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Perception of urban population characteristics through dietary taste patterns based on takeout data

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ABSTRACT

Research on commercial activities and their spatial structure is an important topic in urban geography and economic geography. As an online-to-offline business activity, takeout ordering is an important approach for urban residents to solve their catering needs. It can well reflect the working and living conditions of the population and is a source for studying urban life. Based on the takeout data in the city of Hangzhou, China, this study uses the customers' detailed order information to extract three dietary taste patterns: spicy, sweet, and light. We then combine the dietary taste patterns with points of interest and land use data to identify the location attributes of order destination and explore the temporal and spatial distribution characteristics of dietary taste patterns. The results show differences in dietary behavior of people at the community scale, and help us understand the local culture and socio-demographic characteristics from the perspective of diet. Dietary taste pattern is closely related to timing and location, which reflects differences in consumption tendencies, and socio-demographic heterogeneity. This research helps to present the dietary characteristics of different population groups and their spatial distribution, and supplements the content of urban research on foodscape.

1. Introduction

The emergence of big data allows us to rethink broader questions about theory and methodology in urban geography (Stock, 2018). Liu et al. (2015) proposed the term "social sensing" to denote such individual-level large geospatial data and related analytical methods. Each individual plays the role of a sensor. Big data can capture socio-economic characteristics well. With the development and popularization of location-based services and mobile social networks, a large amount of trajectories or geotag data are constantly accumulating, which brings unprecedented opportunities to create computational characterization of urban residents (Goodchild, 2011). Geospatial big data that can be used to capture spatiotemporal patterns of human activities include taxi trajectories (Kang & Qin, 2016), cell phone records (Lee et al., 2018; Xiong et al., 2021), social media or social network data (Steiger et al., 2015), smart card records in public transportation systems (Long & Thill, 2015; Wang et al., 2017), and so on. From the activity time rhythm presented in the data, we can find people's daily activities, social network coverage, the spatial distribution of urban occupation and housing, etc. (Cai et al., 2019; Cao et al., 2021; Gao et al., 2018; Gong et al., 2017; Liu et al., 2021; Zhang et al., 2020). Methods for mining different geospatial big data include analysis of temporal features, interactions, and spatially embedded network.

One of the issues when using existing social sensing data is that the data may only capture proxy activities (e.g., foot traffic) rather than the specific activities of individuals (e.g., type of food for eating). To fill this gap, in this research, we proposed takeout data as a new social sensing data source to explore urban population work and life rhythms, so as to provide insights on new perspectives and practices to capture dietary patterns of urban population (i.e., food taste). With the development of the mobile Internet and the improvement of express delivery systems in cities, takeout has become a very popular and convenient way of dining among the urban population (Lachat et al., 2011). According to the 2017 China Internet Local Life Services Blue Book (2018) issued by Ele.me (https://www.ele.me/), the number of online catering users exceeded 300 million, and the delivery dataset has significant user characteristics:

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the largest user population are white-collar workers, which account for over 80 % of the total delivery orders, and the second largest user population are college students. Based on big data for takeaway, the derived distribution of urban food space provides insights for understanding the consumption tendencies of different groups of people, especially working people, in different parts of a city. Such information is useful to provide better services to the general public, specifically, recommendations and insights for restaurant location selection and population health based on big data on food delivery.

The human eating habits system is related to the propensity to consume certain foods and can be characterized as formed eating patterns (Maksimov et al., 2020). Food choices are influenced by a variety of factors such as cultural influences, taste, mood, environment, health, etc. (Feeney et al., 2011). Data for most diet studies are derived from surveys, including questionnaires or face-to-face interviews. Nguyen et al. (2021) evaluated dietary taste patterns in early childhood and classified them as "neutral", "sweet and sour", "sweet and fat", "fat" and "salt, umami and fat". A number of studies have shown that the regional characteristics within one country may cause differences in dietary habits (Freisling et al., 2010; Green et al., 2016; Pestoni et al., 2019).

In this study, we introduce takeaway data as a new data source, and from the perspective of ingredient usage frequency, we obtain dietary patterns (DP) or dietary taste patterns based on the idea of clustering. According to the ordering content of takeout orders, the dietary characteristics of people in different areas of the city can be effectively determined. Cluster analysis is useful in nutrition studies because it can be used to create groups of people with distinct dietary patterns (Bailey et al., 2006; Hu, 2002). These clusters can then be treated as independent variables for further analysis of associations between dietary patterns and mealtime or geographical location. A national survey in Australia showed that food skills (e.g., meal planning, food shopping and preparation) may be of greater importance than cooking skills in terms of the relationship with diet quality (Lavelle et al., 2020). For a dish, its quality has a greater relationship with the ingredients than with the cooking process. Therefore, it is reasonable to use the ingredient list to quantify the food taste preference. This provides an idea for our research on how to extract the characteristics of food taste based on takeout data.

The order time and geographic location information in the takeaway data can be combined with the dietary taste pattern to explore the temporal and spatial characteristics of eating. The main determinant of human eating behavior is the social model, through which people can use other people's meals as a guide for the content and amount of food eaten (Cruwys et al., 2015). Spatial modeling of eating patterns is partially mediated because of behavioral mimicry. From the perspective of geography, the concept of foodscape is derived from the connection between diet and locality. Spatial approaches using statistics and spatial analysis are one of the approaches to characterize the diversity of urban foodscapes and their impacts on diet and health, at city or neighborhood scales (Vonthron et al., 2020). A sociocultural study in Manchester demonstrated that a sense of community in the bonding and affirming of relationships is related to takeaway food consumption, as well as 'Resources' including time, availability, cost and quality (Blow et al., 2019). It gives evidence of that takeaway order data can be used to identify statistically significant hot spots within the confidence interval at the community scale, Therefore, we can use spatial analysis tools to explore the dietary taste patterns revealed by takeaway data from the city scale to the finer community scale.

As a new Internet city, Hangzhou has a large takeaway market. "Ele.me" is a professional catering online-to-offline (O2O) platform in China, with a high share of the online food delivery market (iiMedia Research, 2019). POI data is a kind of point data representing real geographic entities, including location information such as latitude, longitude and address, and attribute information such as business name and place category. This research focuses on the spatio-temporal patterns of the food delivery data from the "Ele.me" platform to explore the taste preference patterns of urban people in Hangzhou. In addition, we explore the temporal and spatial characteristics of taste preference, and its correlation with the workplace and residence areas. Differences in the consumption of takeout food can be found according to their socio-demographic characteristics (Lake et al., 2010, 2012). Using food delivery data and urban points of interest (POI) data, it is possible to study the living habits of urban population and hot spots of activities (Fraser et al., 2010). This research help understand the spatial socio-demographic and population work characteristics from the perspective of diet.

The remainder of this paper consists of the following sections. In Section 2, we introduce the study area and data. Then, in Section 3.1, we introduce the quantification method of dietary taste patterns, which associates the ingredient information of the gourmet website with the takeout data, and extract patterns based on clustering. Sections 3.2.-3.4 introduce the spatial analysis methods used in our research, including kernel density estimation, average nearest neighbor, and spatial association analysis. In Section 4, we present the experimental results in the city of Hangzhou. Then, we discuss broad implications of this research in Section 5. Finally, our conclusions are drawn in Section 6.

2. Study area and data

The takeaway data is retrieved from the Ele.me platform on November 1, 2018 (Thursday). It contains 57,790 orders in the city of Hangzhou. Each takeaway order includes the location of the customer's delivery location, the food ordered, and the delivery time. Personal privacy-related information is eliminated from the data. Our research area is the main urban area of Hangzhou, including six administrative districts of Xihu District, Shangcheng District, Xiacheng District, Binjiang District, Jianggan District and Gongshu District. Hangzhou has formed a focused and multi-centered spatial structure, with the city-level commercial development center at *Wulin Square* and *Qianjiang New City*, the city's sub-centers such as *Xiasha* and *Future Technology City*, and regional centers such as *West city*. This study uses the six core areas of the city as the research area (as shown in Fig. 1), containing several high-tech companies such as Alibaba, NetEase, Hikvision, and Huawei, as well as government agencies and public facilities. The land in this area provides a variety of services such as housing, commerce, and education. We take the community as a basic geographic unit to study the spatial distribution characteristics of food delivery data, and select 667 communities that have takeaway data served for research. The community boundary data is obtained from the local survey and mapping agency.

The taste of the dishes is obtained from the Douguo Food website (https://www.douguo.com/), which contains the name of the dishes and ingredients (for example, ingredients used in the Sichuan cuisine "spicy boiled fish" include salt, sugar, dry red pepper, Chinese prickly ash, onion, garlic, etc.).

The POI data of Hangzhou collected in 2017 comes from a digital map content and location business intelligence solution provider in China. Each POI contains its place name, category, location coordinates and other business information. In total, there are 132,895 POI records covering 15 place categories in this dataset.

3. Methods

3.1. Quantification method of dietary taste patterns

We use web crawlers to obtain the recipe information of each dish from the Douguo Food website (shown in Table 1). Since the recipe does not have a unified measurement standard for the amount of ingredients used, we start from the perspective of the frequency of ingredients usage (Li et al., 2019) to quantify different flavors. The following steps are used in our analysis.

