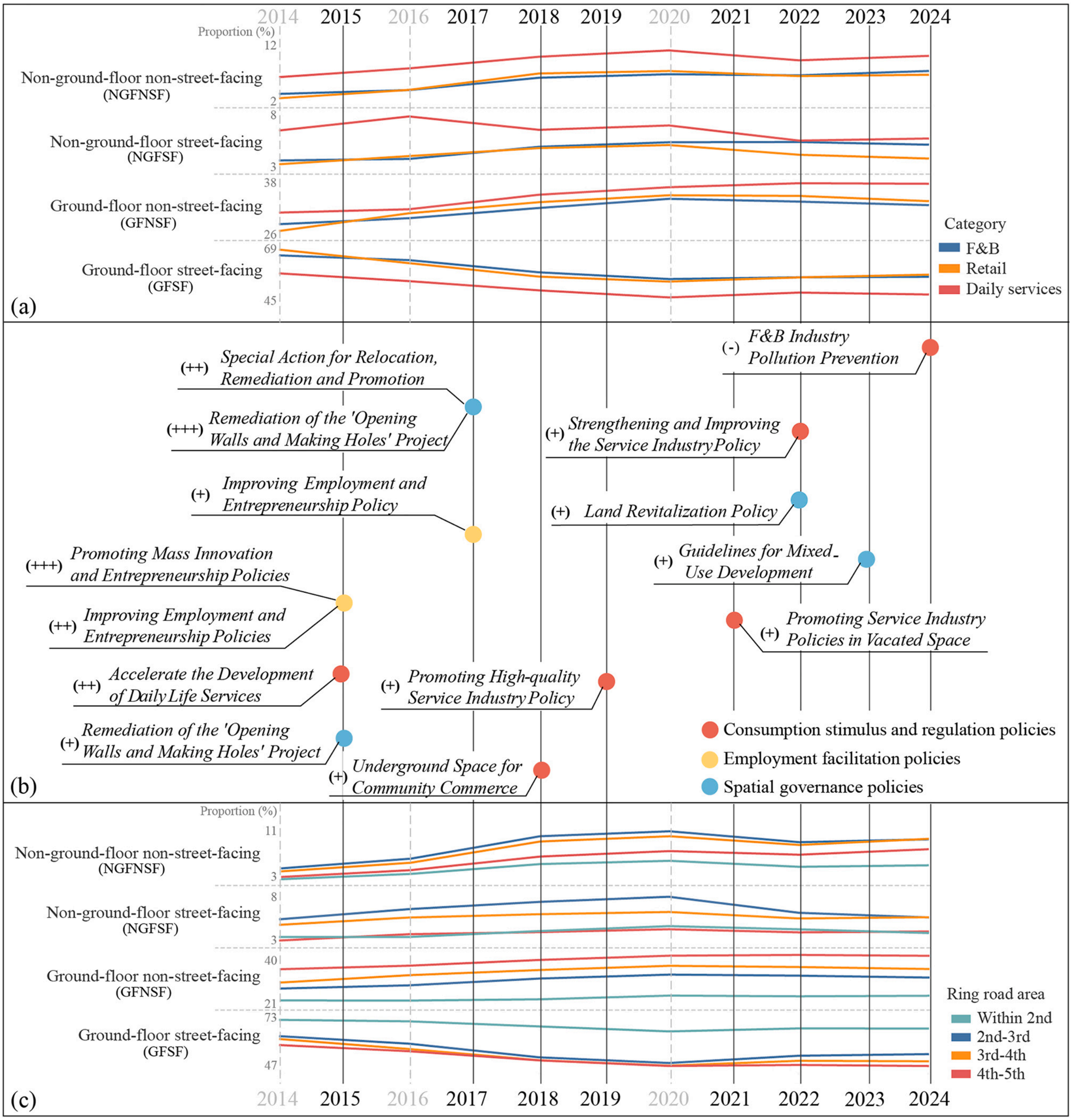

Fig. 9. Key policy implementation events (b) and the distribution evolution of commercial establishments by business category (a) and by ring road area (c). Note: The notations "(+)" and "(−)" indicate the potential facilitation or inhibition of policies for commercial expansion, respectively. The number of "+" or "−" symbols reflects the intensity of policy implementation enforcement at national or local levels, with more symbols denoting stronger enforcement.

