Cyber Food Swamps: Investigating the Impacts of Online-to-Offline Food Delivery Platforms on Healthy Food Choices

Yunke Zhang[1], Yiran Fan[2], Peijie Liu[1], Fengli Xu[1*], Yong Li[1*]

[1]Department of Electronic Engineering, Beijing National Research Center for Information Science and Technology (BNRist), Tsinghua University

[2]Department of Computer Science and Engineering, University of California San Diego,

zyk21@mails.tsinghua.edu.cn, yif032@outlook.com, liupj23@mails.tsinghua.edu.cn, fenglixu@tsinghua.edu.cn, liyong07@tsinghua.edu.cn

Abstract

Online-to-offline (O2O) food delivery platforms have greatly expanded urban residents' access to a wide range of food options by allowing convenient ordering from distant food outlets. However, concerns persist regarding the nutritional quality of delivered food, particularly as the impact of O2O food delivery platforms on users' healthy food remains unclear. This study leverages large-scale empirical data from a leading O2O delivery platform to comprehensively analyze online food choice behaviors and how they are influenced by the online exposure to fast food restaurants, *i.e.,* online food environment. Our analyses reveal significant variations in food preferences across demographic groups and city sizes, where male, low-income, and younger users are more likely to order fast food via O2O platforms. Besides, we also perform a comparative analysis on the food exposure differences in offline and online environments, confirming that the extended service ranges of O2O platforms can create larger "cyber food swamps". Furthermore, regression analysis highlights that a higher ratio of fast food orders is associated with "cyber food swamps", areas characterized by a higher proportion of accessible fast food restaurants. A 10% increase in this proportion raises the probability of ordering fast food by 22.0%. Moreover, a quasi-natural experiment substantiates the long-term causal effect of online food environment changes on healthy food choices. These findings underscore the need for O2O food delivery platforms to address the health implications of online food choice exposure, offering critical insights for stakeholders aiming to improve dietary health among urban populations.

Code & Dataset —
https://github.com/tsinghua-fib-lab/CyberFoodSwamp

Introduction

Over the past decade, with the advancement of technologies of mobile commerce and crowd-sourcing platforms, we have witnessed a surge in the adoption of online-to-offline (O2O) food delivery (Zhao et al. 2021; Shroff, Shah, and Gajjar 2022; Meemken et al. 2022). As of 2023, the size of O2O food delivery user in China reached 545 million, accounting for 50% of the total netizen population of the nation (CNNIC 2023). Through the information matching and dissemination service provided by O2O food delivery platforms, users can access meals from any desired restaurants, thereby reshaping the dining habits of numerous urban residents.

Although the convenience of O2O food delivery is undeniable, concerns persist regarding the nutritional quality of delivered food, with numerous criticisms pointing to its generally low nutritional value (Dai, Wu, and Hu 2022). Drawing on the concept of "food swamps", which describes areas oversaturated with unhealthy food outlets in the physical world (Stowers, Schwartz, and Brownell 2017), O2O food delivery platforms have the potential to expand food access and create virtual food swamps that shape consumer choices towards unhealthy restaurants, leading to adverse health outcomes (Stephens, Miller, and Militello 2020). Therefore, it is essential to assess how online food environments on these platforms influence users' healthy food choices.

Existing studies primarily used surveys and field studies to evaluate O2O food delivery platforms from the perspective of healthiness, including the nutritional value of delivered food (Brar and Minaker 2021; Dai, Wu, and Hu 2022), consumer perceptions of healthy food availability (Dai, Wu, and Hu 2022; Eu and Sameeha 2021; Osaili et al. 2023), and healthy food choices (Osaili et al. 2023; Giacomini et al. 2024). These studies often suffered from limitations in the scale of research samples and lack a direct link between online food environment and consumers' real-world food choices. Furthermore, while significant efforts have been made to examine the impact of traditional dining environments on food choices (Feng et al. 2010; Althoff et al. 2022; García Bulle Bueno et al. 2024), their findings may not directly correspond to the effects of online food environments. This is particularly relevant as O2O food delivery significantly expands the spatial range of food options, highlighting the need to compare offline and online food swamps.

In this study, we aim to provide comprehensive evidence of the healthiness of online food environments and its impact on healthy food choices using large-scale empirical O2O food delivery consumption data through following three research questions:

*Corresponding Authors

RQ1: How healthy are online food environments? Is there overall healthiness discrepancy of O2O food delivery consumption?

RQ2: What are the differences between offline and online food environments?

RQ3: How does online food environment impact consumers' food choices? Are these effects consistent across demographic groups?

To answer the above questions, we conduct comprehensive data-driven analyses and derive insightful findings based on O2O food delivery restaurant and consumption data at both city and individual levels, collected from one of the largest O2O food delivery platforms in China. First, we focus on the macro-level health discrepancies within the O2O food delivery industry. We uncover a scaling law that governs the relation between O2O food delivery consumptions and city sizes, showing larger cities have significantly higher proportions of fast food restaurants and placed delivery orders, which may be attributed to the faster pace of social life in these cities (Bettencourt et al. 2007). Healthiness of food choices is also correlated with demographic, with males, individuals with lower incomes, and younger people exhibiting a significantly higher likelihood of ordering fast food online. This trend, derived from large-scale empirical data, mirrors previous findings on food destinations based on small-sample surveys (Kerr et al. 2012). Second, we compare the distributional patterns between offline and online food environments. The number of accessible O2O restaurants is significantly higher than that of local offline restaurants, while the healthiness of the online food environment is slightly better than that of the offline environment. However, the extended service range of O2O platforms expands the spatial coverage of food swamps. The online food environment shows a stronger correlation with healthy food choices on O2O food delivery platforms. Finally, following the analytic framework proposed by García Bulle Bueno *et al.* (García Bulle Bueno et al. 2024), we examine the relationship between online food environments and healthy food choices. Logistic regressions reveal that a higher proportion of fast food restaurants in a user's location is associated with a higher likelihood of ordering fast food. Notably, low-income individuals and younger users are more affected by this environment, underscoring the heterogeneous susceptibility of users on online platforms (Li et al. 2022; Sukiennik, Gao, and Li 2024). A quasi-natural experiment based on users who permanently change their ordering context further substantiates the gradual, negative causal impact of online food environments dominated by unhealthy fast food options on healthy dining habits, highlighting the urgent need for regulations addressing "cyber food swamps".

Our main contributions can be summarized as follows.