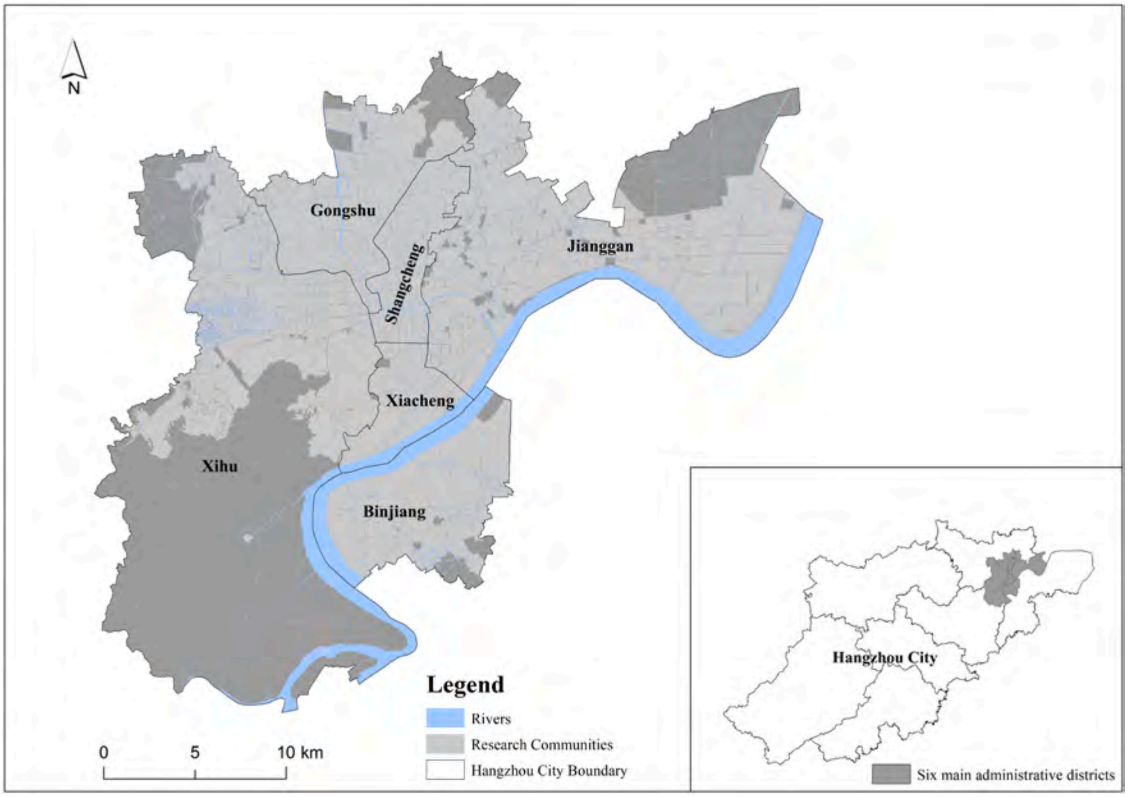

Fig. 1. The study area of Hangzhou, China.

3.2. Kernel Density Estimation

Kernel Density Estimation (KDE) measures the density of features in a neighborhood around those features (Gatrell et al., 1996). It produces a continuous raster representing the point distribution pattern, that is, the kernel density map. It can intuitively show the distribution pattern of points, the location, size and shape of point clusters. This research uses the following KDE function (calculated as Eq. (1)) to obtain the distribution characteristics for order points of various dietary taste patterns, and then draw relevant research conclusions.

$$f(s) = \sum_{i=1}^{n} \frac{1}{h^2} k\left(\frac{s - c_i}{h}\right). \quad (1)$$

where *f(s)* is the computed density at the location *s*, *k* is a spatial weight function (Yin, 2020) which determines the weight of a feature point c_i at location s; the Quartic kernel is used in this study (Silverman, 1986); *h* is search radius, *n* is the number of feature points whose distance from position *s* is not greater than *h*.

3.3. Average Nearest Neighbor

The Average Nearest Neighbor analysis determines the average distance between each feature and its nearest neighbor (Clark & Evans, 1954). According to the ratio R of the observed mean distance (d_i) and the expected mean distance (d_e), we can evaluate the spatial distribution characteristics of takeaway orders. If R is <1, the pattern for takeaway orders exhibits a spatially clustered pattern; If the index is >1, the trend is toward dispersion. The smaller the R, the greater the degree of clustering (Yang et al., 2016; Yang & Xiaohong, 2017). The Average Nearest Neighbor ratio is given as:

$$\mathrm{R} = \frac{d_i}{d_e}, \quad (2)$$

where d_e is the expected mean distance for the features given in a random pattern.

$$d_e = \frac{1}{2}\sqrt{\frac{N}{A}}. \quad (3)$$

N corresponds to the total numbers of takeaway point features, and *A* is the area of study region. The null hypothesis based on complete spatial randomness is used for statistical significance testing with z-scores and *p*-value.

3.4. Local indicators of spatial autocorrelation (LISA)

Local Getis-Ord Gi* statistic (Getis & Ord, 1992; Ord & Getis, 1995) is used to measure whether there is a significant local spatial association between each observation and its neighboring features, which is a typical LISA (Anselin, 1995). The index of local spatial autocorrelation can identify where features with either high or low values cluster spatially, called hot and cold spots respectively. We utilize the local Gi* statistic to evaluate the spatial distribution of hot and cold spots for orders of different dietary taste patterns, which is mathematically represented by Eqs. (4) to (6).

$$G_i^* = \frac{\sum_{j=1}^{n} \omega_{i,j} x_j - \overline{X} \sum_{j=1}^{n} \omega_{i,j}}{S\sqrt{\frac{\left[n \sum_{j=1}^{n} \omega_{i,j}^2 - \left(\sum_{j=1}^{n} \omega_{i,j}\right)^2\right]}{n-1}}}, \quad (4)$$

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n}, \quad (5)$$

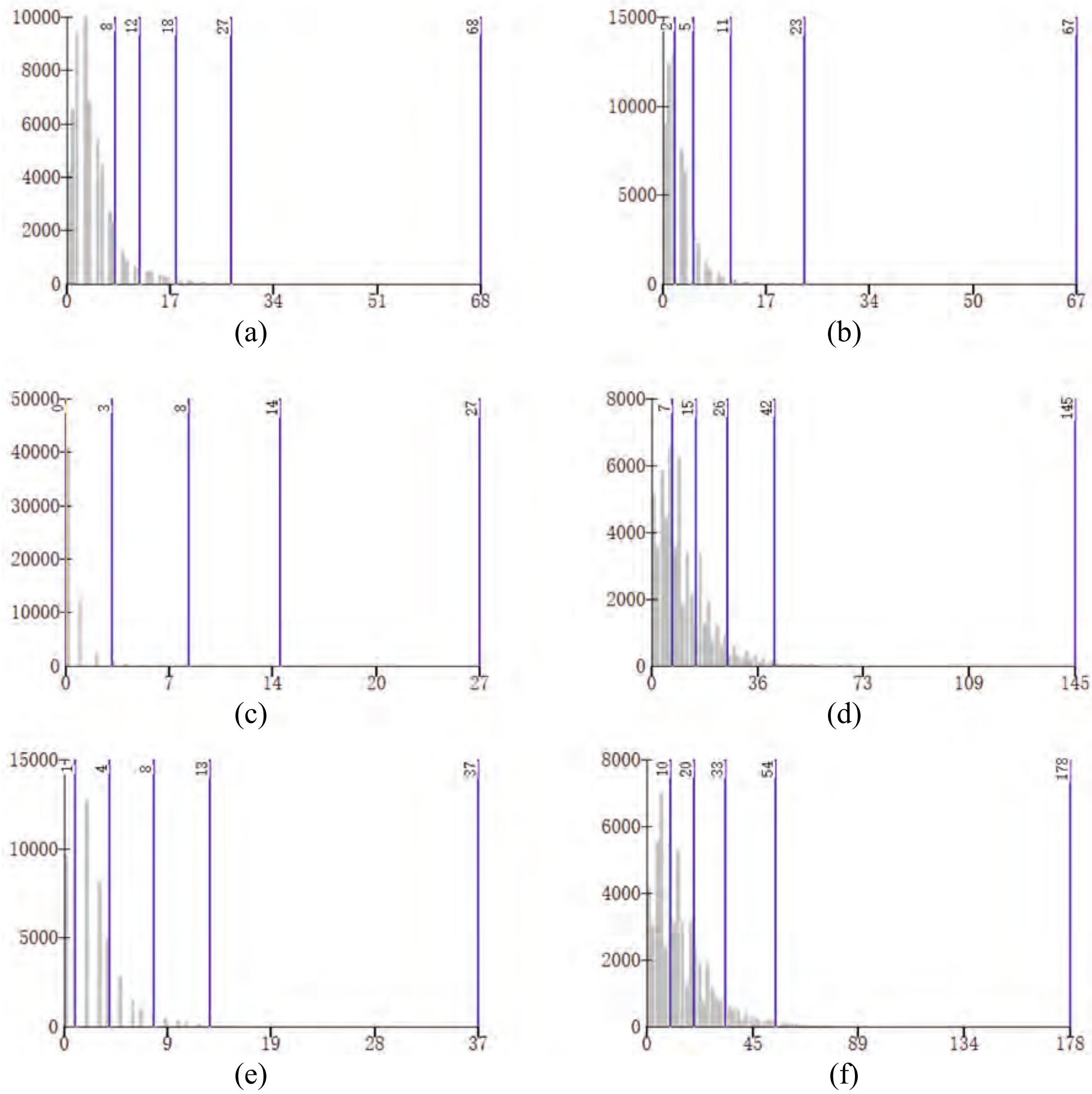

Fig. 2. Taste reclassification results, including salty(a), sweet(b), sour(c), spicy(d), fresh(e), and incense(f). In each subgraph, the x-axis is the absolute value of each flavor, the y-axis is the number of orders, and the blue line is the break values for different classes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\overline{X})^2}. \tag{6}$$

where x_j is the analysis field value of feature j, $\omega_{i,\,j}$ is the spatial weight between feature i and j and its value is determined by the adjacency relationship between two polygons (1 is adjacent otherwise 0), n is total number of features.

