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The form of China's urban commercial expansion in the digital era

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The digital era has reshaped urban commercial spaces, driving the emergence of less-visible shops in non-ground-floor and non-street-facing areas. To deepen the investigation of this transformation, this study analyzes the spatial evolution of commercial establishments across 287 Chinese cities from 2015 to 2023, using data from Dazhong-Dianping—a leading public review and rating platform for commercial premises. The results reveal a widespread trend of establishments expanding horizontally within street blocks and vertically across building floors (excluding shopping centers). In particular, the proportion of non-street-facing and non-ground-floor shops increased steadily, with accelerated growth post-COVID despite an overall decline in shop numbers. This shift was particularly prominent in experiential consumption sectors, such as entertainment, exercise and beauty services, which exhibited robust expansion. Higher socioeconomic tier cities experienced these changes earlier and more intensely. These findings provide critical insights for mixed-use development, adaptive urban governance and retail innovation in the digital era.

The evolving morphology and spatial configuration of commercial establishments have constituted a longstanding research focus in urban morphology and retail geography scholarship[1]. From traditional pedestrian streets and open-air markets to contemporary central main streets and enclosed shopping malls[2], the spatial organization of commercial entities has maintained a dynamic reciprocal relationship with urban morphological evolution[3]. Key factors in urban morphology such as agglomeration[4,5], accessibility[6] and visibility[7] influence the location choices and operational strategies of commercial establishments across temporal and spatial dimensions. In turn, the ongoing transformation of retail landscapes actively contributes to regeneration processes and the reorganization of urban functional structures, producing multiscalar impacts that range from storefront design to urban streetscape reconfiguration[1]. In recent decades, the advancement of information and communication technologies, the rise of the platform economy[8] and the proliferation of online-to-offline[9] business models have reshaped consumer behavior[10,11] and spatial use patterns[12,13]. These shifts present both challenges and opportunities for physical movements[14,15], socioeconomic vitality[16,17], and the overall structure and morphology of cities[18,19]. Therefore, understanding the spatial evolution of commercial establishments in the digital era is essential for urban planners, economists and policymakers to refine urban development strategies and foster sustainable urban renewal.

Existing literature has extensively examined the challenges faced by traditional commercial establishments in the digital era, exploring solutions to regenerate vibrant urban public life and revitalize streets[20]. The rise of e-commerce and digital platforms has redefined consumer behavior, leading to reduced demand for physical retail spaces[21] and increased storefront vacancies and business closures on the streets[22]. In response, some retailers have adopted strategies such as clustering at the street level to leverage agglomeration effects[5], embracing omnichannel strategies to integrate offline experience with online purchase[23], and enhancing in-store experiences through interactive technologies[24] and experiential design[2].

On the other hand, recent studies have highlighted the emergence of new retail and service landscapes less reliant on traditional

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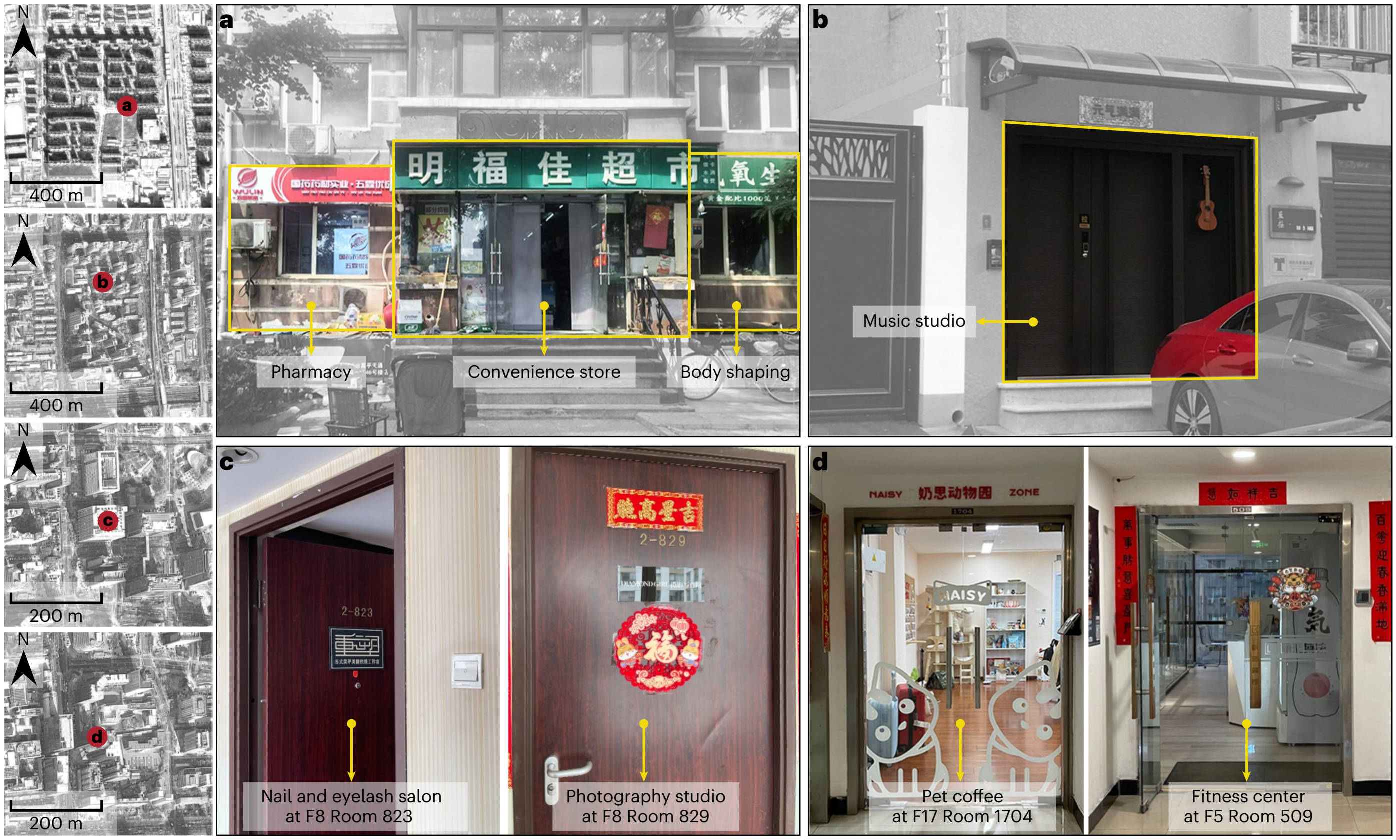

Fig. 1 | Emerging horizontal and vertical expansions of commercial establishments. **a**, A single retail unit within a residential community shared by or subdivided into several smaller shops. **b**, A residential house repurposed for commercial use. **c**, Shops established within office buildings. **d**, Shops situated within residential apartments. Satellite images © 2024 Google, Airbus.

shopping centers and high-visibility main streets[25]. Concepts such as dark/ghost kitchens[26,27], dark stores[28], inconspicuous restaurants[29], location-less restaurants[30] and invisible/implicit spaces[31–33] reflect a growing trend of businesses thriving in less-visible but lower-rent areas, relying on electronic word-of-mouth[34,35] and on-demand delivery services[36,37] on digital platforms. These establishments operate in private residential buildings[26] or office complexes[23,30] by subdividing retail units in residential communities into smaller independently operated shops and sharing spaces with workplace and residential apartments, moving away from prime retail locations (Fig. 1). As William J. Mitchell foresaw two decades ago, the conventional relationship between retail façade and backrooms is being reconfigured, as digital interfaces play roles of physical signage and display windows on the retail floor[38]. Consequently, backrooms for stock and services do not necessarily have to be located in prominent, high-rent areas to perform representational roles[39], enabling retailers to opt for less conspicuous, cost-effective sites.

To quantitatively identify these less-visible establishments, several studies have begun to leverage fine-grained data to measure the horizontal or vertical distributions of commercial establishments. Results showed that platform-dependent businesses tend to be more spatially dispersed[39], located farther from city centers[40], and less reliant on transport accessibility[25]. These establishments are increasingly found in private residential communities[29], old industrial towers and non-commercial buildings[25,30]. Unlike traditional studies that emphasize streets as vital interfaces for public activities[41,42], these establishments expand horizontally within street blocks and vertically across building floors, exhibiting less visibility in urban public spaces.

However, research on this topic is still emerging, with a lack of quantitative investigations, limited coverage of business types and a bias toward large metropolises. Most studies focus on the distribution of restaurants, particularly those relying on delivery services[29,30]. Although some research has expanded to include other types of establishment, such as experiential shops[25], murder mystery game clubs[23] and life service[31] businesses, these studies largely concentrated on the central areas of large cities like Sydney, Wuhan, Changsha and Nanjing. Verifying this phenomenon in more general types of commercial establishment and a broader range of cities requires further investigation. Has this phenomenon shown a notable and continuous growth trend, especially in the post-COVID period? How widespread is it across urban contexts, particularly in medium-sized and smaller cities? Furthermore, do different types of business demonstrate varying capacities for expansion in response to this trend?

This study seeks to identify the general patterns of commercial establishment expansion beyond streets and ground floors, across a wide spectrum of cities, sectors and time periods, as well as exploring variations among different commercial categories and cities' socioeconomic tiers. Our definition of establishment expansion is not restricted to dark kitchens or implicit shops, which are typically understood as those lacking service rooms or display windows. Instead, we define establishment expansion from the perspective of urban public spaces, specifically referring to shops with limited visibility from public urban areas. Since street-facing storefronts and ground-floor spaces are deemed crucial interfaces between public and private spaces and essential for urban socioeconomic dynamics[1,41], we focus on commercial establishments expanding horizontally within street blocks and vertically across building floors.