- We leverage empirical O2O food delivery consumption data to comprehensively understand the healthiness of the online food environment and its impact on healthy food choices, highlighting the significant potential for exploring the interplay between the web and society using data-driven methods.
- We demonstrate macro-level health discrepancy within the online food environment by uncovering city-level scaling laws of O2O food delivery adoption and identifying disparities in healthy food choices across demographic groups.
- We compare the healthiness of offline and online food environments and confirm the amplifying effect of O2O food delivery on real-world food swamps.
- We reveal the effects of online food environments on healthy food choice behaviors through a quasi-intervention experiment utilizing a detailed, individual order-level dataset, indicating the negative health impacts of "cyber food swamps".

Related Works

We categorize the related works into three dimensions.

O2O Food Delivery Adoption and Health Perception Many previous studies and reports have substantiated the rapid growth of O2O food delivery in global cities, highlighting it as a convenient and viable solution to address limited access to healthy food options (Dillahunt, Simioni, and Xu 2019; Yeo, Goh, and Rezaei 2017). During the COVID-19 pandemic, social distancing measures made O2O food delivery a primary means of obtaining food, further accelerating the industry's growth (Dsouza and Sharma 2021; Li, Mirosa, and Bremer 2020; Hong et al. 2021). At the same time, the nutritional and health implications of O2O food delivery have attracted increasing attention from researchers worldwide. As for users' perceptions of delivered food, surveys conducted in Jordan (Osaili et al. 2023), Malaysia (Eu and Sameeha 2021), and China (Dai, Wu, and Hu 2022) found that most participants believe food delivered through O2O food delivery is generally less healthy than food served in restaurants. However, many of these participants still report a high reliance on such services. Several studies have evaluated the healthiness of O2O food delivery meals through sampling. An analysis of food delivery menus in Canada revealed that the majority of menus scored below the standards set by the Healthy Eating Index (Brar and Minaker 2021). Similarly, a study on the nutritional quality of food sold on Chinese O2O food delivery platforms found that most popular items have low nutritional value (Dai, Wu, and Hu 2022) – younger consumers, in particular, tend to pay less attention to the nutritional content of delivered meals, which can lead to health issues such as elevated cholesterol and obesity with long-term consumption. In Italy, an analysis of differences in willingness to use food delivery services among users found that individuals with lower health literacy are more dependent on O2O food delivery (Giacomini et al. 2024). Most current studies are limited to small-scale data collection through surveys or sampling, without assessing the overall health preferences of O2O food delivery users across a broader population. In our study, we leverage a large-scale empirical dataset covering the consumption behaviors of hundreds of thousands of users to comprehensively analyze their online food environments and healthy food choices.

Health Impacts of Food Environment Extensive efforts have been made to investigate the impact of healthy food accessibility on residents' food choices and health outcomes, which can be categorized into three stages based on data sources. Initially, researchers relied on interviews and field surveys to understand individuals' eating habits and the dining environment in their residential areas. However, the limited scale of these studies made it difficult to conduct comprehensive research across different regions, resulting in mixed and non-generalizable findings. For example, some studies reported an association between high exposure to fast food outlets and residents' unhealthy diets and obesity rates (Wang et al. 2008; Li et al. 2008), while others found no significant correlation (Simmons et al. 2005; Jeffery et al. 2006). With the advent of mobile applications, researchers gained access to vast amounts of self-reported food choice data and could automatically track individuals' locations (Allcott et al. 2019). For instance, large-scale dietary tracking data revealed an association between residential communities with greater healthy food accessibility and better dietary quality (Althoff et al. 2022). However, as more food consumption occurs far from residential areas, focusing solely on residential environments may not fully capture individuals' exposure to food environments. Recent studies have used mobility data to examine urban residents' exposure to food environments, finding that higher exposure to fast food outlets in mobile environments increased the likelihood of visiting fast food restaurants (García Bulle Bueno et al. 2024). Building on the concept of linking food environments with food choice behaviors, this study aims to extend previous knowledge by clearly defining the online food environment and quantifying its impact on online food choices.

Online Service Data and Health of Citizens Digital data collected from online services, including activity tracking, GPS traces, and social media posts, have been widely linked to the health outcomes of urban residents in existing research (Lin et al. 2020; Zhang et al. 2021a,b; Xu et al. 2025). Large-scale physical mobility data collected via smartphone applications has been used to reveal the discrepancy in urban residents' health status (Chen et al. 2022; Zhang et al. 2024, 2025a). For example, such discrepancy significantly decreases as city walkability improves (Althoff et al. 2017). A study based on mobile GPS data found that while large cities offer more recreational and social options, they tend to direct individuals to locations frequented by people of similar socioeconomic status, increasing the segregation of social activities and leading to new public health risks, such as lack of physical activity and imbalanced diets (Nilforoshan et al. 2023; Chen et al. 2023; Fan et al. 2025). Social media data, spanning multiple modalities, are also emerging as promising proxies for public health indicators. Posts on X (formerly Twitter) have been used to predict county-level public health metrics such as obesity and diabetes rates (Culotta 2014; Abbar, Mejova, and Weber 2015). Food-related photos on Instagram, combined with location information, can accurately reflect offline food deserts (De Choudhury, Sharma, and Kiciman 2016). YouTube videos have been applied to track dietary changes during the COVID-19 pandemic (Mejova and Manikonda 2023). Additionally, online recipe platforms are being used to nudge healthier food adoption by promoting specific healthy recipes (Jesse, Jannach, and Gula 2021; Chelmis and Gergin 2023). Similarly,

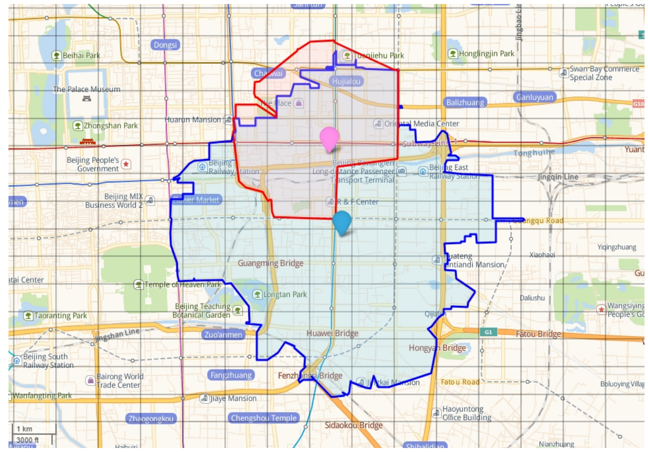

Figure 1: Examples of service ranges for O2O food delivery restaurants.

data generated by O2O food delivery platforms hold the potential to reflect the health-related information of urban residents.