4. Results

4.1. Classification results of dietary taste patterns

The appropriate cluster number for the abovementioned quantification method (Section 3.1) based on k-means is determined using the silhouette score (Rousseeuw, 1987). Fig. 3 shows that the highest value is reached when the cluster number k equals 3. Therefore, the optimal cluster number is identified as 3.

The takeaway orders (57,790 in total) are grouped into three typical taste patterns (see Fig. 4(a)). Class A is significantly higher than the other five flavors in the index of “spicy”, which can be regarded as a dietary taste pattern that prefers spicy food (hereinafter referred to as “Spicy DP”). Class B is prominent in the “sweet” indicator and can be referred to as “Sweet DP”. The six taste indicators of class C are all low and relatively balanced, which can be regarded as a preference for light taste patterns (referred to as “Light DP”). The proportion distribution of the three modes “Spicy DP”,” Sweet DP” and “Light DP” is shown in Fig. 4(b). The “Spicy DP” group accounts for about 65 % of all takeout orders while the “Sweet DP” and “Light DP” account for 32 % and 3 %, respectively. Young people are heavy consumers of fast food (with lots of spicy dishes) and sugary beverages, while light consumers of fruits and vegetables (Patetta et al., 2019). Meanwhile, young people happen to be the main force in the city's takeout orders, so “Spicy DP” orders account for the majority.

According to the delivery time, the hourly patterns of the three types of orders are shown in Fig. 6 as dotted lines. The orders of three DPs all have a large peak during lunch time and a small peak during dinner time as expected. The “Spicy” DP takeout group has the highest order volume,

Table 1
Part of recipes and ingredients crawled.

No.	Dish name	Ingredients	Regional Cuisine	Quantity of Ingredients
1	Shredded chicken thigh	Chicken thigh, ginger, scallion, red wine vinegar, soy sauce, garlic, sesame oil, salt, chili peppers, green pepper, coriander.	Szechwan cuisine	11
2	Mapo Tofu	Tofu, chili powder, Chinese prickly ash, Pixian County Bean Paste, leek, ginger, soy sauce, corn syrup, starch, water, oil.	Szechwan cuisine	11
3	Fish-flavored Shredded Pork	Pork tenderloin, winter bamboo shoots, carrots, black fungus, minced leek, minced ginger, minced garlic, chopped peppers, mixture of water and starch.	Szechwan cuisine	9
4	Poached Pork Slices	Pork tenderloin, carrots, black fungus, garlic, aromatic vinegar, soy sauce, refined white sugar, bean paste, green pepper, starch.	Szechwan cuisine	10
5	Spicy incense pot	Streaky pork, dried bean curd, fish ball, lotus root, Shiitake mushroom, shrimp, potato, fungus, broccoli, fried beancurd sticks.	Szechwan cuisine	10

a. Summarize the information in recipes and merge synonymous ingredients.
b. Mark the flavor label for each ingredient, for example, if the ingredient contains "red pepper", the "spicy flavor" frequency of the dish plus 1.
c. Count the frequency of the various flavors marked on each dish, and get the usage frequency of the six flavors (salty, sweet, sour, spicy, fresh, and incense) of each dish.
d. Match the dishes in takeaway orders to the crawled recipe dish names, and get the six flavor values of each takeaway order.
e. The Jenks Natural Breaks (Jenks, 1967) classification method is used to reclassify the six flavor values. This method was proposed by George Jenks to minimize the variance within each class and maximize the variance between classes. Each flavor value is reclassified into 5 levels, as shown in Fig. 2. For example, a "spicy flavor" of "1" means that this takeaway order does not contain spicy dishes, and a "sweet flavor" of "5" means that this takeaway order is among the sweetest and contains multiple desserts.
f. Normalize the flavor values and treat them as six-dimensional vectors, then use k-means for clustering to get three dietary taste patterns.

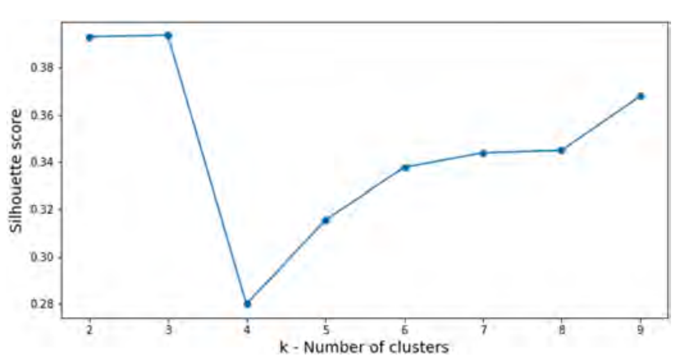

Fig. 3. Silhouette scores in different numbers of clusters.

followed by the "Light DP" group, and the curves of the two groups are similar. Due to the small number of "Sweet DP" orders, its temporal fluctuation is not obvious.

4.2. Spatial distribution characteristics of dietary taste patterns

4.2.1. Delivery address analysis

By using the address of the takeaway data and the name of the POI data combined with its location, we obtain the urban function type of each delivery address, which is divided into five categories: residence, business, workplace, education and culture, and others. The categories are defined in Table 2 and their ratios are shown in Fig. 5. The delivery address of takeaway orders classified as "others" may not be in the other four categories, or there may be, but it has not been successfully identified. This type of order addressed is uncertain, so they are not included in the subsequent analysis.

The line chart in Fig. 6 shows the changes in the number of orders in the four types of delivery destinations over time (solid lines). It can be seen that four curves all have peaks during lunch and dinner time. The curve of the workplace order is highest at lunch peak, that is, the lunch demand of the working population on weekday is significantly higher than that of other populations. The main reason for ordering takeout at workplace is to save time. In this environment, workers eat quickly during the short lunch break so that they can return to work on time. Orders at residential area increase enormously at the dinner time, which is greater than other areas in the same period. It is speculated that some working people's activities transfer from workplace zones to residential areas. The temporal curves of commercial districts and cultural and educational districts are similar, but peak dinner orders in cultural and educational districts are more than those in commercial districts.

The peak of "Sweet DP" in residential areas lasts for a long time. This is because the afternoon tea or fruit ordering behavior in residential areas is less affected by work or school schedules than in workplaces or cultural & educational areas. Compared with the peak of sweet orders in the residential area, there are two slightly narrower peaks in the cultural & educational area, indicating that compared to the relatively idle time in the residential area, the people in this area have a relatively fixed and similar dining rhythm. For example, after the school's course is over, or after the library or theater closes. Furthermore, the relationships between determinants and university students' dietary habits seemed to be moderated by university characteristics, such as residency, student societies, university lifestyle and exams (Deliens et al., 2014), so it is more possible that students present a very similar dietary taste pattern, that is, clustered. This provides reference for the type and location of catering shops, as well as timing of food preparation, so as to improve people's life satisfaction.

The temporal curves of the order volume for different addresses of the three DPs are shown in Fig. 7. Graph (a) and (c) are similar, because spicy and light are the flavors that most people choose for lunch or dinner. One day from the early hours to 9 am, the overall order volumes in Fig. 7(a), (b), (c) are very small. From 9 am to 11 pm, the number of orders rise sharply, in which "Spicy DP" and "Light DP" have large volumes and are concentrated in the workplace area. The "Sweet DP" orders in the workplace first usher in the peak of afternoon tea. The professionals in the workplace consumed sweets shortly after lunch to soothe their mood and replenish energy for the afternoon work. The "Sweet DP" peak hours of the cultural and educational districts are staggered, located in the time before dinner. In the residential area, "Sweet DP" orders begin to increase after lunch, and rise sharply after dinner. The possible scenarios behind this phenomenon might be that after young office workers return home from a day's work, they may need to season their life with sweetness to drive away tiredness. Teenagers go back home from school and may need sweetness to help them finish their homework at night.

Taste buds are closely related to dining time and location, and people's dining habits and dietary preferences are significantly different during dinner time and snack time. In residential or working areas, the dietary taste pattern during dinner time may be spicy or light. There is little difference in the temporal pattern between "Spicy DP" and "Light DP" in Fig. 7 (a) and (c), but there is a difference in their spatial

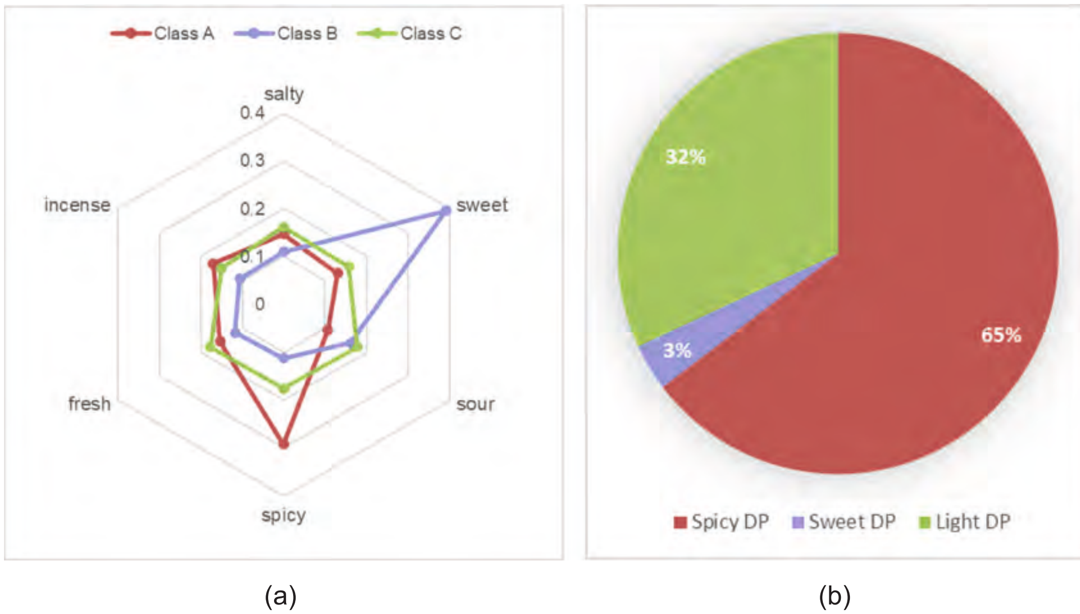

Fig. 4. Three typical taste patterns in takeout orders (a) and their proportion distribution (b).