Specifically, this study analyzes urban commercial expansion patterns across 287 Chinese prefecture-level and above cities (Fig. 2a,b), across a variety of cities with populations ranging from 0.32 million to

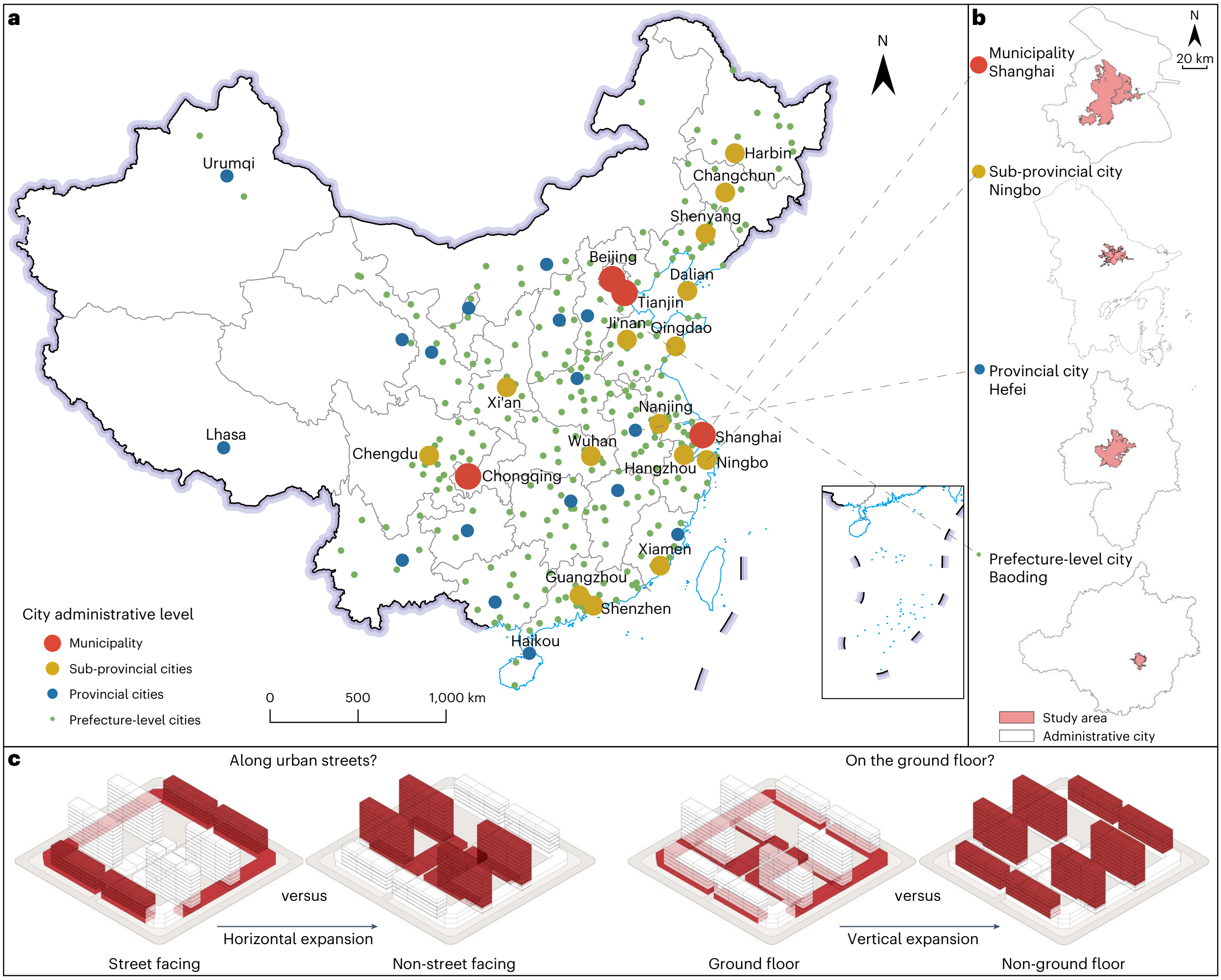

Fig. 2 | Study area and schematics. a, Locations of the 287 studied cities in China (all at or above the prefectural level). **b**, Administrative boundaries and study areas for four representative cities. **c**, Demonstrations of horizontal and vertical expansions of commercial establishments (excluding shopping centers). Note: in China, a municipality refers to a city directly under the jurisdiction of the central government, with an administrative status equivalent to that of a province. Sub-provincial cities are prefecture-level cities with vice provincial administrative authority, often including provincial capitals but not exclusively, granting them greater autonomy than regular cities. A provincial city is the capital city of a province. Prefecture-level cities refer to administrative divisions that lie between the provincial and county levels. Cities are categorized into a five-tier hierarchy according to socioeconomic development levels, where lower numerical designations correspond to higher levels of development. Basemap in **a** reproduced with permission from the Chinese Ministry of Natural Resources (no. GS(2019)1676).

32.13 million (2023 data). We use data from Dazhong-Dianping (also known as Dianping—the Chinese counterpart to Yelp, Foursquare and TripAdvisor) for the years 2015, 2019 and 2023, to track spatial evolution and capture variations across commercial categories. This dataset is particularly valuable as it directly influences consumer behavior, providing accurate and detailed information about shops that rely on this digital platform. To measure the horizontal and vertical expansions of these establishments, we adopt a binary classification approach to identify non-street-facing and non-ground-floor shops (Fig. 2c and Supplementary Section A), which is widely measured in similar studies[5,20,25,30]. In particular, we exclude establishments located within shopping centers, as these spaces are typically considered public or quasi-public areas[23]. The proportions (rather than absolute counts) of non-street-facing and non-ground-floor shops in different years, categories and cities' socioeconomic tiers ensure better comparisons of the expansion extents. To validate the reliability of our methods and provide further insights into category and city variations, we conduct additional analyses using segmented classifications for the horizontal and vertical distributions of establishments. Furthermore, we apply alternative thresholds and datasets, and consider other rules and factors to perform robustness checks.

Results

Given that binary variables capture overall distribution differences more effectively than segmented classifications (Extended Data Fig. 1), this study separately examines whether a shop is street-facing and whether it is on the ground floor. We analyze the developmental trends in the counts and proportions of non-street-facing and non-ground-floor shops, and compare disparities among different categories and city tiers.

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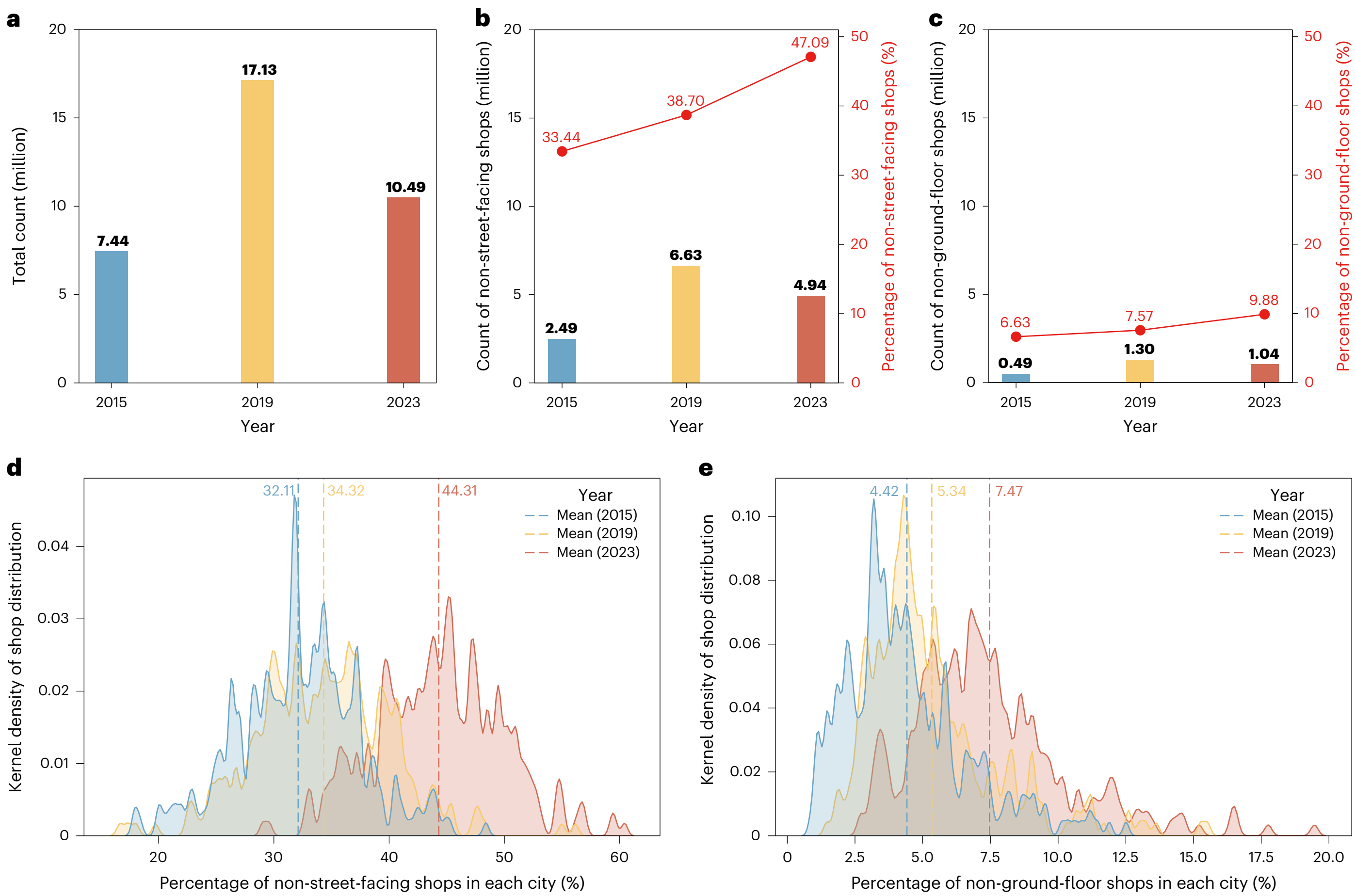

Fig. 3 | Growth of non-street-facing and non-ground-floor shops (2015–2023). **a**, Total number of commercial establishments in 287 Chinese cities. **b**,**c**, Trends in non-street-facing (**b**) and non-ground-floor (**c**) shops, showing absolute counts (bars) and proportions (lines). **d**,**e**, Kernel density estimates of city-level proportions for non-street-facing (**d**) and non-ground-floor (**e**) shops (n = 287 cities; annual measurements).