Data Description

In this study, we mainly use three categories of data, *i.e.*, O2O food delivery restaurant data, O2O food delivery consumption order data, and demographic data.

O2O Food Delivery Restaurant Data We collect information on O2O food delivery restaurants from one of China's largest O2O food delivery platforms. For each restaurant, the platform provides its name, category, and service range. Each restaurant is assigned to a single, specific category. To assess the healthiness of the restaurants, we classify those within the "fast food and snacks", "western fast food", and "fried food" categories, as these are often regarded as having low nutritional value and may contribute to health issues such as obesity (Hu et al. 2016). All other categories are considered non-fast food restaurants. On average, 18.77% of restaurants are categorized as fast food restaurant.

The service range of each O2O food delivery restaurant indicates the urban areas that can access its delivery services. As depicted in Figure 1, the restaurant marked in blue has a broader service range than the one marked in pink. Utilizing this data, we can identify O2O food delivery restaurants accessible to each urban area. We divide the city of Beijing into Geohash-6 "regions" (approximately 1.2×0.6 kilometers), represented as rectangles in Figure 2(a). For each region c, the "unhealthiness" of its corresponding online food environment $\phi(c)$ is defined as the ratio of the number of accessible fast food restaurants to the total number of accessible restaurants. Figure 2(a) illustrates the spatial distribution of $\phi(c)$ across 4,921 regions in Beijing.

O2O Food Delivery Order Data To depict the healthy food choices of O2O food delivery users, we further collect O2O food delivery order data that record the consumption behaviors of platform users. Specifically, we gather a

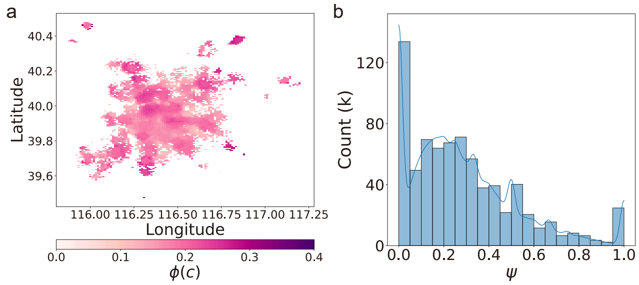

Figure 2: Distributions of online food environment and preferences. (a) The spatial distribution of regions' ratio of accessible fast food restaurant $\phi(c)$ in Beijing. (b) The distribution of users' fast food preference ψ.

city-level order number dataset and an *individual-level* order record dataset from the same platform.

The city-level dataset records the number of daily O2O food delivery orders, including fast food orders, across 283 Chinese cities in 2018 and 2024, respectively. For the individual-level dataset, we randomly sample 850,000 platform users in Beijing and collect their order records from January 2017 to May 2018. Additionally, we gathered order records from 20,000 users in Beijing, 10,000 users in Chengdu (a second-tier city in southwestern China), and 10,000 users in Xiamen (a third-tier city in southeastern China) for the period from January 2023 to December 2024. Each entry includes the user ID, order time, user location (at the Geohash-6 region level), expenditure amount, and the corresponding O2O food delivery restaurant. For the largest Beijing dataset from 2018, each user placed 50.3 orders on average. Based on these detailed order records, we calculate the fast food preference ψ of each user, defined as the ratio of fast food orders to the total number of orders. Figure 2(b) illustrates the distribution of ψ on the sampled population. On average, 27.98% of O2O food delivery orders are placed at fast food restaurants.

Demographic Data To establish a connection between healthy food choices and user attributes, we further obtain demographic data from the platform, which includes gender, income level, and age, as inferred by the platform's machine learning algorithms from user-provided profiles and user behaviors. We filter out users whose demographic profiles have a confidence level below 95%. To ensure user privacy, income levels are categorized into three groups: "high-income", "medium-income" and "low-income". Similarly, age groups are segmented into "below 25", "25 to 40", and "over 40". The demographic distributions of the sampled population are depicted in Figure 3.

It is important to note that all the above datasets are processed under stringent user privacy protection protocols. Specifically, users provide consent for the access and use of their order behaviors and demographic information via a confidentiality agreement with the food delivery platform. The datasets are anonymized by the platform, ensuring that no actual user IDs are accessible during processing. To safeguard against online privacy breaches, the datasets are stored offline, and access is strictly limited to authorized researchers only. These precautions ensure that our analysis upholds high standards of user privacy protection.

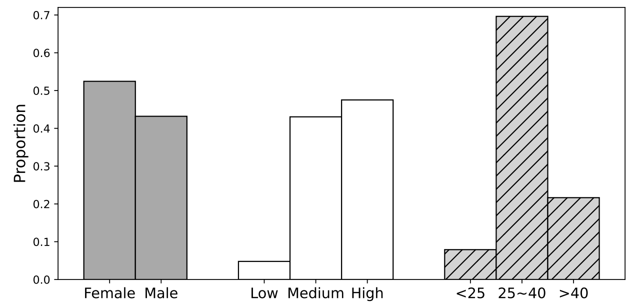

Figure 3: Demographic distributions of sampled users.

Methods and Results

Macro-level Health Discrepancy of O2O Food Delivery (RQ1)

Urban Scaling Laws of O2O Food Delivery We first demonstrate the macroscopic city-level health discrepancy of O2O food delivery. Urban services and economic activities often follow a scaling law, expressed as $Y_i = Y_0 N_i^{\alpha}$ (Bettencourt 2021; Xu et al. 2021; Ribeiro and Rybski 2023), where Y_i represents a measure of socioeconomic activity or resources, and N_i denotes the city i's population. An exponent $\alpha < 1$ indicates sublinear growth of Y relative to the city population, typically associated with urban infrastructure such as gas stations or road length, where the per-capita infrastructure decreases in larger cities (Um et al. 2009). In contrast, socioeconomic factors like GDP or crime rates often exhibit $\alpha > 1$, signifying superlinear growth, where per-capita values increase more rapidly in larger cities due to intensified social interactions (Bettencourt 2013; Succar and Porfiri 2024).