Table 2
Definition of urban function categories used in this study.

Category	Definition
Residence	Commercial accommodation and residential accommodation, including hotels, communities, residential buildings, etc.
Business	Wholesale and retail places, including general retail (department stores, supermarkets), beverage, tobacco and alcohol retail, daily necessities, sports goods, medical supplies, automobile retail and other retail places.
Workplace	Office buildings, science parks, financial and insurance institutions, public facilities such as government and management institutions, etc.
Education and culture	Educational institutions include schools at all levels, colleges and universities, and training institutions. Cultural media organizations include newspaper offices, libraries, television stations, museums, and activity centers.
Others	Not in the above category, or not successfully recognized.

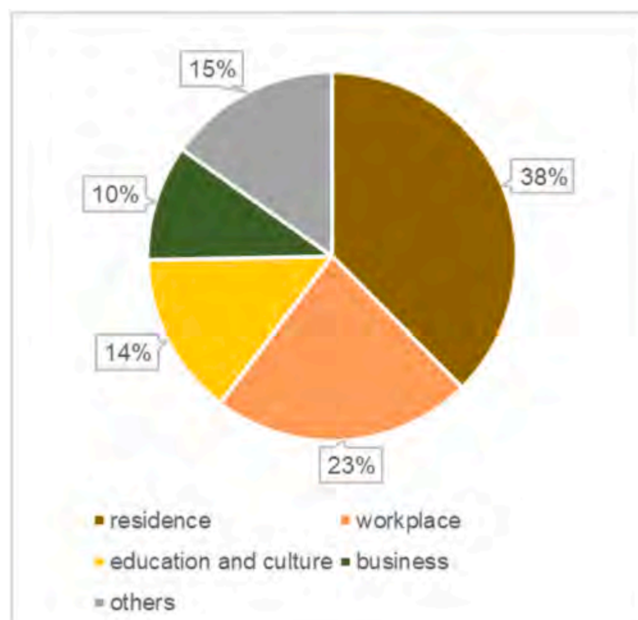

Fig. 5. The urban function types of delivery addresses.

distributions (as shown in Fig. 8), that is, the spatial location and attributes of the hot spots of the two dietary taste patterns are different. While "Sweet DP" has some uniqueness in space, it is significantly different from the other two DPs in terms of their order time distributions as shown in Fig. 7(b).

Regarding commercial areas, the addresses which the takeout is delivered to includes the retail industry and the catering industry, that is, the places where food markets, supermarkets, shopping malls or the snack streets locate. Since the place of delivery is identified mainly by using the text of the address combined with its geographic location, the business district (often represented as a city landmark) might be easily radiated to other surrounding areas. Therefore, an order identified as a business district may cover larger areas than the landmark itself. Compared with the accommodation and working areas, the results of business area identification is more complicated and the result uncertainty should be noted.

4.2.2. Spatial pattern analysis

4.2.2.1. Average Nearest Neighbor. The Average Nearest Neighbor method is used to test the agglomeration characteristics of the spatial distributions of the three DPs of takeout orders. As shown in Table 3, the nearest neighbor index R values for the three DPs are all <1, and the Z-scores are all less than −2.58 at the 0.01 significance level, showing the significant clustering pattern. The R value of "Spicy DP" is smallest, so its spatial agglomeration is the most significant. "Light DP" shows a fairly spatially gathering pattern. "Sweet DP" clusters slightly, whose distribution is relatively balanced.

4.2.2.2. Kernel density estimation. The kernel density estimation method is used to calculate the density of delivery locations of the three DPs, and the bandwidth is set to 500 m. As shown in Fig. 9, the spatial distribution of takeout orders for the three DPs in the main urban area of Hangzhou presents an obvious spatial agglomeration pattern, with each agglomeration center being balanced and relatively independent.

The distribution patterns of "Spicy DP" and "Light DP" are almost the same. The clustering centers appear in Huanglong commercial district,

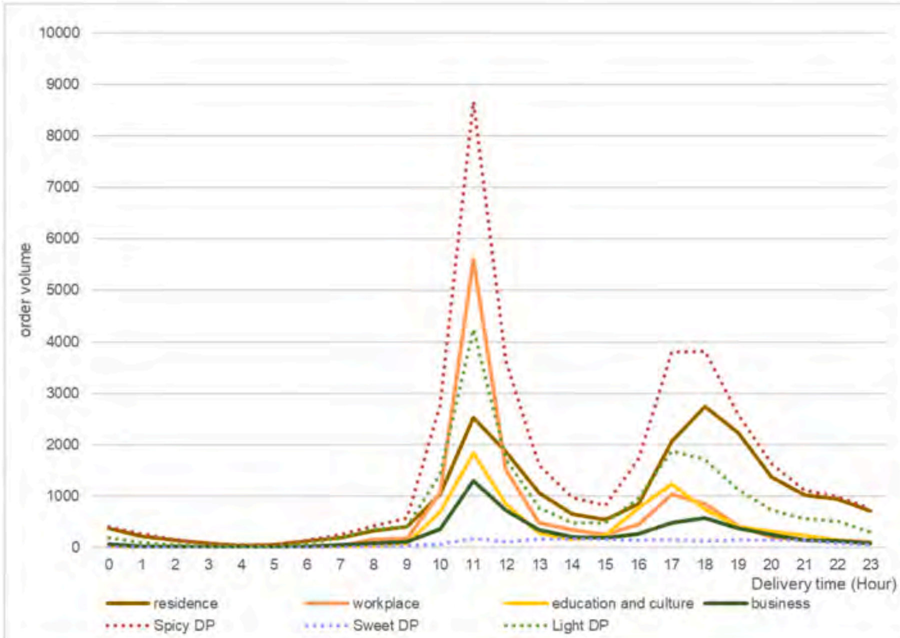

Fig. 6. The temporal patterns of the order quantity of the three DPs (dotted lines) and four types of delivery addresses (solid lines).