Overall trends of horizontal and vertical expansions of establishments

The results reveal a notable transformation in the retail landscape, with commercial establishments exhibiting notable horizontal and vertical expansions across Chinese cities. The number of non-street-facing and non-ground-floor commercial establishments nearly doubled from 2015 to 2023 in 287 cities, increasing from 2.49 million to 4.94 million for non-street-facing shops and from 0.49 million to 1.04 million for non-ground-floor shops, respectively. The proportion of non-street-facing establishments correspondingly rose from 33.44% to 47.09%, whereas non-ground-floor establishments increased from 6.63% to 9.88%. In particular, despite a decline in the total number of establishments during the COVID period (from 17.13 million in 2019 to 10.49 million in 2023), the proportion of non-street-facing and non-ground-floor shops continued to increase, with accelerated growth rates (Fig. 3a–c). Non-street-facing shops saw a more substantial increase in quantity and proportion compared with non-ground-floor shops, indicating a stronger preference for horizontal expansion (Fig. 3b,c).

The kernel density of shop distribution measures the evolving probability distribution of non-street-facing and non-ground-floor shop proportions across cities over multiple years, which further corroborates this trend (Fig. 3d,e). To account for variations in establishment sizes among cities, we focus on proportions rather than absolute numbers to capture the overall changes in establishment expansion. The proportion of non-street-facing shops in each city followed a nearly normal distribution, whereas the proportion of non-ground-floor shops displayed a positively skewed distribution, with a small number of cities exhibiting higher values. Both distributions shifted toward higher values over time, particularly from 2019 to 2023. The average proportion of non-street-facing shops increased from 32.11% in 2015 to 34.32% in 2019, reaching 44.31% by 2023. Similarly, the average proportion of non-ground-floor shops increased from 4.42% in 2015 to 5.34% in 2019 and 7.47% in 2023. These trends align with the broader patterns observed across all establishments in 287 cities.

Sector-specific trends: higher expansion in experiential consumption

The transformation is also evident across different establishment categories, though the extent of horizontal and vertical expansions varies by sector (Fig. 4a,b). From 2015 to 2023, the proportion of non-street-facing and non-ground-floor shops in each city increased steadily across most categories. Training is an exception, which saw a temporary decrease in the proportion of non-ground-floor shops from 2015 to 2019, and a remarkable rise afterward. Although horizontal expansions were relatively consistent across sectors, vertical expansion showed a much wider range of variations. Sectors such as food and beverage (F&B), retail goods and daily services tend to have a lower proportion of non-ground-floor shops compared with exercise, entertainment, beauty and training. The results with segmented classifications of distributions also validate higher variations for vertical expansion among different establishment categories than horizontal expansion (Extended Data Fig. 2). Exercise and F&B have a higher proportion of shops on the underground floors, whereas daily services and beauty sectors preferred to occupy higher rises of buildings than

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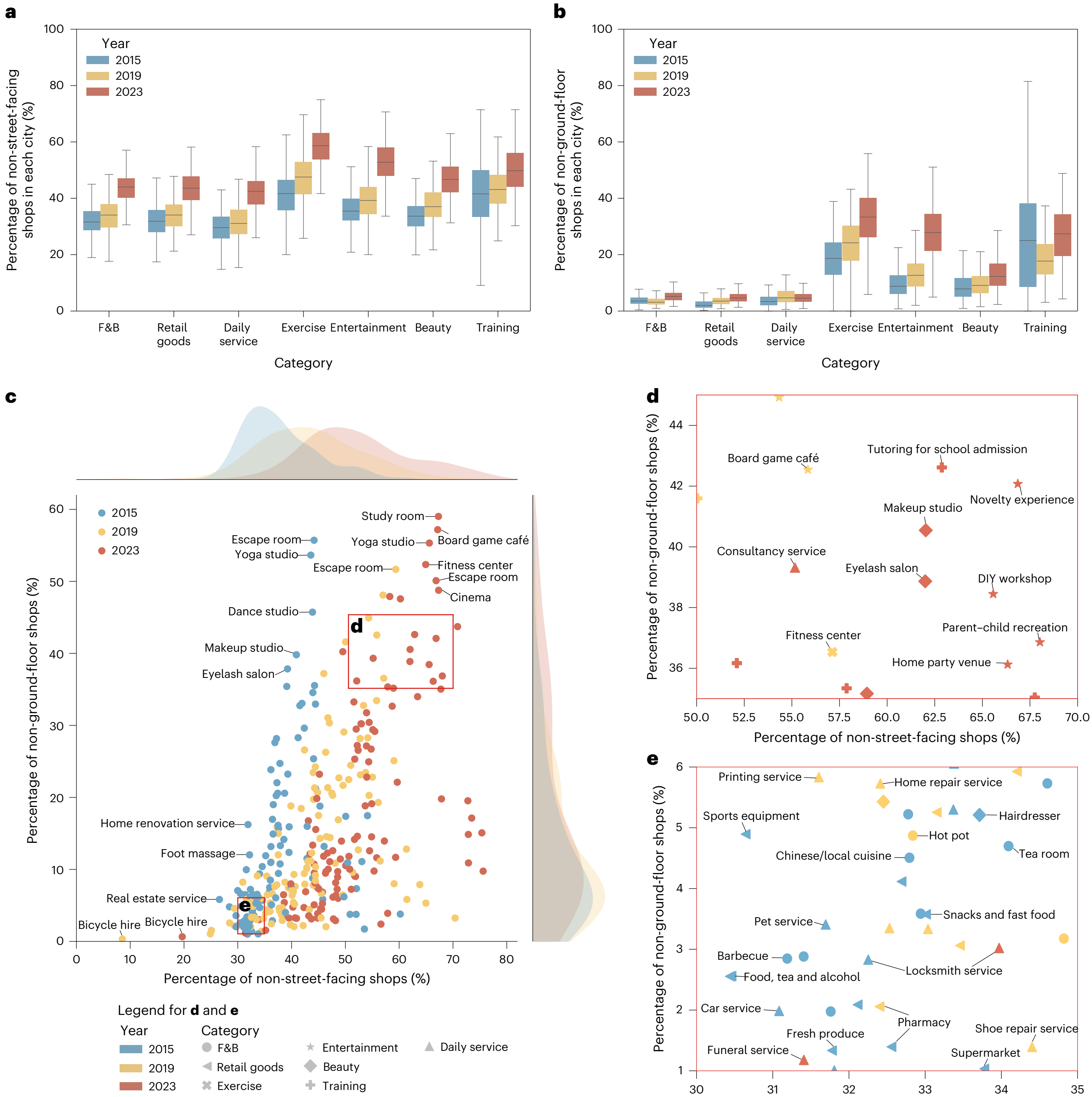

Fig. 4 | Category-specific expansion patterns of commercial establishments (2015–2023). a,**b**, Temporal variations in non-street-facing (**a**) and non-ground-floor (**b**) shop proportions across establishment categories, with three box plots per category showing annual distributions (2015/2019/2023) among 287 cities (boxes, 25th–75th percentiles; whiskers, 1st–99th percentiles; lines, medians). **c**–**e**, Scatter plots of bivariate expansion patterns for subcategories with >100 establishments/year (2015, $n = 104$; 2019, $n = 120$; 2023, $n = 118$) (**c**), with subsets highlighting high-expansion (**d**) and low-expansion (**e**) subcategories.

other categories for those have experienced vertical expansion. In particular, although exercise, entertainment and training show higher proportions of vertical expansion, low-rise areas remain their primary location choice.

A detailed analysis of the subcategories reveals similar trends and more specific disparity (Fig. 4c,d). Scatter plots illustrating the proportions of horizontal and vertical expansion shops within each subcategory show a shift toward higher values from 2015 (blue) to 2019 (yellow) and 2023 (red) on both horizontal and vertical axes (Fig. 4c). Experience-based categories in entertainment, beauty and exercise sectors, such as study room, board game café, escape room, yoga studio, cinema, dance studio, eyelash salon and makeup salon, demonstrate substantial expansion in both dimensions, suggesting a strong preference for less-visible spaces (Fig. 4d). By contrast, sectors providing essential daily services, F&B and retail goods, such as bicycle hire, real estate service, funeral service, pet service, pharmacy and barbecue,