We collect city population from China City Statistical Yearbook[1] and analyze the scaling law of O2O food delivery. As an innovative form of urban services, O2O food delivery in Chinese cities also exhibits scaling behavior. The fitted lines in Figure 4(a) and (c) indicate that the scaling exponent α for the number of O2O food delivery restaurants and the number of O2O food delivery orders are 0.86±0.07 and 1.17±0.10, respectively. This corresponds to the typical sublinear and superlinear growth patterns of urban infrastructure and economic activities, with $\beta = \frac{5}{6}$ and $\frac{7}{6}$, reflecting higher infrastructure utilization efficiency in large cities (Bettencourt 2013). Similarly, these patterns are also observed in the 2024 dataset, as depicted in Figure 12.

Furthermore, the scaling exponents for fast food restaurants and orders in 2018 are significantly higher than those for all food categories ($P < 0.05$, two-sided t-test), as shown in Figure 4(b) and (d). Specifically, doubling the city population increases the proportion of fast food restaurants by 4.0% and the proportion of fast food orders by 5.4%. This

[1] https://www.stats.gov.cn/sj/ndsj/2019/indexch.htm

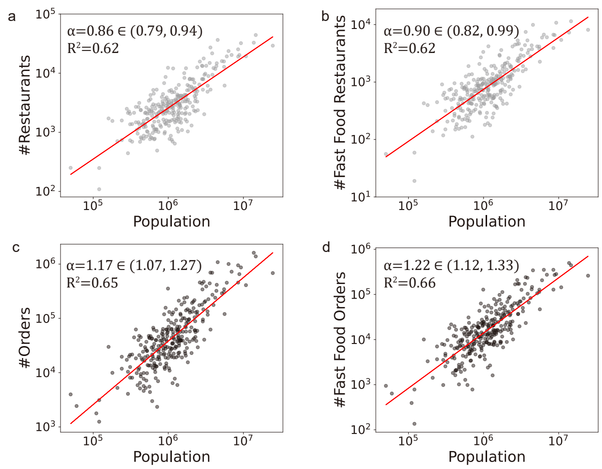

Figure 4: Scaling laws of O2O food delivery restaurants (a), fast food restaurants (b), O2O food delivery orders (c), and fast food orders (d) in Chinese cities in 2018. The axes are in logarithmic scales.

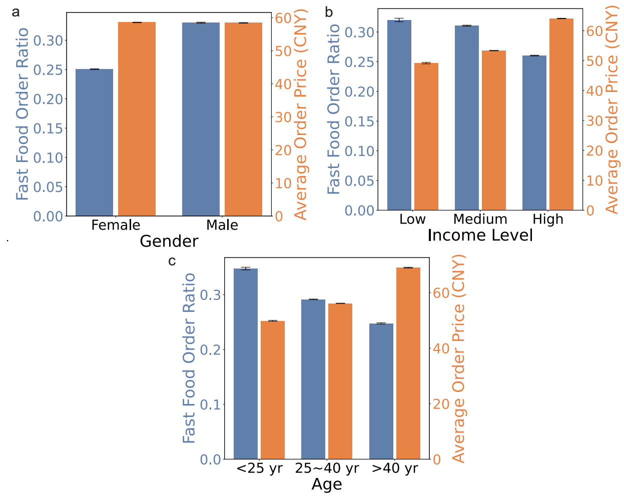

Figure 5: The average fast food order ratio and order price across different gender (a), income level (b), and age (c) groups in Beijing. Error bars represent 95% confidence intervals.

difference suggests a health discrepancy across cities, with larger cities demonstrating a greater reliance on fast food restaurants through O2O food delivery (Bettencourt et al. 2007). However, this trend is not observed in 2024 (Figure 12(b) and (d)), where the scaling coefficients for all food categories and fast food restaurants show no significant differences, indicating a shift toward healthier dining habits among metropolitan residents post-pandemic.

Health Discrepancy in Online Food Choices The observed health discrepancies across cities of different sizes may be related to variations in the composition of urban populations. To test this assumption, we further investigate the relationships between user demographics and their behaviors on O2O food delivery platforms. We focus on three demographic attributes – gender, income level, and age – and compare the average proportion of fast food orders and the average order price for each group. The values and corresponding 95% confidence intervals are shown in Figure 5.

The proportion of fast food orders among male users (33.0%) is higher than that of female users (25.0%) in 2018, while the average price of food delivery orders is nearly identical for males (58.4 CNY) and females (58.6 CNY). This indicates that male users have a significant stronger preference for fast food delivery compared to female users ($P < 0.001$, two-sided t-test). In terms of income level, the average order price increases with higher income, while the proportion of fast food orders decreases. Users of highest income level only have 26.0% fast food orders, while the ratio of the lowest income level reaches 32.0%. This suggests that higher-income groups tend to opt for more expensive, healthy food delivery options, whereas lower-income groups prefer cheaper, less healthy food options ($P < 0.001$, two-sided t-test). Similarly, the average price of food delivery orders rises with age, while the proportion of fast food orders declines from 34.8% among users under 25 years to 24.8% for users over 40 years, indicating that younger people are more inclined to choose fast food, while older individuals tend to prefer higher-priced alternatives ($P < 0.001$, two-sided t-test).

This overall health discrepancy remains robust across three Chinese cities in 2024, as shown in Figure 13. This consistent trend highlights the heterogeneous healthy food choices of O2O food delivery platform users, which may be influenced by factors such as service pricing (Zhang et al. 2025b), the online food environment, user preferences, and attention to healthy eating.

Differences Between Offline and Online Food Environments (RQ2)

O2O food delivery services extend the service range of local restaurants, though their impact on real-world food swamps remains unclear. In this section, we apply statistical learning algorithms to investigate the spatial clustering of offline and online food environments and compare their unhealthiness.

We cluster regions (Geohash-6 grids) based on the accessibility of local (offline) and O2O food delivery (online) restaurants, with each region represented by a 104-dimensional vector reflecting the number of accessible restaurants across 104 categories. Local restaurants are defined as those located within 1 kilometer of the region. We employ the K-means clustering algorithm (Lloyd 1982) and use the elbow method (Thorndike 1953) to determine that the optimal number of clusters is 5. As shown in Figure 6(a) and (b), both offline and online restaurant accessibility exhibit distinct spatial clustering. We compare the number of accessible fast food restaurants across each cluster in Figure 6(c). The core areas of the city (clusters 1 and 2) have the highest availability of O2O food delivery, with cluster 1, representing two key business districts (Zhongguancun and Guomao), having the highest access.