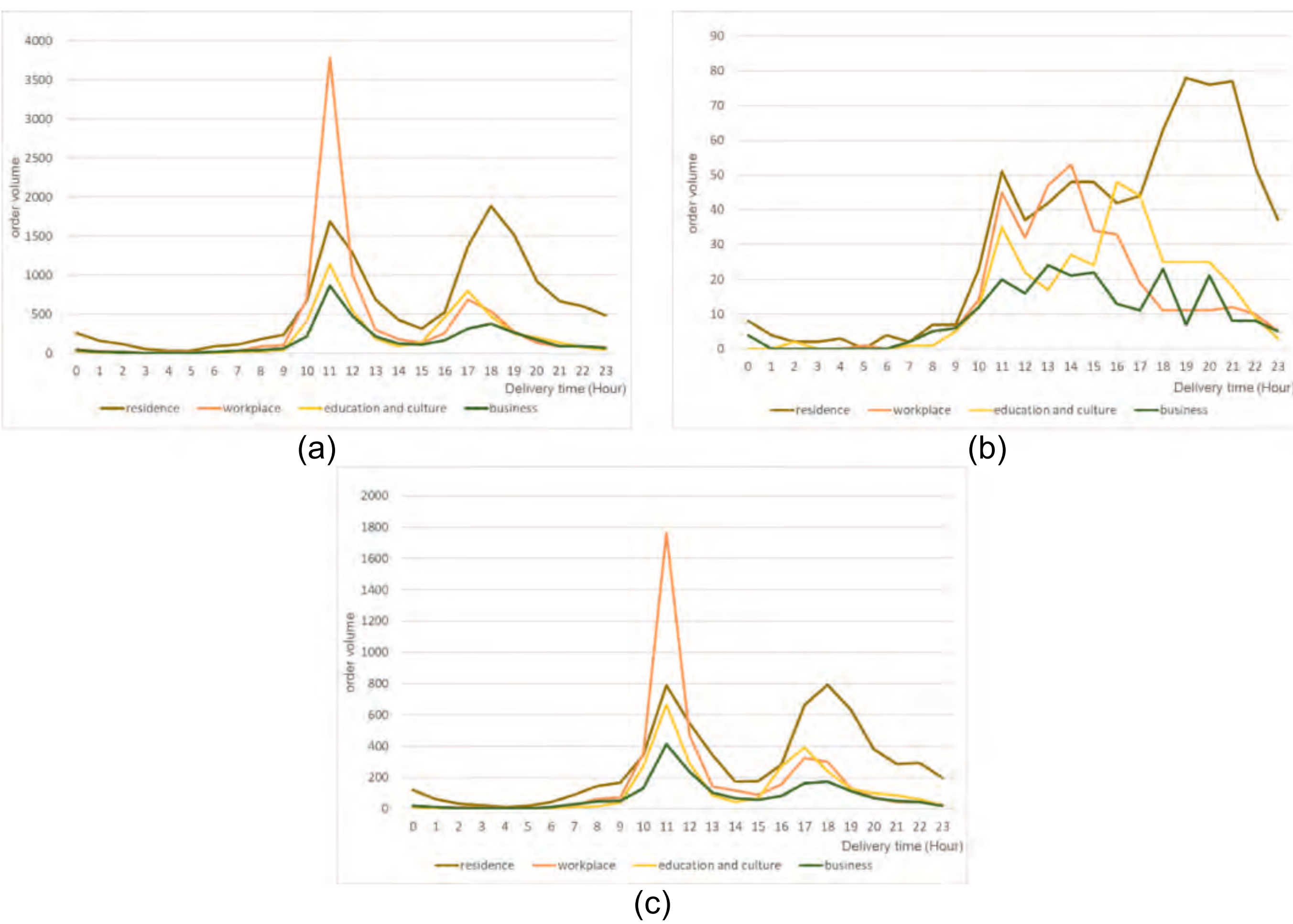

Fig. 7. The temporal patterns of order volume at different addresses for “Spicy DP” (a), “Sweet DP” (b), and “Light DP” (c).

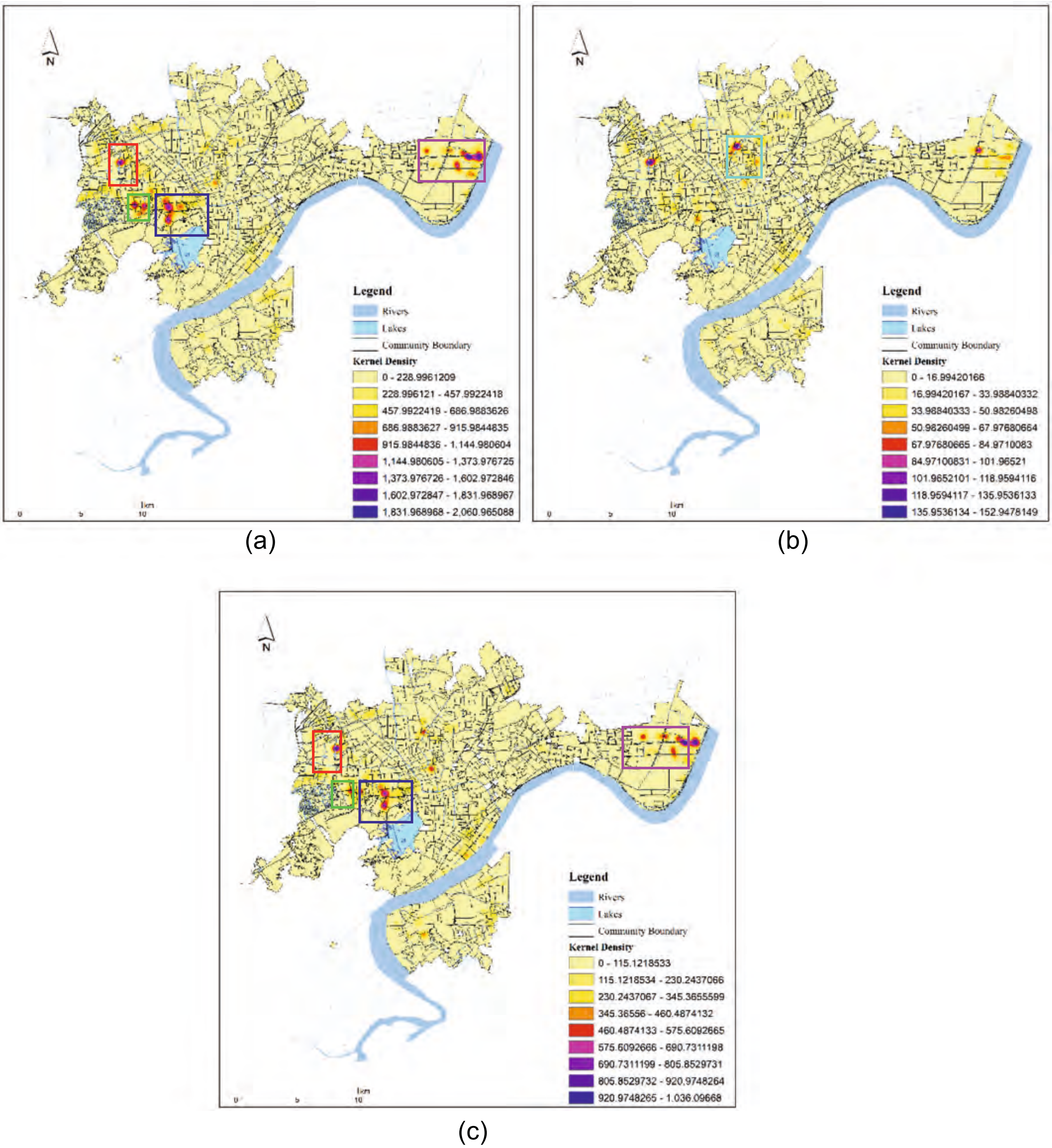

Fig. 8. Kernel density maps of takeout orders for “Spicy DP” (a),”Sweet DP” (b), and “Light DP” (c). Squares with different colors represent different spatial clustering centers.

Lianhua business district, Zijingang Campus of Zhejiang University (red framed in Fig. 8 (a) and (c)), and Xiasha University Town (purple framed in Fig. 8 (a) and (c)), etc., the degree of gathering gradually decreases toward the periphery. Huanglong commercial district (blue framed in Fig. 8 (a) and (c)) is adjacent to the Zhejiang Provincial Government to the north, and has commercial complexes such as medium-sized shopping centers and large office buildings. It is also included in the Zhejiang Library, the Xixi Campus and Yuquan Campus of Zhejiang University. The Lianhua business district (green framed in Fig. 8 (a) and (c)) is mostly residential buildings, and it is a community-based business district that serves the surrounding communities.

The “Sweet DP” clustering centers appear in the Zijingang campus of Zhejiang University, the City College of Zhejiang University and the Zhaohui campus of Zhejiang University of Technology (cyan framed in Fig. 8(b)). The cultural and educational areas have a relatively high population density and a large number of orders per unit area.

Table 3
Average Nearest Neighbor analysis results of 3 DPs.

	R value	P value	Average nearest neighbor distance (meter)	Z value	Distribution pattern
"Spicy DP"	0.245920	0.00	18.7008	−278.834295	greatly gathering
"Sweet DP"	0.416082	0.00	133.4651	−49.721829	slightly gathering
"Light DP"	0.273217	0.00	29.5237	−188.852252	fairly gathering

Therefore, clustering centers tend to appear in these areas, rather than residential areas and workplace areas where orders are spatially scattered.

Generally, most of the takeaway orders delivered to the cultural & educational districts are ordered by students, academics and administrative personnels. Among these, the student group deserves attention. After the transition from high school to university, when independency increases, students are continuously challenged to resist heavy-tasting foods. According to reports (Deliens et al., 2014), students' eating habits are affected by individual factors (e.g. taste preferences, self-discipline, time and convenience), their social networks (e.g. (lack of) parental control, friends and peers), physical environment (e.g. availability, accessibility, and prices of food products), and macro environment (e.g. media and advertising). In food stores around school, the ratio of energy-dense and nutrient-poor food and beverage products relative to healthy food and beverage products is high (Roy et al., 2019). For example, there are snack streets and many milk-tea shops near universities, which also provide convenient delivery services. So, students tend to order desserts such as milk tea, cakes, cookies, etc. when they finish their courses.

4.2.2.3. Community hot spots. Taking the community (neighborhood) as a geographic unit, the research area is divided into 667 community areas based on local authority, the number of takeout orders of each DP is counted, and the local Getis-Ord Gi* index is used to explore the hot spots that prefer spicy, sweet, and light orders, respectively. The common hot spots for three DPs with *Z*-score >1.96 (*p*-value<0.05) are the Zijingang Campus of Zhejiang University, Huanglong Commercial District, and Xiasha University Town (Area A, B, C respectively in Fig. 9), etc.

Among the hotspot areas where the Z score > 1.96 and p-value <0.01, the area unique to "Spicy DP" is *Xingmin Village Community* (framed in Fig. 9(a)). Within the area of this community, there are Jiangling Road Metro Station, Binjiang District Government, some high-tech enterprises and office buildings. The order time chart and DPs ratio graph for this area are shown in Fig. 10 (a) and (b). It can be seen that Fig. 10(a) is similar to the time curve in Fig. 6 where the delivery place is workplace, that is, the order volume during lunch time is significantly higher than that during dinner time. The proportion of the total number of "Spicy DP" in this region reaches 77 %, which is higher than the "Spicy DP" proportion in the overall study area (65 %), and the "Spicy DP" order volume during lunch or dinner time is significantly higher than other DPs.

According to the proportion of "Spicy DP" orders delivered in different dining periods, 77 % of the "Spicy DP" orders are delivered to the workplaces during lunch time (10:00 to 14:00), while during dinner time (17:00 to 21:00) the ratio changes to 50 %, and during supper time (21:00 to 6:00 the next day) 57 % are delivered to residential areas. It can be observed that most areas of this community are office buildings for companies in industries such as financial or information technology, with a large proportion of workplaces to residence, and a larger number of people who prefer to eat spicy food (Fig. 11).