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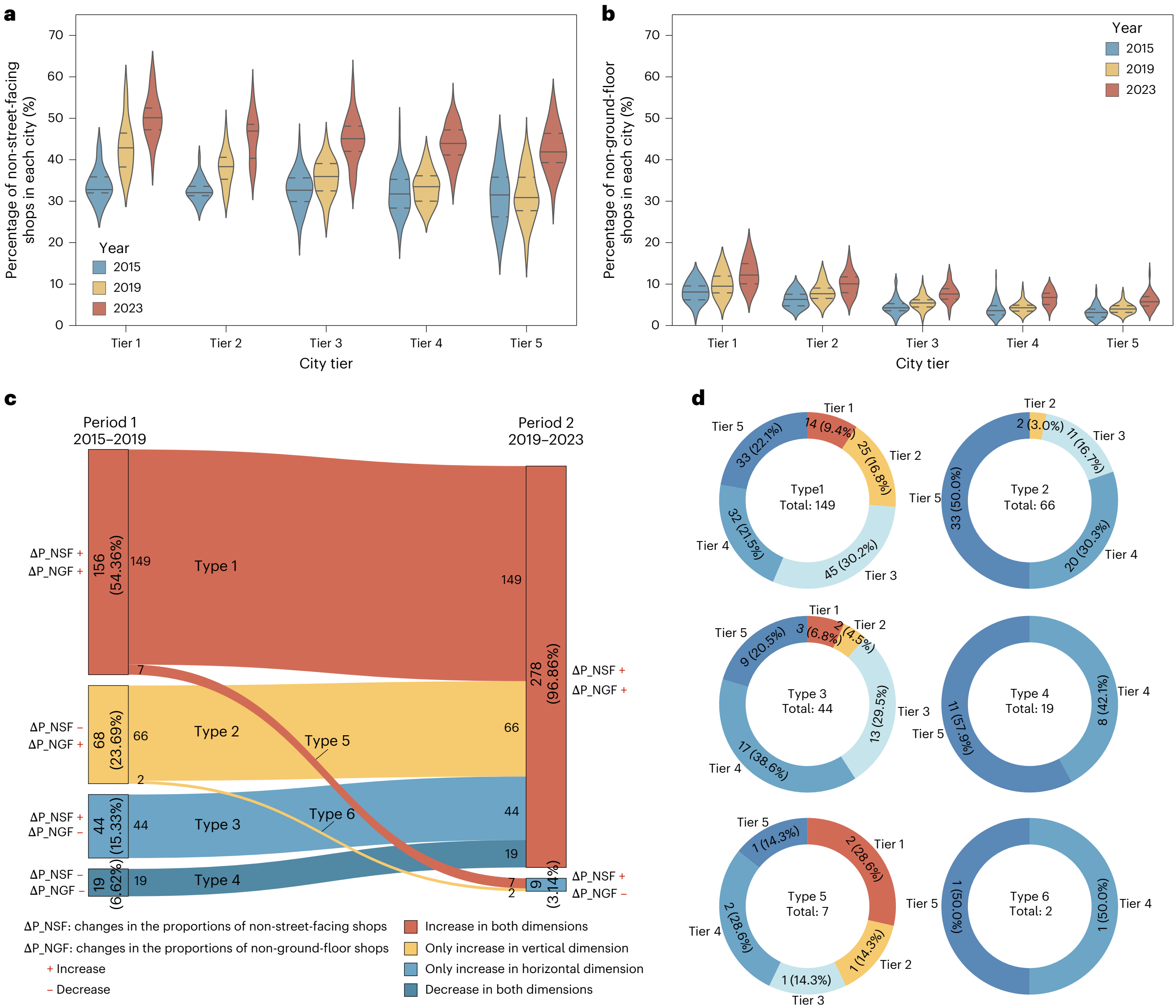

Fig. 5 | City-tier expansion patterns of commercial establishments (2015–2023). **a**,**b**, Temporal variations in non-street-facing (**a**) and non-ground-floor (**b**) shop proportions across five socioeconomic city tiers, with three violin plots per tier showing annual distributions (2015/2019/2023) among the included cities. The violin width represents probability density, with internal lines marking the median and interquartile range (25th–75th percentiles). **c**, Sankey diagram of expansion proportion transitions in the 2015–2019 and 2019–2023 periods. **d**, Proportional representation of cities by socioeconomic tier (tiers 1–5) for each transition scenario.

have lower proportions of non-street-facing and non-ground-floor shops (Fig. 4e). Nevertheless, these subcategories still show steady growth in both horizontal and vertical expansions, although at a slower rate compared with experience-based commercial establishments.

City-wide trends: earlier and greater expansion in higher-tier cities

Analysis across city socioeconomic tiers reveals a consistent increase in both horizontal and vertical expansions, with higher-tier cities exhibiting higher degrees (Fig. 5a,b). From 2015 to 2023, the proportion of non-street-facing and non-ground-floor establishments in each city rose steadily, with the former showing greater degrees and growth. Cities with higher socioeconomic development levels tend to have higher proportions of both forms of expansion. Supplementary analysis with segmented classifications (Extended Data Fig. 3) shows that higher-tier cities tend to have higher proportions of shops located farther from street-facing and ground-floor areas, whereas shops in lower-tier cities prefer to center around streets (within 20–60 m to the street façade and on lower floors). The disparities in horizontal expansion across different city tiers widened substantially between 2015 and 2019, followed by a convergence during 2019–2023. By contrast, the disparities in vertical expansion demonstrated a consistent and progressive amplification throughout the study period.

Examining changes before and after COVID-19 (2015–2019 versus 2019–2023) highlights the dynamics of shop expansion in both horizontal and vertical dimensions across cities. The Sankey diagram (Fig. 5c) shows that 54.36% of cities experienced an increase in both horizontal and vertical expansions, whereas 23.69% and 15.33% of cities experienced growth in only vertical or horizontal expansion, respectively, from 2015 to 2019. In the post-COVID period, 96.86%

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of cities showed increases in both dimensions, with only nine cities experiencing growth in horizontal expansion alone. In particular, 19 cities that showed no growth in either dimension in the first period, exhibited increases in both dimensions in the second one. Nine cities that only exhibited horizontal expansion growth in the second phase had already shown a vertical expansion increase in the former period. These findings confirm that despite differing stages and sequences, all cities experienced an increase in the proportion of non-street-facing and non-ground-floor shops over the last decade.

The changes observed in the two periods across city tiers suggest that cities with higher socioeconomic tiers tend to experience earlier expansion of commercial establishments. The Sankey diagram's six change scenarios exhibited clear hierarchical patterns: continuous bidirectional growth dominated tier-1 cities, whereas mid-tier cities (tiers 2 and 3) followed four pathways. Lower-tier cities (tiers 4 and 5) participated in all scenarios, predominantly showing the single-period, dimension-specific growth patterns of types 4 and 6 (Fig. 5d).

Robustness checks

This study conducts four robustness checks to ensure the reliability of the findings. First, using different thresholds to define street-facing shops consistently shows an increase in the proportion of non-street-facing shops from 2015 to 2023 across all the tested thresholds, confirming the robustness of the conclusions (Extended Data Fig. 4). Second, applying alternative building datasets to measure horizontal distributions shows that proportions of non-street-facing shops and their changes from 2015 to 2023 align with the initial analysis, further reinforcing the reliability of the findings (Extended Data Fig. 5). Third, an analysis restricted to shops with clear floor signs suggests that the approach used in the main study is conservative, potentially underestimating the proportion of non-ground-floor shops (Extended Data Fig. 6). This implies that the actual level of vertical expansion could be higher than reported. Finally, a fixed-effect regression accounting for the influence of urban construction standards and local spatial regulations on street-level shops further supports the finding for city variations (Supplementary Section B-4). The analysis reveals statistically significant positive correlations between key socioeconomic indicators (resident population size, per capita gross regional product and tertiary sector share of the gross regional product) and the prevalence of non-street-facing, non-ground-floor commercial spaces. This pattern suggests that economically advanced cities demonstrate more substantial vertical and horizontal commercial expansion.

Discussion

This study examines the horizontal and vertical expansions of commercial establishments across 287 Chinese cities from 2015 to 2023. Our findings reveal a steady increase in the proportion of non-street-facing and non-ground-floor shops over the past decade. Although the extent of expansion varies, similar trends are observed across establishment sectors and city tiers, with experiential consumption and higher-tier cities exhibiting a greater prevalence of such establishment expansion. Our study extends the growing body of literature on dark kitchens[26], location-less shops[30] and the vertical integration of services in office buildings[23,30], broadening the scope from specific urban areas in large cities to a wider range of cities. By using a longitudinal approach and considering both horizontal and vertical expansions, we explore the general forms of commercial establishment expansion. Variations across commercial subcategories and city tiers provide new insights into their spatial evolution and disparities.

These findings illuminate the evolving retail landscape and its implications for urban functional spaces in the digital era. First, we need to mention that low-visibility establishments existed before the Internet era, often sustained by word-of-mouth within specific consumer communities[29]. Recently, e-commerce and door-to-door delivery service for material-based consumption[30,40] and the e-word-of-mouth and real-time digital navigation for experience-based consumption[16,25] have accelerated the proliferation of non-street-facing and non-ground-floor shops. Experience-based retailers—relying more on consumer feedback—increasingly occupy upper-floor and interior positions. Nevertheless, material-based shops (for example, F&B and retail goods) persist near ground and street areas despite delivery reliance, since ground-floor access markedly improves courier pickup efficiency. Post-COVID (2019–2023), the annual growth rate of non-street-facing shop proportion rose to 2.10% (pre-2019, 1.32%), whereas non-ground-floor shops increased from 0.24% to 0.58%. This acceleration suggests that the pandemic-driven adoption of digital services might expedite their horizontal and vertical expansions, which is also observed in previous studies on the rise of dark kitchens in the post-COVID era[28]. In particular, this study also reveals that cities' socioeconomic levels can influence the pace and extent of establishment expansion, suggesting greater potential for shopkeepers to select less-visible spaces in large cities.