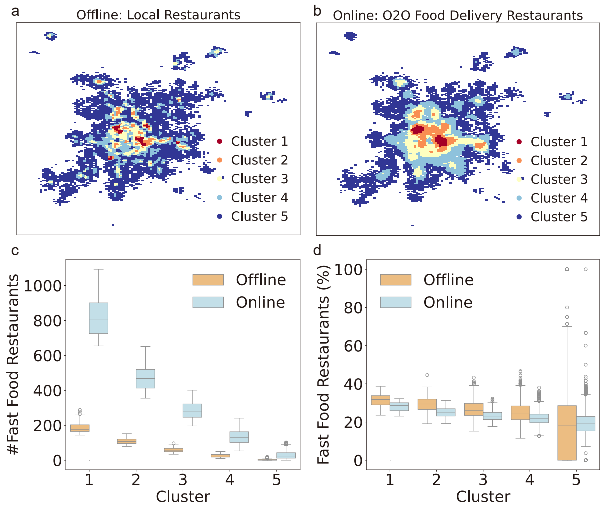

Figure 6: The comparison of offline and online food swamps. (a) Spatial clustering based on regions' local restaurants. (b) Spatial clustering based on regions' accessible O2O food delivery restaurants. (c) Differences in the number of accessible fast food restaurants across clusters. (d) Differences in the proportion of accessible fast food restaurant across clusters.

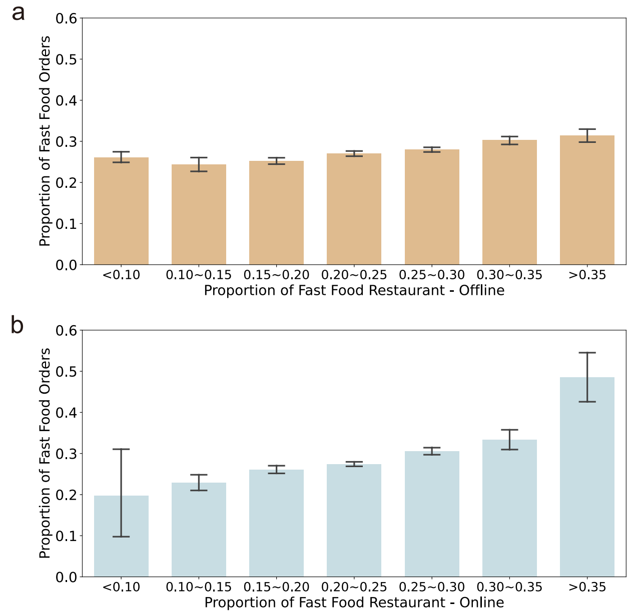

Figure 7: The average choices on fast food orders of regions within different levels of offline (a) and online (b) food environment ϕ, as represented by the proportion of accessible fast food restaurants. Error bars indicate 95% confidence intervals.

The number of accessible online restaurants is approximately three times greater than that of offline restaurants, highlighting the pivotal role of O2O food delivery services in expanding access to convenience food options. Figure 6(d) shows the proportion of fast food restaurants (ϕ) in each cluster for both offline and online food environments. In regions near the city center, the proportion of fast food restaurants is higher. Notably, the proportion of fast food in the online food environment is slightly lower than in the offline environment (with regional averages of 21.2% and 22.1%, respectively), though the online food environment still contains a substantial proportion of fast food. Moreover, by comparing the red and orange clusters in Figure 6(a) and (b), we observe that O2O food delivery has expanded the size of clusters with the highest fast food count and proportion. This indicates that O2O delivery services may further exacerbate real-world food swamps, potentially creating a "cyber food swamp".

By comparing the unhealthiness ϕ of offline and online food environments with fast food preferences in regional O2O food delivery orders, we find that the correlation is stronger for online environments ($r = 0.204$) compared to offline environments ($r = 0.092$). Figure 7 demonstrates that variations in online food environments are associated with more distinct differences in healthy food choices. In Figure 7(b), regions with lowest ϕ exhibit significant lower proportion of fast food orders compared with regions with $\phi > 0.25$ (P <0.05, two-sided t-test). These findings suggest notable differences between online and traditional offline food environments. The stronger relationship between the online food environment and healthy food choices underscores the need for further investigation into their causal connections.

Impact of Online Food Environment on Healthy Food Choice (RQ3)

Given the diversity of online food environments within urban contexts and the heterogeneous healthy food choices exhibited by users on O2O food delivery platforms, it is essential to understand the potential impact of these environments on food choices. Previous studies have demonstrated that increased exposure to fast food restaurants can contribute to higher obesity rates (Cooksey-Stowers, Schwartz, and Brownell 2017) and increased visitation (García Bulle Bueno et al. 2024). As O2O food delivery significantly expand the range of available restaurant options, they hold substantial potential to influence users' healthy food choices.

To accurately quantify the relationship between the environment and healthy food choices, it is essential to dissect the influence of users' personal preferences from the impact of the environment. For instance, individuals may choose to order food from a fast food restaurant either due to a personal preference for fast food or because the delivery environment is saturated with fast food options. Building on this notion, we adopt the analytic framework in García Bulle Bueno *et al.* (García Bulle Bueno et al. 2024). We first conduct an individual-level regression analysis on the determinants of O2O food delivery orders, followed by a quasi-natural experiment to quantify the causal impacts of changes

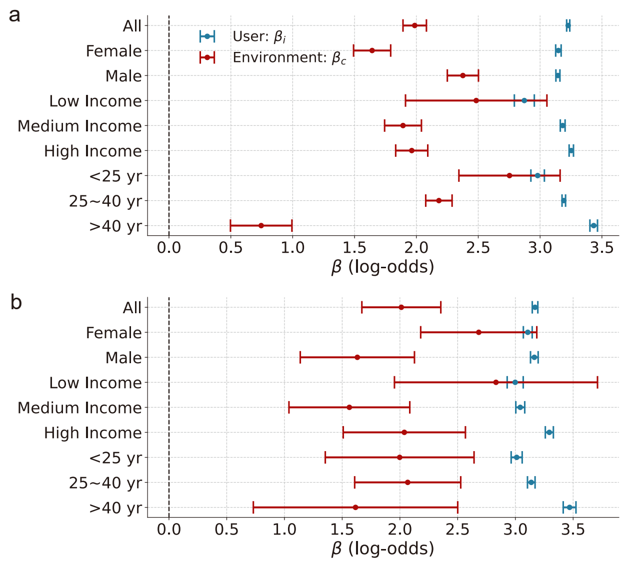

Figure 8: Effect of user's historical preference (β_i) and online food environment (β_c) on the probability of placing a fast food delivery order over a non-fast food delivery order for different gender, income, and age groups in 2018 (a) and 2024 (b). Error bars represent 95% confidence intervals for β's.

in online food environment on healthy food choices.