Among the hotspot areas with Z score > 1.96 and *p*-value < 0.01, the areas with a preference for "Light DP" are near the Shengli community and the Shenjia community in Shangcheng District (blue framed in Fig. 9 (c)), and the Chengxing community around the municipal government (green framed in Fig. 9(c)). The Shangcheng District is an ancient and central district of Hangzhou. As the seat of the imperial palaces of the Wuyue (907–978 CE) and Southern Song dynasties (1127–1279 CE), there are as many as 92 cultural relics and cultural landscapes. A large number of old Hangzhou people have lived here for a long time, and many communities have rich traces of life in the old Hangzhou style. Table 4 (Hangzhou Bureau of Statistics, 2019) shows a higher proportion of the elderly population in the Shangcheng District. Moreover, the distribution of nursing homes in the study area (Fig. 12) shows that the Shengli Community and Shenjia Community in the Shangcheng District have a nursing home located in each, and there are several scattered welfare and nursing homes around the two communities (in Fig. 12.). This implies that these two communities may be concentrated areas of the elderly and middle-aged population.

This helps us understand the local culture and sense of place from a dietary perspective. The light taste preference of dwellers in old neighborhoods is a manifestation of the interaction between sensory memory and local environment, and it is also a demonstration of the folk culture of "local taste", which can play social functions such as transmitting information, communicating interpersonal relationships and regulating behavior activities in the process of social operation (Zhai, 1995).

The Chengxing Community (green framed in Fig. 9(c)) is a hot spot of "Light DP" cluster, which is located near the core area of the Qianjiang New Town in Sijiqing Street. Most of the workplaces here belong to government agencies, public facilities and financial centers such as Hangzhou Municipal Government, Civic Center, etc. Regions mentioned above can be validated by land use in the city master plan obtained from Hangzhou Municipal Government (Fig. 15).

The temporal pattern of the dietary taste patterns in this area (Fig. 13) is similar to that in Fig. 6 where the delivery place is working area, that is, the order volume during lunch time is significantly higher than that during dinner time. The proportion of orders with "Light DP" (Fig. 14) among three dietary taste patterns has increased in the evening, with 43 % of orders delivered to residence areas and 36 % for working areas. Compared with the Xingmin Village community, the proportion of orders for dinner in the Chengxing community is slightly higher. It may be due to the different occupational nature that job responsibilities are different. Compared to the internet companies in the Xingmin Village community, government agencies or financial institutions in this area has earlier off work hours. Because stress has an impact on eating habit (McKay et al., 2021). If people's working hours are more regular, their pressure might also be more stable. People work here with relatively fixed work rhythm and pressure, so they are more likely to prefer light food with less oil and salt.

5. Discussion

Mining the distribution of urban food space through takeaway data provides ideas for understanding the consumption tendencies of different groups of people in cities, which is not only related to the demographic characteristics of the population such as age, but also related to the environment, sense of place, nature of work, life rhythm and mood. The distribution of different DPs provides valuable references for understanding cultural meaning of food. People's dietary awareness has a sense of identity with the "root" (Mou, 2016), which may be particularly obvious in some groups. This would facilitate the understanding of the heterogeneity of a city, especially from cultural aspects. It may help build a food culture space with rich connotation and distinctive local characteristics in urban planning practices.

From the perspective of urban planning and construction, this research provides ideas for the location of catering shops in the city, thereby improving residents' life satisfaction, and providing suggestions

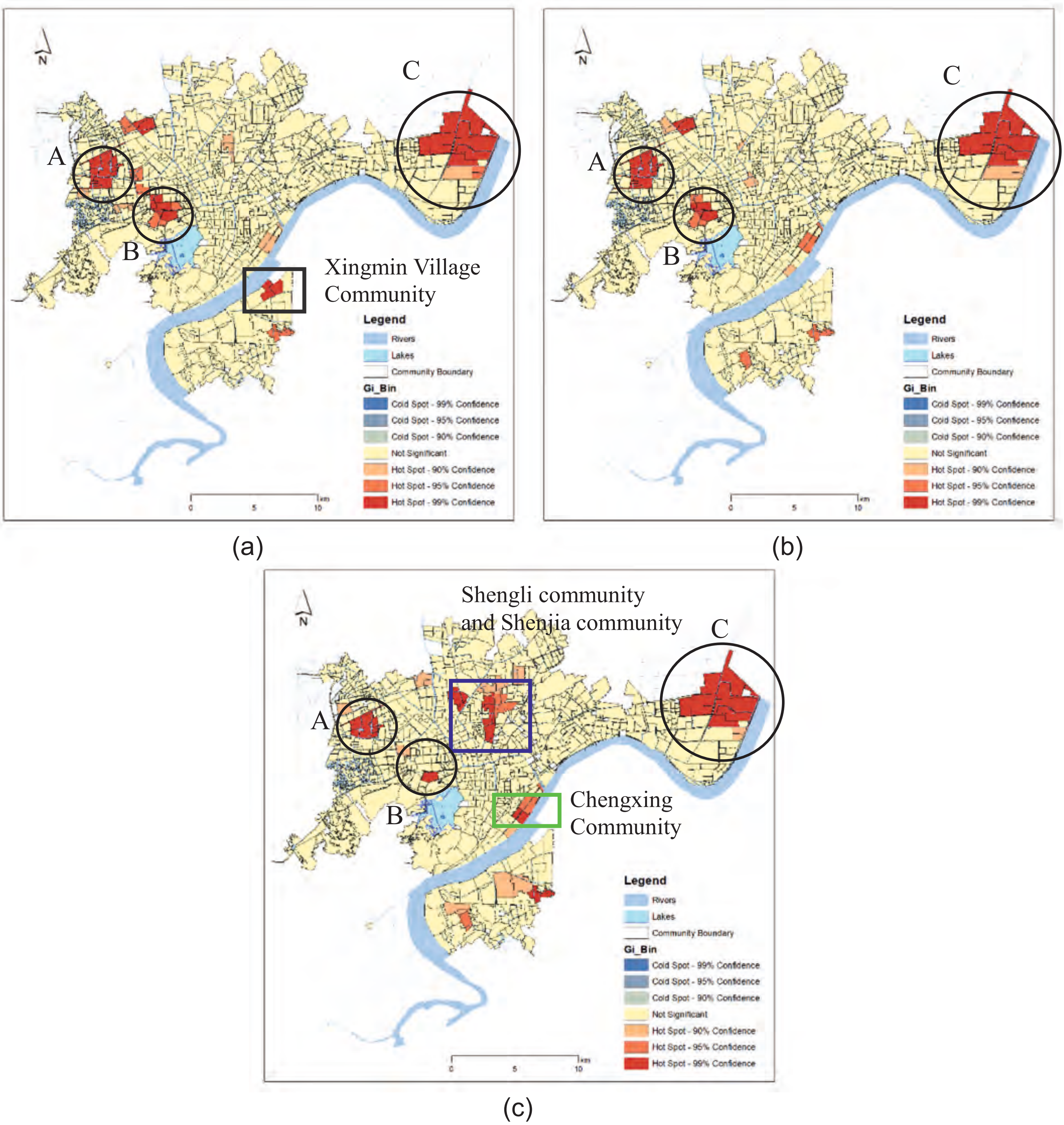

Fig. 9. Community hot spots for “Spicy DP” (a),”Sweet DP” (b), and “Light DP” (c). Black squared area is Xingmin Village Community. Blue squared area is Shengli community and Shenjia community. Green squared area is Chengxing Community. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

for location marketing methods and advertising. The physical location of take-out shops is critical to their sales. The food delivery app “Eleme” is a crowdsourcing platform that provides delivery services for takeaway stores. In addition to customers, riders also choose shops that are close to take orders. The distance between the stores will also affect the recommendation probability of riders. The existing retailer location theory mainly considers factors including retail format (Ramesh et al., 2011), supply chain design (Ross et al., 2017), customer characteristics (Glaeser et al., 2019; Grewal et al., 2009) and geographical environment factors (Benoit & Clarke, 1997; Murad, 2011). Among them, customer characteristics are important considerations for retailer location selection. Most theories only consider the situation of offline shoppers, and there are few studies on strategies that consider online needs, especially the immediate needs of online customers. The customer characteristics considered mainly include two aspects: customer geographical distribution characteristics and customer behavior characteristics. Jiao et al. (2020) modeled delivery distance and order volume based on takeaway data to characterize the geographic distribution of customers. Our

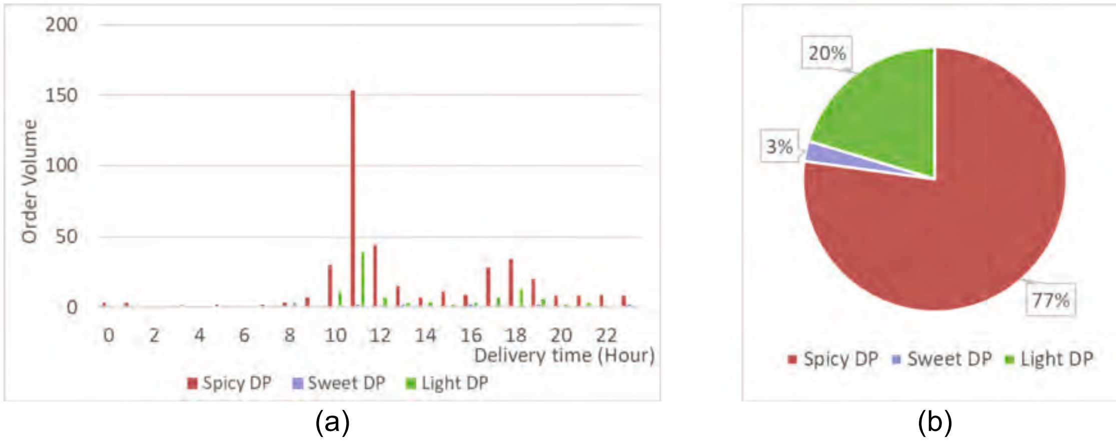

Fig. 10. Order time chart (a) and DPs ratio graph (b) for the Xingmin Village Community.