Second, our findings can partially explain the rising vacancy rates of street-level stores[22,43] but do not contradict the study on the occupation of omnichannel retail on the main streets in city centers[23]. Existing studies have identified the structural reconfiguration of main streets, where storefronts on the main street are becoming increasingly valuable[23] and more digitalized[24]. Our research unveils the other facet of emerging transformations of urban retail landscapes, with increasing establishments expanding into higher and inner spaces. Combining these findings, we can suggest that brick-and-mortar shops are not disappearing but rather demonstrating remarkable resilience through complex spatial adaptations, manifesting simultaneously along main street façades, within neighborhood interiors, and across vertical building levels. Although digitization enables flexible location choices[19,38], the decision ultimately reflects a trade-off between shopkeepers' needs and consumer preferences. Factors such as rent gaps, sensitivity to location visibility and the pursuit of brand spillover effects drive varying operational strategies[23,25]. For instance, cost-sensitive stores and those leveraging the branding potential of main streets may adopt different location choice strategies. This divergence also explains the uneven expansion patterns across commercial categories. With regard to stores that were previously constrained by locations now enjoy greater flexibility and transformative resilience[44], how to balance the digitalization of storefronts and urban public life in public realm design and how to manage increasing retail spaces intermingled with residential and working spaces needs more investigation in the future.

Third, the horizontal and vertical expansions of commercial establishments has dual implications for urban morphology and functional structures. Vertical expansion among different building layers can mitigate rising office vacancy rates and declining rents[23], whereas horizontal expansion within street blocks enhances service accessibility within 15-min zones[39]. Moreover, this transformation can contribute to a bottom-up development of horizontal and vertical mixed uses[45], especially for high-rise and high-density cities. However, such expansion may also generate conflicts with residents and office workers, raising concerns about safety, privacy and regulatory oversight. As information and communication technology applications continue to expand, similar trends may emerge in smaller and medium-sized cities across China and globally, akin to the post-COVID rise of dark kitchens in developing countries[26]. Therefore, urban researchers, retail geographers and planners should recognize this phenomenon and develop appropriate regulations.

Although this study provides important insights, we recognize several methodological limitations that suggest valuable directions for future research. First, the scope and accuracy of the data used constrain the precision of our findings. Future research could benefit from more granular and accurate data, which would facilitate a more nuanced comparison of horizontal and vertical expansion patterns.

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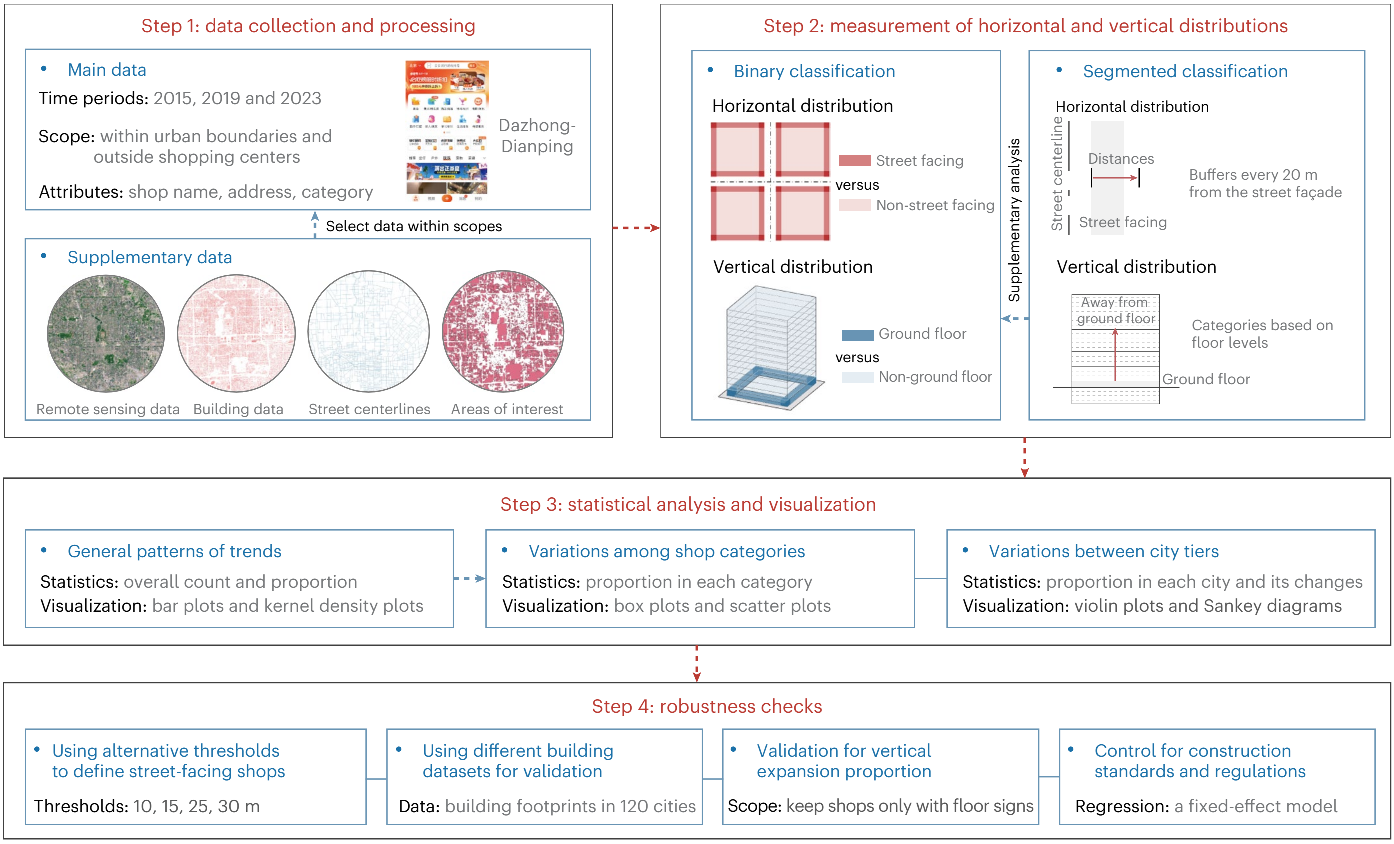

Fig. 6 | Four-step analytical framework. Step 1, collection and processing of main and supplementary datasets. Step 2, measurement of horizontal expansion and vertical distribution using binary and segmented classification. Step 3, comprehensive statistical analysis and visualization of general patterns and variations across categories and city tiers. Step 4, systematic robustness checks through four methodological approaches.

Expanding the data sources to include shops not captured by Dazhong-Dianping would also provide a more comprehensive understanding of consumption spaces. Second, further investigation into spatial variations within cities is warranted. Future studies should explore differences between central and peripheral urban areas, the role of transport accessibility, proximity to other functions, and the spatial dynamics of aggregation and dispersion of these less-visible establishments. Furthermore, there is a need to assess the impact of factors such as digitization, rent disparities, shop size, the presence of chain stores, shopping centers and diverse business models in shaping the patterns of horizontal and vertical expansions. Finally, extending studies to a broader international context would enhance our understanding of retail evolution in the digital era.

Methods

This section details the study's methodological framework, including study areas, data sources and analytical approaches used in this study.

Study area

This study focuses on China, a unique context for examining the evolution of urban commercial spaces due to its rapid urbanization, large-scale economic transformation and the growing role of digital platforms on consumer behavior. China offers a wide range of urban environments, from megacities to smaller ones, making it an ideal setting for comparing the pace and extent of commercial expansion across cities of varying sizes. Additionally, the integration of digital technologies, such as local business platforms like Dazhong-Dianping, has profoundly influenced the development of urban commercial spaces, providing valuable data for analyzing shifting patterns. This diverse urban landscape, combined with ongoing digital transformation, positions China as a critical case study for understanding trends in urban consumption spaces.

Initially, this study considered 297 cities at or above the prefectural level. However, due to insufficient Dazhong-Dianping data in certain cities, ten cities were excluded from the analysis. These cities include Heze, Sansha, Bijie, Pu'er, Xigaze, Qamdo, Linzhi, Hami, Shannan and Naqu. Consequently, we focus on 287 cities, comprising 4 municipalities, 15 sub-provincial cities, 17 provincial capital cities and 251 prefecture-level cities. According to ref. 46, these cities are classified into 19 tier-1 cities, 30 tier-2 cities, 70 tier-3 cities, 80 tier-4 cities and 88 tier-5 cities (Supplementary Section C provides the detailed classification system). We study urban areas, rather than the entire administrative city, as urban areas represent the core zones with high population density, built environment intensity and economic activity. These areas are characterized by well-developed infrastructure, vibrant streets and a high density of commercial spaces, distinguishing them from broader administrative boundaries that may include less urbanized or peripheral zones. To mitigate the potential impact of urban sprawl from 2015 to 2023, the study uses urban boundaries as they existed in 2015. These boundaries are derived from remote sensing data with a resolution of 30 m. For each city, the largest impervious surface, as interpreted from remote sensing imagery, is selected as the study area.

Research framework

This study follows a four-step process to examine the general patterns and variations of commercial establishment expansion (Fig. 6). First, we collect commercial establishment data from the Dazhong-Dianping platform for the years 2015, 2019 and 2023, along with supplementary data such as remote sensing data, building data, street centerlines and area-of-interest data to measure the locations of commercial

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establishments. Second, we use improved spatial analysis and natural language processing techniques to assess both horizontal and vertical distributions of commercial establishments. The main study uses a binary method to identify horizontal and vertical expansion shops, whereas segmented classifications are used to supplement the findings. Third, we analyze the overall expansion trend and its variations across categories and city tiers through statistical analyses and visualizations. Finally, we examine the robustness by using alternative thresholds and data to measure horizontal distributions, using a stricter way to calculate the proportion of vertical expansion, and controlling for the impact of construction standards and local spatial regulations on city variations.

Data

Dazhong-Dianping data. Commercial establishment data are harvested from Dazhong-Dianping (https://www.dianping.com/), a leading public review and rating platform for commercial premises in China. Dazhong-Dianping supports services such as group purchasing and reservations, which are integral to online-to-offline consumption activities, including online searching, booking, ordering, onsite experiential consumption, and post-consumption feedback and comments. The dataset includes point-of-interest (POI) information for each shop, such as shop ID, name, category, geographic coordinates, address text, number of reviews and ratings. Additional details on Dazhong-Dianping and data description are provided in Supplementary Section D. We make great efforts to process and standardize the categorization of shop data between different years and classify POIs into seven categories: F&B, retail goods, daily services, exercise, entertainment, beauty and training. Detailed classification criteria are outlined in Supplementary Section E.