Regression Analysis For the online food order decision y_{it} by user i located in region c_{it} at time t, we characterize the online food environment using $\phi(c_{it})$ (the proportion of accessible fast food restaurants), and user i's fast food preference $\psi_i(t)$, as the proportion of fast food orders made by user i within six months prior to time t. We focus on 91,879 users who have made at least 20 orders, extracting 3.86 million orders to fit a logistic regression model to estimate the effect of online food environment $\phi(c_{it})$ on the decision to choose fast food over non-fast food:

$$\Pr(y_{it} = 1) = \text{logit}^{-1}(\beta_0 + \delta_t + \beta_i\psi_i(t) + \beta_c\phi(c_{it})), \quad (1)$$

where $y_{it} = 1$ represents ordering fast food, $\text{logit}^{-1}(x) = \frac{e^x}{1+e^x}$ is the logistic function, β_0 is the fixed intercept term, and δ_t is a fixed effect term accounting for monthly variation. β_i and β_c characterize the separate effect of user preference and online food environment, respectively, as shown in Figure 8 and Figure 14.

The regression model reveals that both online food environment and personal preference are significantly associated with fast food choice, with personal preference exhibiting a higher log-odd coefficient ($\beta_i = 3.227 \pm 0.012$ in 2018, $\beta_i = 3.170 \pm 0.024$ in 2024, $P < 0.001$, two-sided t-test) than the online food environment ($\beta_c = 1.987 \pm 0.095$ in 2018, $\beta_c = 2.012 \pm 0.342$ in 2024, $P < 0.001$, two-sided t-test). These results can be interpreted as follows: when a user has a 10% higher historical preference for fast food, the odds of making a fast food order increase by $e^{\beta_i \times 0.1} - 1$=38.1% for 2018 and 37.3% for 2024, and when the online food environment consists of 10% more fast food restaurants, the odds increase by $e^{\beta_c \times 0.1} - 1$=22.0% for 2018 and 22.3% for 2024. Similar patterns are observed in Chengdu and Xiamen. Although the influence of the online food environment is relatively minor, it still has a significant association with users' consumption behaviors, suggesting a potential negative impact of "cyber food swamps" on health outcomes.

We also observe heterogeneous effects of the online food environment on healthy food choices across different demographic groups. Figure 8 illustrates the fitted log-odds β's for orders made by specific demographic groups. Across all groups, user preference consistently has a stronger influence than the online food environment, although the magnitude of β_c varies between groups. Low-income individuals and users under the age of 25 are more influenced by the environment and less by personal preference compared to their counterparts. Notably, users over the age of 40 are the least influenced by the online food environment, with $\beta_c = 0.745 \pm 0.249$ in 2018, meaning that the odds of ordering fast food increase by only 7.7% when the online food environment contains 10% more fast food restaurants. This pattern aligns with the disparity trend shown in Figure 5, where groups more prone to making less healthy food delivery choices are also more affected by the online food environment. This suggests that these users may be more susceptible to online platform's recommender system when ordering food (Li et al. 2022; Sukiennik, Gao, and Li 2024), rather than using the platform to place an order after already deciding what to eat.

Causal Impacts of Online Food Environment on Healthy Food Choice Although the regression analysis confirms an association between the online food environment and consumers' healthy food choices, our understanding of the causal impact of the environment on food choices remains limited, especially when the influence is gradual and non-immediate as users adapt to a new location. To investigate this causal impact, we follow the semi-causal framework introduced in García Bulle Bueno *et al.* (García Bulle Bueno et al. 2024) and design a quasi-natural experiment to examine the relationship between order context and decision-making. The approach involves identifying users who have experienced a significant shift in their food delivery context, represented by the Geohash-5 grid in which they are located, and quantifying how the change in the online food environment ϕ between two contexts affects their fast food order preference ψ. This setting simulates a natural experiment scenario where users randomly shift their context, allowing for the derivation of causal impacts.

To identify users who changed their preferred food delivery locations during the observation period, we extract the Geohash-5 grids (approximately 5×5 kilometers) for each order and select users who placed more than five orders across two different grids, with each grid representing more than 30% of their total orders. We then construct a binary time series for these users, capturing their order activity in the two grids, as shown in Figure 9. We apply a mean change detection method (Truong, Oudre, and Vayatis

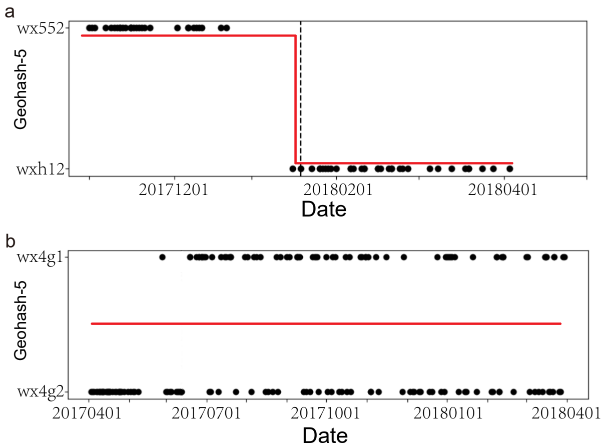

Figure 9: Examples of detecting the change of food delivery order context, defined as the Geohash-5 grid where user make food delivery orders. (a) Significant context change detected in January 2018. (b) No significant context change detected.

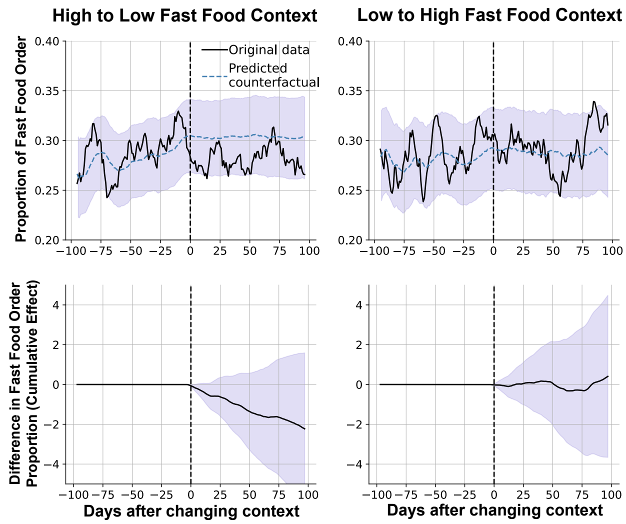

Figure 10: Evolution of the proportion of fast food orders (top) and cumulative differences in proportion of fast food order (bottom) for user groups transitioning from a high fast food ratio online food environment to a low ratio context (left), and from low to high context (right) in Beijing, 2018. Shaded areas represent 50% confidence intervals of predicted counterfactual and cumulative effects.