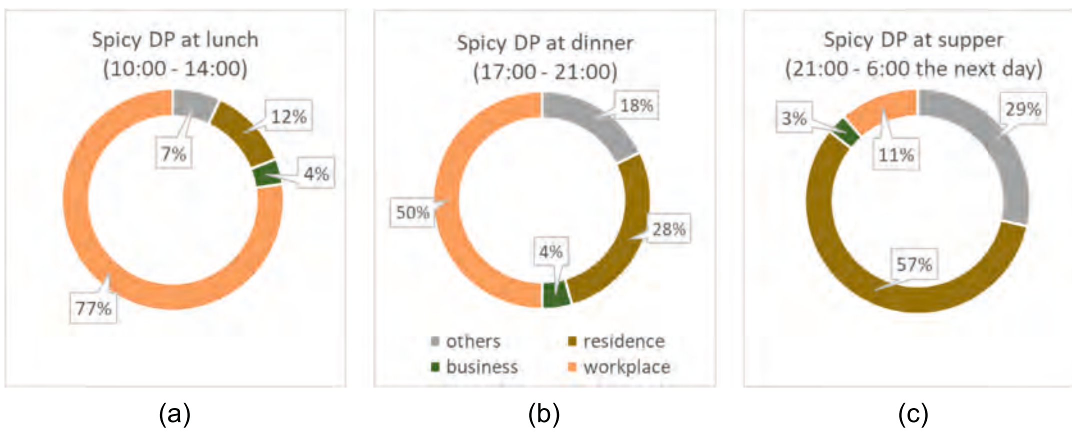

Fig. 11. The proportion of different addresses delivered for “Spicy DP” orders at lunch(a), dinner(b) and supper(c).

Table 4
Population age composition structure of the six administrative districts in Hangzhou (by the end of 2018).

Districts	% of the total population in the district			
	Under 18	18–35 years old	35–60 years old	Over 60 years old
Shangcheng District	12.03	20.20	36.20	31.56
Xiacheng District	13.19	23.78	35.91	27.12
Jianggan District	21.37	23.59	36.30	18.74
Gongshu District	17.31	20.54	37.38	24.77
Xihu District	19.46	24.33	38.04	18.16
Binjiang District	22.97	28.33	35.07	13.63

research focuses on users' choice of take-out meals, and uses dietary patterns to describe customer behavior characteristics to assist decision-making, which supplements the location strategy theory of traditional offline retailers. For example, a spicy takeaway local store can choose to be in a hot spot region or at the junction of several hot spots.

At the same time, it provides a valuable reference for the construction and improvement of the city's logistics management system. Generally speaking, enterprises generally adopt the modes of unified distribution, joint distribution, night distribution, etc. Some enterprises try to adopt crowdsourcing methods to improve the distribution efficiency and service level, and at the same time relieve the pressure on the urban road network (Li et al., 2021). Based on this research, enterprises in hotspot areas of DPs can negotiate and cooperate with each other when distributing food raw materials and condiment. The nodes in the logistics distribution system can also refer to this information for site selection and scheduling, thereby reducing costs and becoming more efficient and environment friendly.

The increased availability and accessibility of food provided by the O2O food delivery system has resulted in a convenient dining experience, but health concerns have also arisen (Zhao et al., 2021). Different timing preferences sometimes may cause or exacerbate certain issues, e.g., digestive, metabolic, psychological and other problems of specific populations. Also, intake of macronutrients in different DPs is critical in the aetiology of hypertension, grains, edible oils and animal-source foods (Zhai et al., 2013). People with heavy tastes or unbalanced DP over a long period of time should be encouraged to increase their consumption of fruits, whole grains, nuts and seeds and reduce their salt intake. Yang et al. (2013) believes that the government needs to set goals and indicators for health development, monitor key health risk factors, choose intervention strategies, and track policy implementation at the national level. This leads to effective policies involving multiple sectors.

The main limitation of this study is the use of contents of order dishes and ingredients from a cookbook website without an indication of serving size. This study simply uses the frequency of the ingredients to quantify the taste, but the effects of different flavors' ingredients on the tastes of a dish may not be the same, and are difficult to quantify. For example, people have different perceptions of the “salty” taste of 10 g of salt and 10 g of sesame sauce. 10 g of salt and 10 g of sugar have different characterization degrees of “salty” and “sweet”, even though the weight of salt and sugar are the same. Moreover, different food stores may use different magnitude of ingredients even for the same dish. The lack of

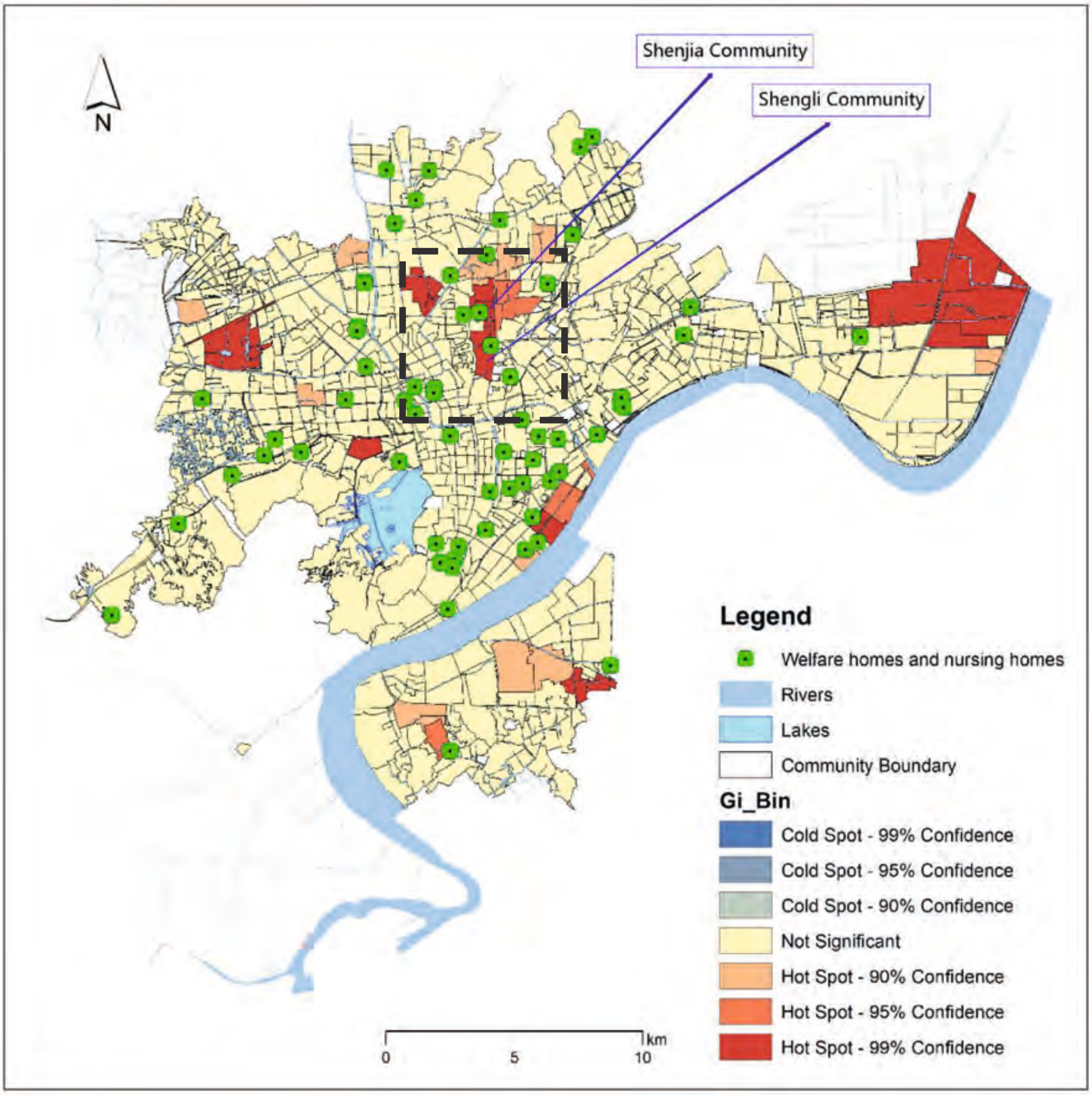

Fig. 12. Distribution of welfare and nursing homes in the study area.