Supplementary data. To select commercial establishments within urban boundaries and outside shopping centers and measure their horizontal and vertical distributions, this study incorporates multiple built environment datasets. These include remote sensing data for 2015, urban road centerline data for 2018, building data for 2019, and area-of-interest data for 2018 and 2023. The urban road centerline data are derived from the road network in Gaode Map (one of China's leading digital navigation maps, also known as Amap; https://ditu.amap.com/) and processed via the GeoHey platform (https://geohey.com/). We check the road topology and clean and merge the data to obtain road centerlines for analysis. The area-of-interest data, sourced from Gaode Map (2018) and Baidu Map (2023; another leading digital navigation map in China; https://map.baidu.com/), are used to exclude traditional shopping centers, such as shopping malls and designated main streets (Supplementary Section F lists the selected categories). Building data are collected from two main sources. For the primary analysis, building rooftop raster data from ref. 47 were converted into vector data using the "raster to vector" tool in QGIS. For robustness checks, building footprint data from Gaode Map (2018) are used for 120 cities. The study assumes limited changes in road networks and street-facing buildings within urban areas from 2015 to 2023 for areas already built in 2015. Therefore, calculations for the distribution of commercial establishments over the years are based on the same built environment data to ensure comparability.

Technical details

Identification of non-street-facing shops. We follow a four-step method to identify non-street-facing shops (Supplementary Section A). First, the distance from each street centerline to the nearest building façade (D_b) is calculated. Next, the distance from each shop POI to the nearest street centerline (D_s) is computed. Then, the distance from the building façade for each shop POI (D_{bs}) is determined by subtracting D_b from D_s. Finally, shops with D_{bs} higher than 20 m are classified as non-street-facing shops. To validate robustness, thresholds of 10 m, 15 m, 25 m and 30 m are tested. Unlike previous studies that often use a 50-m buffer from road centerlines to define street-level activities, this study excludes the influence of road width for different road hierarchies and cities, and focuses solely on the distance to the building's street-facing interface. This method is also preferred over selecting POIs in street-facing buildings due to inconsistent coverage of building footprint data across different cities, especially in smaller cities. Additionally, unlike the building footprint data on the digital map, the building rooftop raster data from ref. 47 lack clear boundaries for each building, making it difficult to accurately identify buildings along streets and determine the POIs inside. We assume that the setbacks of buildings on both sides of the road are consistent for each street segment. Therefore, even if buildings along the street are not entirely identified and recorded in the data source, it does not affect the assessment of the street façade and the identification of street-facing shops. Furthermore, we test the robustness of the results by using building footprint data from the Gaode Map.

Identification of non-ground-floor shops. Shop floor information is extracted from the address text using a rule-based natural language processing method. Since Dazhong-Dianping provides accurate address information for consumer guidance, its addresses are more precise than those from other digital map platforms such as Baidu Map or Gaode Map. Following the typical format of Chinese addresses, we identify keywords such as "room," "floor," "layer" and "basement" and recognize the numeric digit before and after these keywords as floor information. For those with a description of "ground-floor (*di-shang* in Chinese)," we classify them accordingly. For addresses without floor information, we assume they are on the ground floor by default, according to the naming convention in China, which may lead to an underestimation of the proportion of non-ground-floor shops. Detailed methods are described in ref. 48. Finally, shops without ground-floor information are classified as non-ground-floor shops.

Calculation of horizontal and vertical expansion proportions. To account for differences in shop sizes across cities, categories and years, we use proportions rather than absolute counts to describe horizontal and vertical expansions. The proportion refers to the percentage of non-street-facing or non-ground-floor shops to the total number of shops in a specific category, city or year. Equation (1) calculates the proportion of non-street-facing shops or non-ground-floor shops across all cities over time (Fig. 3b,c). Equation (2) calculates the proportion for each city (Figs. 3d,e and 5a,b). Equation (3) calculates the proportion for a specific city, category and year (Fig. 4a,b). Equation (4) calculates the proportion for all subcategories (Fig. 4c–e). The equations are presented as follows:

$$P_{\text{NSF or NGF}}(t) = \frac{\sum_i N_{\text{NSF or NGF}}(i,t)}{\sum_i N_{\text{Total}}(i,t)}, \tag{1}$$

$$P_{\text{NSF or NGF}}(i,t) = \frac{N_{\text{NSF or NGF}}(i,t)}{N_{\text{Total}}(i,t)}, \tag{2}$$

$$P_{\text{NSF or NGF}}(i,c,t) = \frac{N_{\text{NSF or NGF}}(i,c,t)}{N_{\text{Total}}(i,c,t)}, \tag{3}$$

$$P_{\text{NSF or NGF}}(\text{sc},t) = \frac{\sum_i N_{\text{NSF or NGF}}(i,\text{sc},t)}{\sum_i N_{\text{Total}}(i,\text{sc},t)}, \tag{4}$$

where $P_{\text{NSF/NGF}}$ represents the proportion of non-street-facing or non-ground-floor shops, $N_{\text{NSF/NGF}}$ denotes their count and N_{Total} indicates the total shop count. These metrics can be analyzed at different levels: city (i), category (c) and subcategory (sc), as well as across time periods (t), with the specific scope indicated in the parentheses.

Segmented classification for supplementary analysis. In addition to binary classification, we use segmented classifications to refine the analysis of horizontal and vertical distributions. The vertical distribution is categorized into eight groups: underground (below ground floor), ground floor (floor 1), low rise (floors 2 and 3), mid-rise (floors 4–8), high rise L1 (floors 9–16), high rise L2 (floors 17–25), high rise L3 (floors 26–40) and extra high rise (over 40 floors). In particular, in Chinese address naming conventions, layer 1 refers to the ground floor, whereas the upper floors begin at floor 2. For horizontal distribution, we define non-street-facing establishments as those located ≥20 m from street façades. These are further categorized into progressive distance bands (20–40 m, 40–60 m, 60–80 m, 80–100 m, 100–120 m, 120–140 m and >140 m) using a lower-bound-exclusive classification system (for example, 20–40 m denotes >20 m to ≤40 m).

Robustness checks. Four robustness checks are applied to ensure the reliability of the results as follows. First, to assess the impact of the 20-m threshold for identifying non-street-facing shops, alternative thresholds of 10 m, 15 m, 25 m and 30 m are tested. Second, to ensure a broader representation of medium- and small-sized cities, rooftop data from remote sensing sources are used to calculate the distances from street façades to shops in the main study. Given the potential for bias due to varying building heights, robustness checks are conducted using building footprint data from Gaode Map across 120 cities. Given that large cities tend to have more comprehensive building data and taller buildings, the consistency of the findings in the robustness tests suggests that the bias is relatively smaller for smaller cities. Third, considering the potential impact of classifying shops without explicit floor information as ground-floor establishments based on naming conventions in China may influence the proportion calculation for vertical expansion, a robustness check is performed only focusing on those with explicit floor information. Moreover, considering that the variations among cities may also be attributed to the construction standards and local spatial regulations on the street-level shops, this study uses fixed-effect regression models to control for the Building Climate Zone and regulations on curbing informal street trading.

Reporting summary
Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability
The commercial establishment data (2015, 2019 and 2023) are obtained originally from Dazhong-Dianping (https://www.dianping.com/) using Python. Result tables are available via GitHub at https://github.com/zej18/Reshaped-consumption-space.git. Other data are available from the corresponding author upon reasonable request.

Code availability
The code for data visualization in this paper is available via GitHub at https://github.com/zej18/Reshaped-consumption-space.git.

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Author contributions

Conceptualization: E.Z. and J.H. Methodology: E.Z. and J.H. Investigation: E.Z. and J.H. Writing—original draft: E.Z. Visualization: E.Z. Writing—review and editing: J.H. and Y.L. Supervision: Y.L. Funding acquisition: Y.L. and E.Z.

Competing interests

The authors declare no competing interests.

Additional information

Extended data is available for this paper at https://doi.org/10.1038/s44284-025-00254-6.