2020) to identify if and when substantial changes occurred in the time series, enforcing a minimum spatial shift of 2 kilometers and a minimum interval of 21 days between change points to avoid mis-detecting fluctuations. Figure 9(a) illustrates a successful detection of a context change, where the user shifted from grid "wx552" to "wxh12" in January 2018. In contrast, the user in Figure 9(b) uniformly used O2O food delivery services across two grids, with no significant change detected. Using this method, we identify 1,892 users who experienced a substantial change in their order contexts in 2018. On average, the spatial shifts in their order context are 11.66 kilometers, indicating that their online food delivery environment has completely changed, as supported by Figure 1.

Based on whether the user's order context before and after the change is classified as a high fast food context (ϕ >0.2) or a low fast food context (ϕ <0.2), we divide users into four groups. Among them, 957 moved from a low to low fast food context, 481 from a high to high context, 208 from a low to high context, and the remaining 246 from a high to low context. To estimate the causal impact of changes in the online food environment on users' healthy food choices, we employed a method based on Bayesian Structural Time Series (BSTS) (Brodersen et al. 2015). BSTS decomposes time series into multiple structural components to predict temporal behaviors. To assess the effect of shifting from a low to high fast food context, we take users moved from a low to low context as the control group, and those who moved from a low to high context as the experimental group. We compute the time series $\{\psi_t| -100 < t < 100\}$ for each group, where ψ_t represents the proportion of fast food orders after t days of changing context. BSTS then predicts the counterfactual outcome for the experimental group based on $\{\psi_t^{\text{Experiment}}|t < 0\}$ by applying the temporal patterns of $\{\psi_t^{\text{Control}}\}$, as shown by the dashed blue lines in Figure 10. The counterfactual outcomes are then compared with the actual observations of $\{\psi_t^{\text{Experiment}}|t > 0\}$ to derive the causal impact. A similar procedure is applied to estimate the effect of shifting from a high to low context, with users who moved from a high to high context as the control group.

As shown in Figure 10, for users moving from a low to high fast food context, their preference for using O2O food delivery to order from fast food restaurants increases by 1.6%, with a cumulative proportion of fast food order of 0.46 times higher than that of users who remained in a low fast food context. In contrast, users who moved from a high to low fast food context experience a 7.6% decline in their proportion of fast food orders, with a cumulative effect 2.33 times lower than users who stayed in a high fast food context after 100 days. Similar trends were observed in 502 users who shifted their online food environment in 2024, as depicted in Figure 11. Specifically, moving from a low to high fast food context leads to a 0.2% increase in the proportion of fast food orders, while shifting from a high to low fast food context results in a 9.6% decrease in the proportion of fast food orders. These results confirm that the online food environment affects users' healthy food choices, and this influence is not merely a short-term response to visiting a new location but has a lasting impact. Moreover, the negative health impact of moving to high fast food context is less substantial than the positive health impact of moving to a low fast food context. This finding suggests that O2O food delivery platforms could mitigate the negative health effects of "cyber food swamps" by recommending much healthier

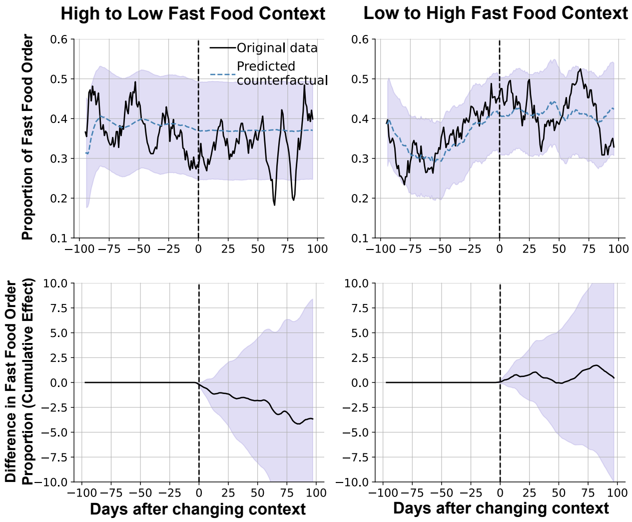

Figure 11: Evolution of the proportion of fast food orders (top) and cumulative differences in proportion of fast food order (bottom) for user groups transitioning from a high fast food ratio online food environment to a low ratio context (left), and from low to high context (right) in Beijing, 2024. Shaded areas represent 50% confidence intervals of predicted counterfactual and cumulative effects.

restaurants to users, even in environments with a high concentration of fast food options.

Discussion

Our findings substantiate the transformative role of O2O food delivery industry in reshaping urban residents' healthy food choices, providing valuable insights for various stakeholders. For O2O food delivery platforms, enhancing recommendation algorithms to guide users towards healthier options is critical. This can be accomplished through personalized search features that prioritize healthier restaurants or meals (Vanderlee and Sacks 2023), along with clear nutritional labeling, such as calorie counts or warnings about high sugar or fat content (Jiang et al. 2019; Greenthal et al. 2023), particularly targeting demographic groups such as males, low-income individuals, and younger users with a high preference for fast food (Orfanos et al. 2009; Adams and White 2015). Restaurants stakeholders can broaden their menus to include a wider variety of healthier choices, demonstrating their commitment to both food quality and public health (Vanderlee and Sacks 2023). Policy makers must address the spatial clustering of cyber food swamps with targeted regulations. For example, they could provide financial incentives and subsidies to encourage O2O food delivery restaurants that offer healthier alternatives (Shill et al. 2012). In addition, regulations should cap the concentration of fast food options in areas characterized by these swamps. Public health campaigns in schools and communities can significantly elevate awareness around healthy eating, a factor strongly associated with healthier dietary choices and improved health outcomes (Iqbal et al. 2021). Moreover, stricter labeling regulations, modeled after initiatives like the Affordable Care Act in the United States (Stein 2010), are essential to ensuring transparent nutritional information for O2O food delivery items.