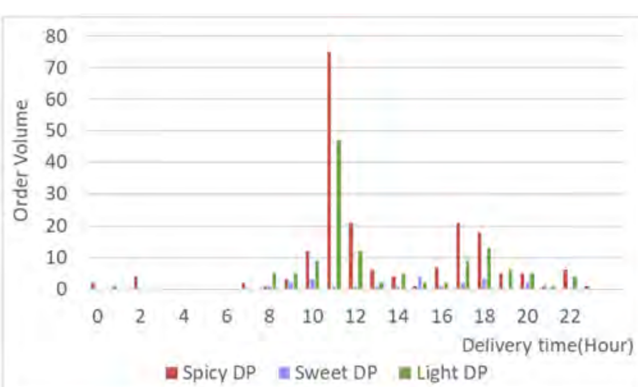

Fig. 13. The order-time chart of the three DPs in Chengxing community.

serving sizes and quantization rule make it impossible to analyze how many people prefer a particular flavor, so it's hard for us to derive more diverse dietary taste patterns.

In addition, due to data access limitation and privacy restrictions, our takeaway data only contains one typical workday in the city and cannot obtain the user's age and other individual information. The 15 % of orders with delivery address of "Other" contain the order points whose delivery location has not been successfully identified, such as "No. XX XX street". Combining the text description and geographic location, the attributes of the delivery location cannot be determined. Such data will increase the systematic error of the statistical analysis.

There is an increasing evidence that the nutritional content of takeaway and fast food may cause various negative health consequences, including cardiovascular disease, insulin resistance, type 2 diabetes, and obesity (Jaworowska et al., 2013). Understanding the impact of takeaway on nutrition and health, as well as the correlation with dietary taste patterns, can help us determine the best strategy to reduce the possible adverse effects of their consumption on public health. However, it is difficult to quantify the nutritional content and health level, and to compare which is healthier (or unhealthier) between takeout orders based on our current data. This would be possible research directions for our future work.

6. Conclusions

"Food" and "accommodation" are the two basic challenges that

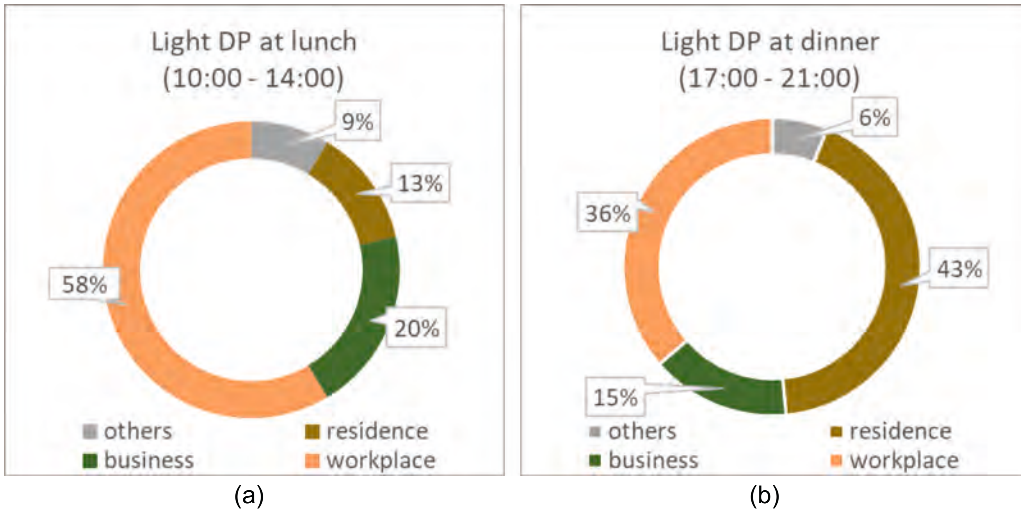

Fig. 14. The proportion of different addresses delivered for "Light DP" orders at lunch(a) and dinner(b).

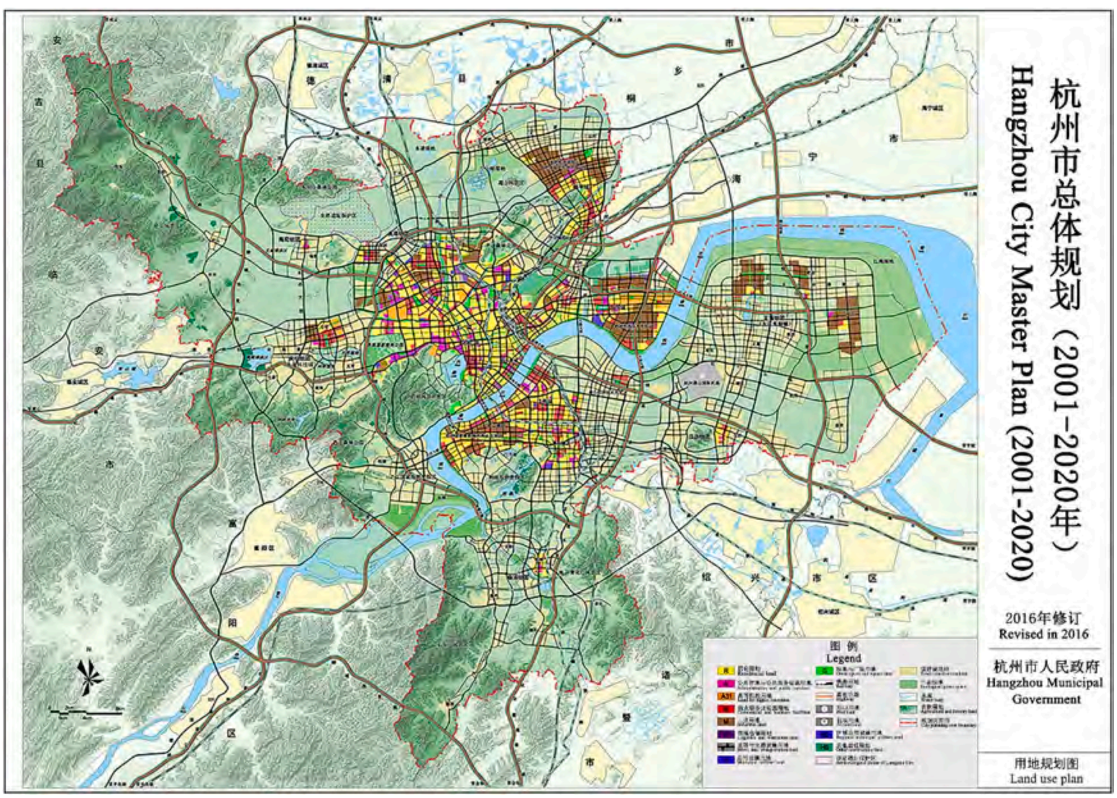

Fig. 15. The Master plan in Hangzhou City, Zhejiang Province, China.

contemporary young people face when living in large cities. In the metropolises, contemporary young people are under greater pressure in life. In order to save time and energy, young adults aged 19–29 years are more inclined to eat out or take-away meals at home, school or work place (Adams et al., 2015). With the development of the Internet, middle-aged people have also kept up with the trend of the times and mastered the convenient means of meal delivery, showing their customized needs and demographic characteristics through dish information, delivery time and location. This study enriches the research on crowdsourced data based on human activities and provides a new perspective for urban planning and population groups' dietary analysis. The existing analyses and researches on spatial food culture are mostly based on catering POI data rather than residents' food takeout data. The taste characteristics represented by the people may reflect the semantics of a place, thereby realizing the perception of urban space.

In this research, we extracted three dietary taste patterns of Hangzhou people based on take-out order data: spicy DP, sweet DP and light DP. We found that the order volume over time in a day has obviously different characteristics according to the different delivery locations and DPs. This information can provide a reference for catering shops to formulate food sales strategies and site selection.

Based on the information obtained from the takeaway data, we understood the occupational nature, work pace, sociodemographic characteristics and other information of the population. Through spatial statistical analyses, we have obtained three statistically significant hot spot areas at the community scale: Xingmin Community, Shengli & Shenjia Community, and Chengxing Community, which illustrate taste preference is the product of the interaction between people and the place. Specifically, (1) Xingmin Community is a hot spot where spicy DP presents a significant spatial cluster. It is an area where more high-tech companies such as information and technical services are distributed. Based on information such as delivery time and address in food delivery data, we can understand people's work rhythm. The fast-paced and high-pressure life is inextricably linked to their spicy eating habits. (2) Chengxing community's order pattern also has a typical working area characteristic. As a hot spot of light DP, most of the workplaces here are government agencies, financial banks, etc. The relatively fixed pace and less stressful work is related to their light taste. (3) As the main urban area of Hangzhou, Shengli & Shenjia communities are home to most old Hangzhou people, and become the high-value cluster of Light DP. The taste of the old Hangzhou people represents lightness, less oil and salt. Our research also confirms that dietary taste patterns based on takeaway data can represent the cultural heritage and historical accumulation of the region.

Our study is the first attempt to summarize the characteristics of dietary taste patterns combining various takeaway orders. Existing studies are mostly based on exploring the dietary taste patterns of people in a certain area from the perspective of nutrition, lack of place-based representations and analysis. Our methods can also be applied in other cities and countries with data accessibility to observe the life style of residents and the distribution of urban functions. In sum, this research utilized a new type of big data from the food delivery industry into urban analytics to reveal population dietary characteristics and spatial distributions, which provides new insights on urban foodscape research and planning for social good.

CRediT authorship contribution statement

Yichen Xu: Conceptualization, Methodology, Visualization, Writing-Original draft
Linshu Hu: Conceptualization, Methodology
Song Gao: Conceptualization and Writing- Reviewing and Editing
Mengxiao Wang: Data curation and Investigation
Jiale Ding: Data curation
Yining Qiu: Data curation
Feng Zhang: Conceptualization, Analysis, Writing- Reviewing and Editing, Funding acquisition
Zhenhong Du: Funding acquisition
Renyi Liu: Supervision

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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