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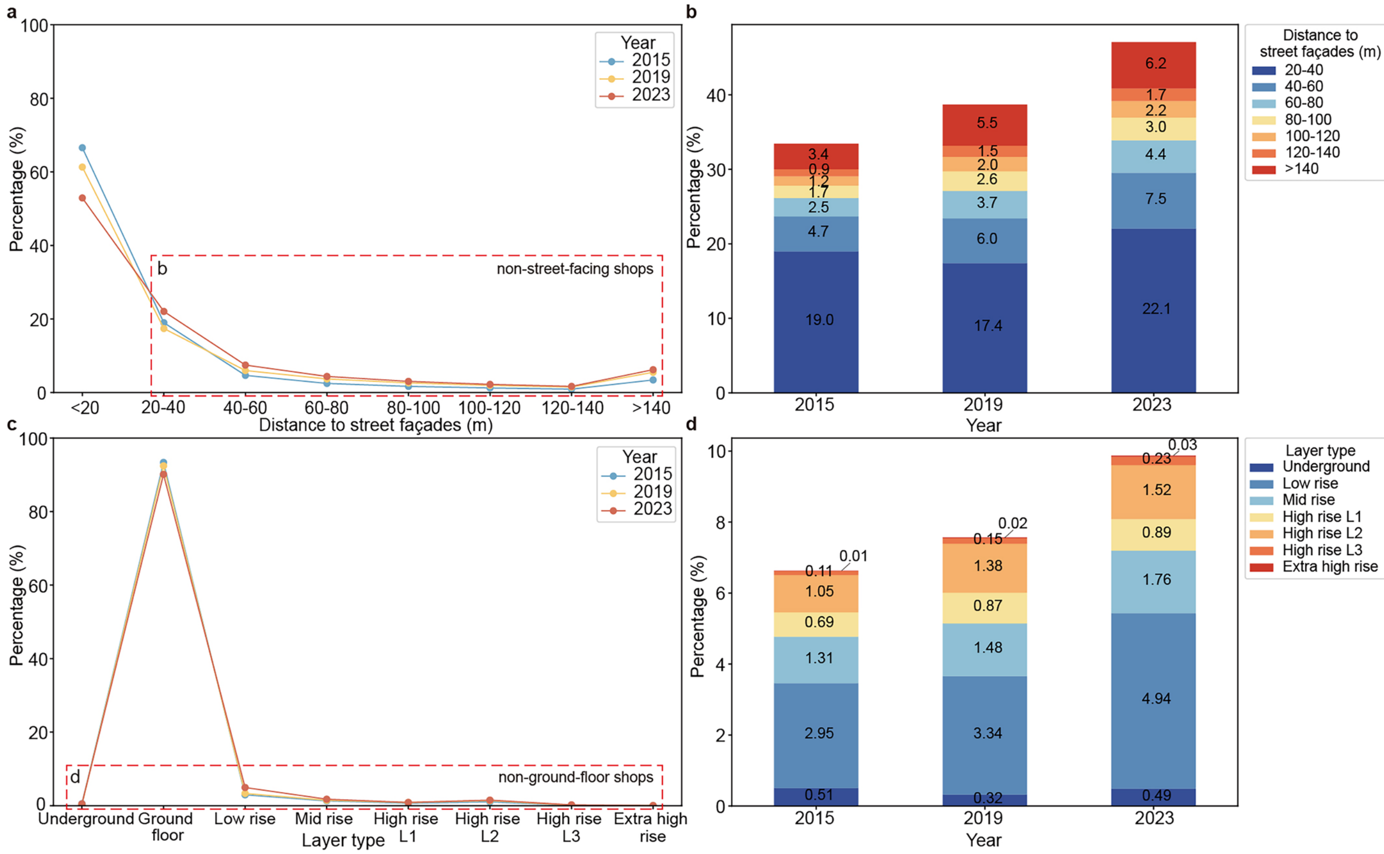
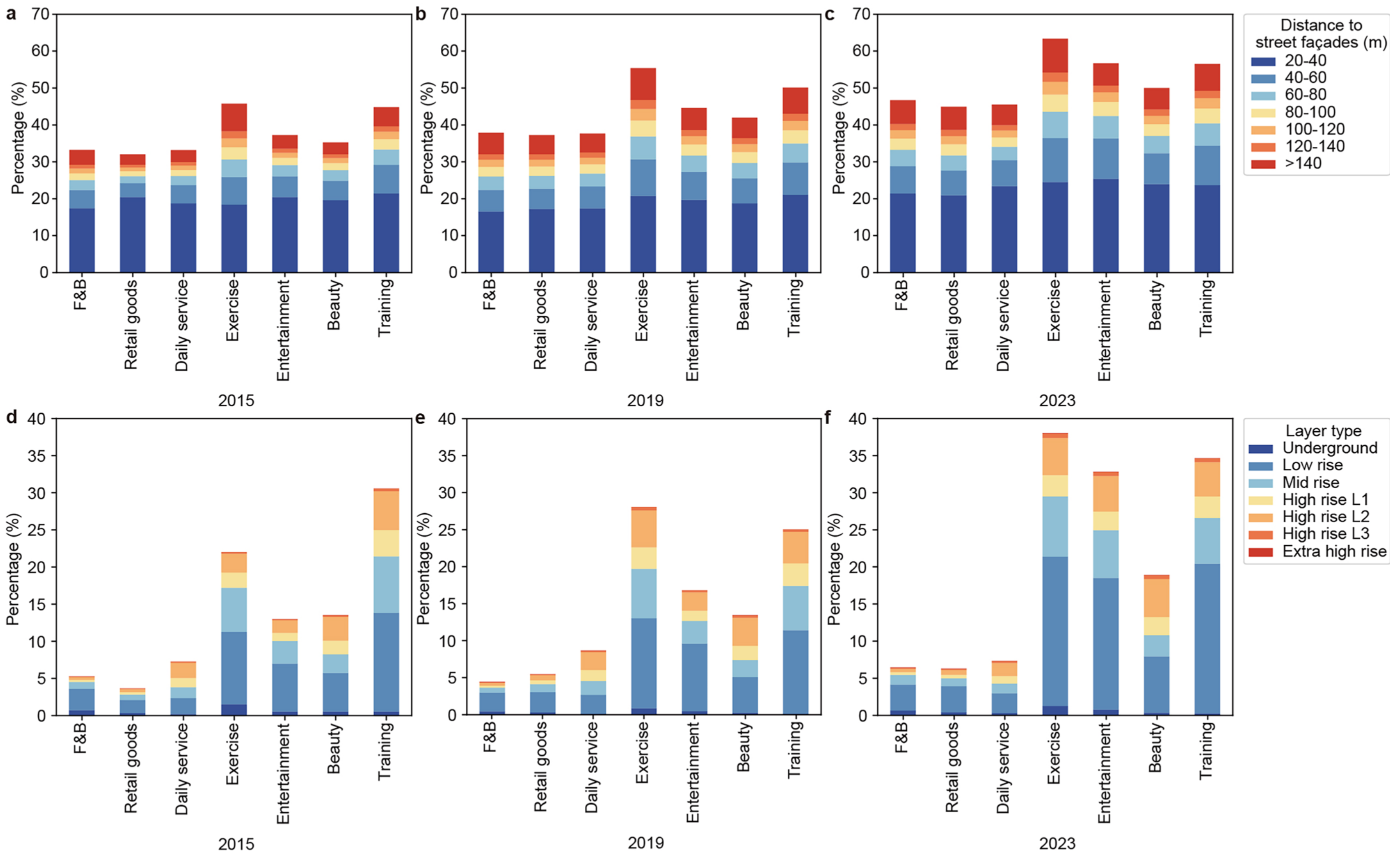


Extended Data Fig. 1 | Spatial distribution trends of all establishments (287 cities, 2015-2023). a-b, Proportional distribution by horizontal location classifications: all locations (**a**) and non-street-facing locations (**b**). **c-d**, Proportional distribution by vertical floor-level classifications: all floors (**c**) and non-ground-floor locations (**d**).

https://doi.org/10.1038/s44284-025-00254-6



Extended Data Fig. 2 | Spatial distribution trends by establishment category (287 cities, 2015-2023). a-c, Proportional distribution by horizontal location classification across years: 2015 (**a**), 2019 (**b**), and 2023 (**c**). **d-f**, Proportional distribution by vertical floor-level classification across years: 2015 (**d**), 2019 (**e**), and 2023 (**f**).

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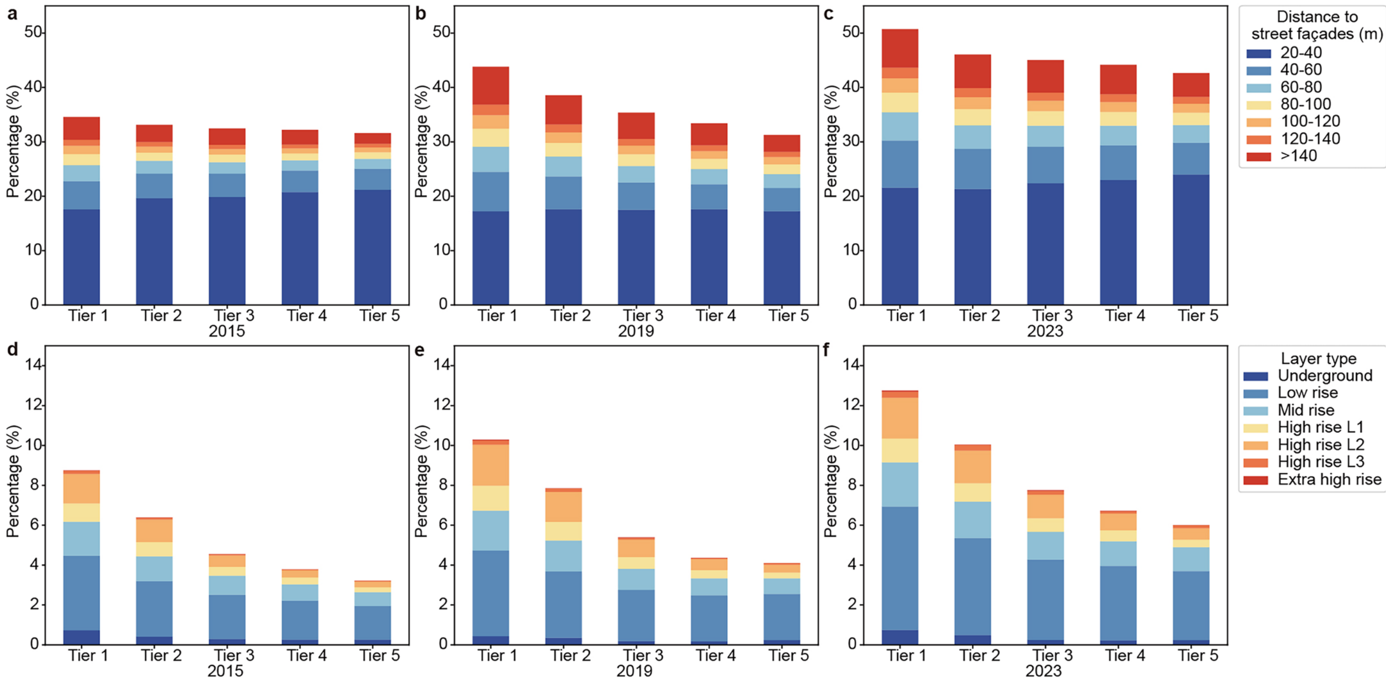
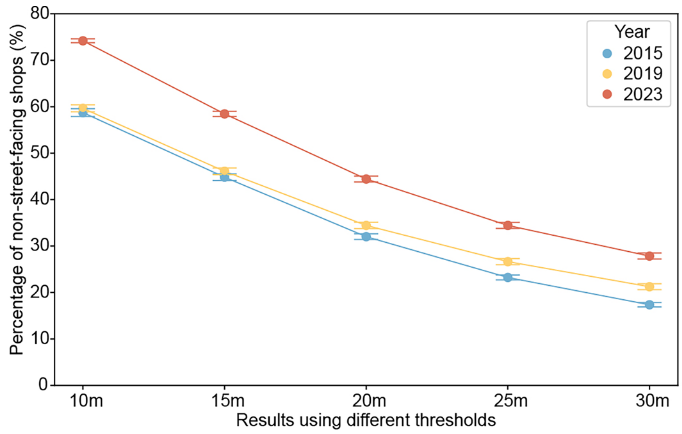