6.2. Limitations and next steps

Although this study provides new evidence on the spatial dynamics of commercial establishments, it has several limitations that present opportunities for future research. Although the integration of *Gaode* and *Dianping* data helps mitigate platform-specific biases to some extent, the absence of records for mobile vendors and other platforms may still introduce biases. Future research could complement this by incorporating offline surveys and official business registration data. Second, the current spatiotemporal resolution limitations in commercial records and built environment data constrain the accuracy of our methodology. Enhanced data granularity coupled with improved update frequency would allow for more accurate identification of street-facing locations and floor-level specifications through building-specific POI mapping, significantly boosting the study's spatiotemporal accuracy. Third, this study does not examine the opening and closure or relocation of stores; future work could track the survival resilience of stores in different locations through longitudinal analysis of the same establishments. Moreover, the impact of digitalization and policies warrants further investigation, particularly through interviews with shopkeepers, consumers, and policymakers or through the employment of quasi-experimental methods, such as Difference-in-Differences (DID) designs, to quantitatively identify causal effects and rigorously measure the impact of specific policies.

7. Conclusion

This study integrates data from *Gaode* and *Dianping* to analyze the three-dimensional spatial dynamics of three types of traditional street-level commercial establishments, using a horizontal-vertical expansion matrix. The analysis reveals key trends in the spatial distribution and characteristics of these establishments, including shifts in their horizontal and vertical expansion patterns, variations across different urban ring road areas and business categories, and the significant role of e-marketing and policies. (1) The trend analysis reveals that the proportion of GFSF establishments steadily decreased before 2020 and increased after that, while GFNSF establishments exhibited relatively stable, mild growth before and after COVID. Both NGFSF and NGFNSF establishments continuously increased before COVID, then experienced a decline and began to recover afterward. (2) Based on the integrated data, the characteristics analysis shows that as the distance from the urban center increases, the proportion of GFSF establishments decreases. Non-ground-floor establishments are more prevalent within the 2nd and 4th ring roads. Retail and F&B sectors have higher proportions in GFSF establishments, which increased post-COVID, while for daily services, non-street-facing establishments had a higher proportion, experiencing a brief decline before recovering after 2022. (3) The digitalization analysis reveals that *Dianping* records a higher proportion of horizontally and vertically expanded establishments, while *Gaode* records a higher proportion of GFSF establishments. *E*-marketing shops have a higher proportion of non-ground-floor establishments with continuous growth, whereas non-e-marketing shops show an increase in GFSF establishments post-COVID. The electronic word-of-mouth represented by online ratings shows higher scores in establishments with less physical accessibility and visibility, while vertically expanded establishments tend to have higher review counts, indicating that digitalization compensates for the physical visibility disadvantages of non-ground-floor shops. This study also highlights the role of national consumption stimulus and employment facilitation policies, and Beijing's local spatial governance strategies, which may have jointly facilitated the expansion of commercial establishments, albeit with varying effects across different ring roads and types of businesses.

Overall, the findings contribute to the emerging body of research on “dark kitchens”, “location-less restaurants”, and “implicit consumption spaces” by verifying their conclusions and providing new knowledge about spatial dimensions and dynamics. The findings reveal the opportunities for individual businesses, especially small and medium-sized enterprises in daily service sectors, to choose less-visible locations to reduce rent costs and maximize land use by leveraging e-marketing on digital platforms. Additionally, this study advocates for adaptive regulations that balance business vitality with social and spatial considerations.

CRediT authorship contribution statement

Enjia Zhang: Writing – original draft, Visualization, Validation, Software, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Li Wan:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Ying Long:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2025.106765.

Data availability

Data will be made available on request.

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