Extended Data Fig. 3 | Spatial distribution trends by city socioeconomic tier (287 cities, 2015-2023). a-c, Horizontal location distribution across time: 2015 (**a**), 2019 (**b**), 2023 (**c**). **d-f**, Vertical floor-level distribution across time: 2015 (**d**), 2019 (**e**), 2023 (**f**).



Extended Data Fig. 4 | Threshold sensitivity in non-street-facing establishment identification (287 cities, 2015-2023). Median values (center points) with 95% confidence intervals (error bars).

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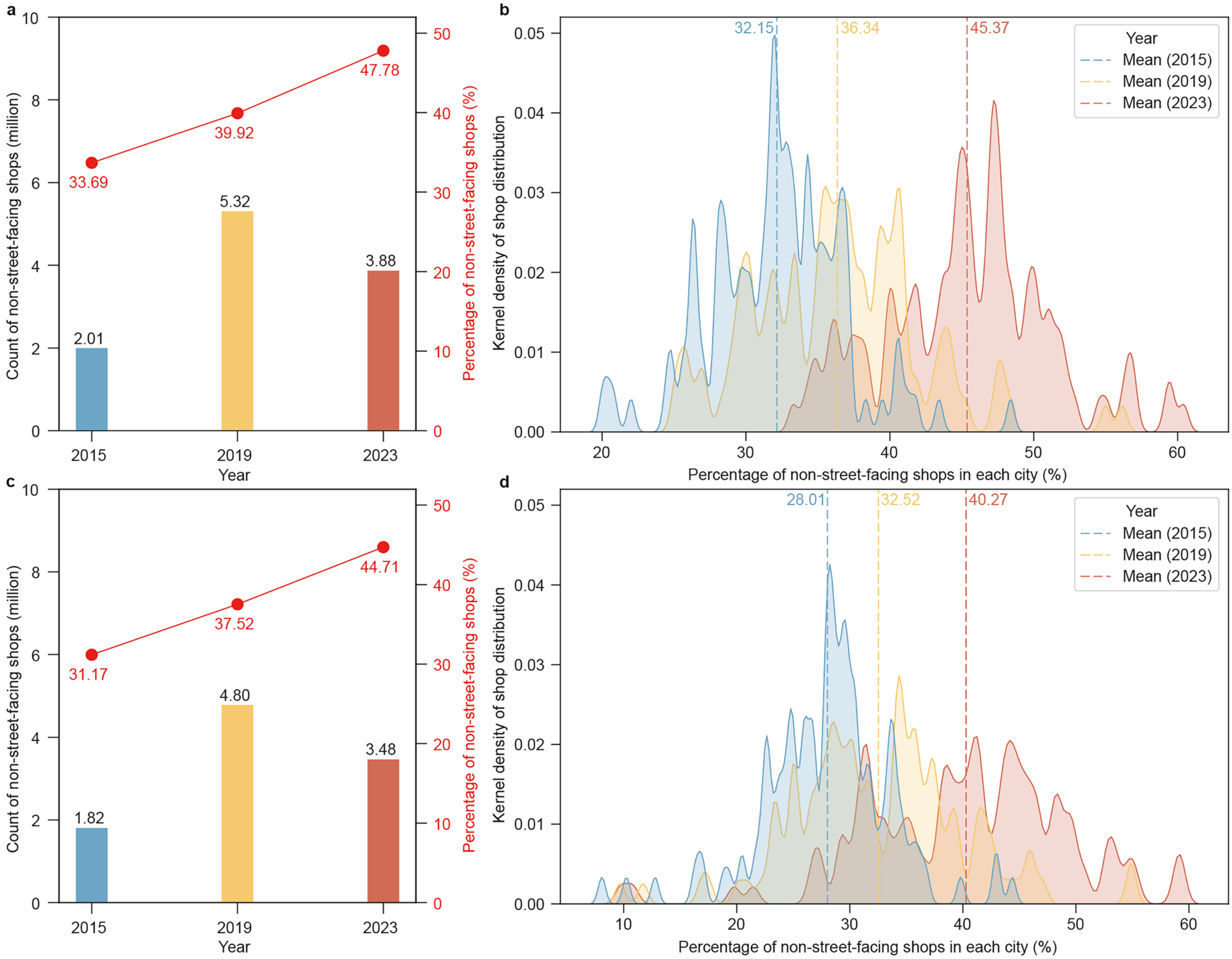

Extended Data Fig. 5 | Comparative evaluation of building datasets for non-street-facing shop identification (120 cities, 2015-2023). a-b, Rooftop data results (used in this study): Count and proportion distribution (**a**) and kernel density estimation (**b**). **c-d**, Footprint data results (from Gaode Map): Count and proportion distribution (**c**) and kernel density estimation (**d**).

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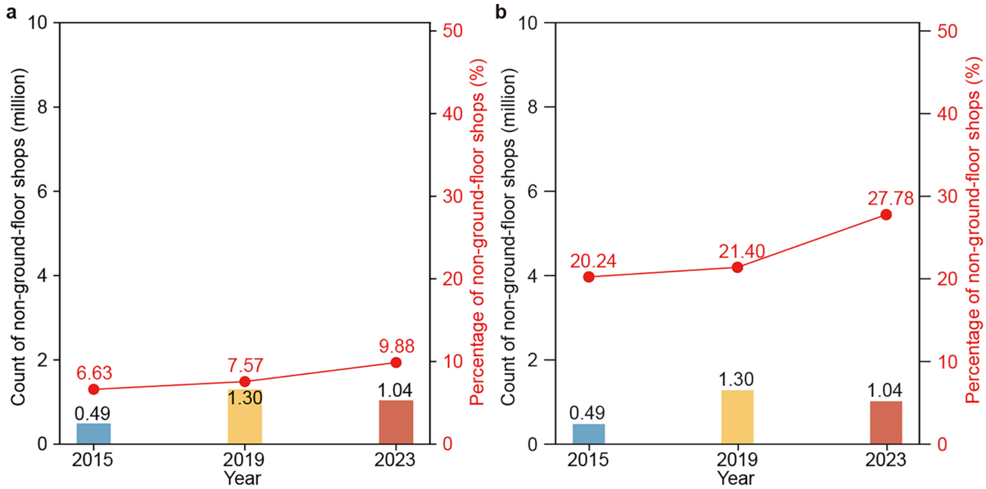

Extended Data Fig. 6 | Non-ground-floor shop identification robustness (287 cities, 2015-2023). a, Conservative approach (primary method) includes all shop records, imputing missing floor data as ground floor. **b**, Strict approach (validation subset) uses only shops with explicit floor indicators.

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Software and code

Policy information about availability of computer code

Data collection	The commercial establishment data for the years 2015, 2019, and 2023 were obtained from Dazhong-Dianping (https://www.dianping.com/) and collected using Python-based web scraping techniques.
Data analysis	The analysis and visualization were conducted using Python. The scripts and the necessary input files used to generate the figures in this paper are available in the GitHub repository at https://github.com/zej18/Reshaped-consumption-space.git.

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The commercial establishment data for the years 2015, 2019, and 2023 were obtained from Dazhong-Dianping (https://www.dianping.com/) and collected using

Python-based web scraping techniques. The final analytical outputs are publicly accessible in the GitHub repository at https://github.com/zej18/Reshaped-consumption-space.git. Additional data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This study analyzes the spatial evolution of commercial establishments, examining their expansion into street blocks and buildings across 287 Chinese cities from 2015 to 2023, and exploring variations in establishment categories and city socioeconomic tiers.
Research sample	Dazhong-Dianping shops within urban boundaries of 287 prefecture-level cities in China
Sampling strategy	A large and representative sample of commercial establishments from Dazhong-Dianping was used. These establishments were selected based on the administrative level of the cities and urban boundaries, rather than being randomly chosen.
Data collection	Shop information for commercial establishments is sourced from Dazhong-Dianping (https://www.dianping.com/). Network centerline and AOI data for 2018 are derived from Gaode Map, while AOI data for 2023 comes from Baidu Map. Building data is collected from two main sources: a dataset shared by Liu et al. (2023) and Gaode Map.
Timing	Data for the years 2015, 2019, and 2023 were used.
Data exclusions	Ten cities were excluded from the main study due to insufficient Dazhong-Dianping data, and one additional city was excluded from the regression model due to a lack of socioeconomic data. Shops outside urban areas and those within shopping centers were also excluded for each city.
Non-participation	No participants were involved in the study
Randomization	N/A As the dataset was not randomly sampled, no formal randomization procedure was applied.

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