Our research also highlights the influence of online content in offline real-world social behaviors, aligning with previous studies on the web and social media (Grinberg et al. 2021; Hu, Farnham, and Talamadupula 2021; De Choudhury, Sharma, and Kiciman 2016; Carpinelli, Islind, and Óskarsdóttir 2024). Meanwhile, O2O food delivery serve as both a substitute for and an expansion of traditional offline dining environments, creating potential trade-offs and interactions that reshape conventional food accessibility (Li and Wang 2022). It remains unclear whether O2O food delivery intensifies or mitigates food swamps. In future research, we aim to compare the offline and online dining behaviors of the same group of users to better understand the unique role of online platforms in shaping dietary habits, as distinct from traditional in-person dining experiences.

Our work has several limitations. First, we use whether an order is placed at a fast food restaurant as a proxy for healthy food choices. While fast food is generally associated with lower dietary quality, the nutritional content of items sold within the same restaurant can vary. Future research should assess the nutritional quality of foods purchased through O2O food delivery at the item level, such as sugar and fat intake, using more granular data. Additionally, the uncertainty in user demographic profiles could impact the validity of the observed differences across demographic groups. However, the platform reports that the inferred demographic profiles have an accuracy of over 90%, and we filter out users with low confidence levels to ensure the reliability of our findings. Furthermore, other observations that do not involve comparisons across demographic groups remain robust and unaffected by this potential uncertainty.

Acknowledgements

This work is supported by the National Key Research and Development Program of China under grant No. 2024YFC3307600. This work is supported by the National Natural Science Foundation of China under grant No. 23IAA02114 and 62472241. This work is supported in part by Tsinghua University-Toyota Research Center.

References

Abbar, S.; Mejova, Y.; and Weber, I. 2015. You tweet what you eat: Studying food consumption through twitter. In *Proceedings of the 33rd annual acm conference on human factors in computing systems*, 3197–3206.

Adams, J.; and White, M. 2015. Prevalence and sociodemographic correlates of time spent cooking by adults in the 2005 UK Time Use Survey. Cross-sectional analysis. *Appetite*, 92: 185–191.

Allcott, H.; Diamond, R.; Dubé, J.-P.; Handbury, J.; Rahkovsky, I.; and Schnell, M. 2019. Food deserts and the causes of nutritional inequality. *The Quarterly Journal of Economics*, 134(4): 1793–1844.

Althoff, T.; Nilforoshan, H.; Hua, J.; and Leskovec, J. 2022. Large-scale diet tracking data reveal disparate associations between food environment and diet. *Nature communications*, 13(1): 267.

Althoff, T.; Sosič, R.; Hicks, J. L.; King, A. C.; Delp, S. L.; and Leskovec, J. 2017. Large-scale physical activity data reveal worldwide activity inequality. *Nature*, 547(7663): 336–339.

Bettencourt, L.; Lobo, J.; Helbing, D.; Kühnert, C.; and West, G. 2007. Growth, Innovation, Scaling, and the Pace of Life in Cities. *Proceedings of the National Academy of Sciences of the United States of America*, 104: 7301–6.

Bettencourt, L. M. 2013. The origins of scaling in cities. *science*, 340(6139): 1438–1441.

Bettencourt, L. M. A. 2021. *Introduction to Urban Science: Evidence and Theory of Cities as Complex Systems*. The MIT Press. ISBN 9780262366441.

Brar, K.; and Minaker, L. M. 2021. Geographic reach and nutritional quality of foods available from mobile online food delivery service applications: novel opportunities for retail food environment surveillance. *BMC Public Health*, 21: 1–11.

Brodersen, K. H.; Gallusser, F.; Koehler, J.; Remy, N.; and Scott, S. L. 2015. Inferring causal impact using Bayesian structural time-series models. *The Annals of Applied Statistics*, 9(1): 247 – 274.

Carpinelli, C.; Islind, A. S.; and Óskarsdóttir, M. 2024. The Quiet Power of Social Media: Impact on Fish-Oil Purchases in Iceland during COVID-19. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 18, 203–213.

Chelmis, C.; and Gergin, B. 2023. Recipe Networks and the Principles of Healthy Food on the Web. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 17, 95–102.

Chen, L.; Xu, F.; Han, Z.; Tang, K.; Hui, P.; Evans, J.; and Li, Y. 2022. Strategic COVID-19 vaccine distribution can simultaneously elevate social utility and equity. *Nature Human Behaviour*, 6(11): 1503–1514.

Chen, L.; Xu, F.; Hao, Q.; Hui, P.; and Li, Y. 2023. Getting Back on Track: Understanding COVID-19 Impact on Urban Mobility and Segregation with Location Service Data. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 17, 126–136.

CNNIC. 2023. The 53rd statistical report on China's Internet development. Technical report, China Internet Network Information Center.

Cooksey-Stowers, K.; Schwartz, M. B.; and Brownell, K. D. 2017. Food swamps predict obesity rates better than food deserts in the United States. *International journal of environmental research and public health*, 14(11): 1366.

Culotta, A. 2014. Estimating county health statistics with twitter. In *Proceedings of the SIGCHI conference on human factors in computing systems*, 1335–1344.

Dai, X.; Wu, L.; and Hu, W. 2022. Nutritional quality and consumer health perception of online delivery food in the context of China. *BMC Public Health*, 22(1): 2132.

De Choudhury, M.; Sharma, S.; and Kiciman, E. 2016. Characterizing dietary choices, nutrition, and language in food deserts via social media. In *Proceedings of the 19th acm conference on computer-supported cooperative work & social computing*, 1157–1170.

Dillahunt, T. R.; Simioni, S.; and Xu, X. 2019. Online grocery delivery services: An opportunity to address food disparities in transportation-scarce areas. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–15.

Dsouza, D.; and Sharma, D. 2021. Online food delivery portals during COVID-19 times: an analysis of changing consumer behavior and expectations. *International Journal of Innovation Science*, 13(2): 218–232.

Eu, E. Z. R.; and Sameeha, M. J. 2021. Consumers' perceptions of healthy food availability in online food delivery applications (OFD apps) and its association with food choices among public university students in Malaysia. *Frontiers in nutrition*, 8: 674427.

Fan, B.; Chen, L.; Li, S.; Yuan, J.; Xu, F.; Hui, P.; and Li, Y. 2025. Invisible Walls in Cities: Leveraging Large Language Models to Predict Urban Segregation Experience with Social Media Content. *arXiv preprint arXiv:2503.04773*.

Feng, J.; Glass, T. A.; Curriero, F. C.; Stewart, W. F.; and Schwartz, B. S. 2010. The built environment and obesity: a systematic review of the epidemiologic evidence. *Health & place*, 16(2): 175–190.

García Bulle Bueno, B.; Horn, A. L.; Bell, B. M.; Bahrami, M.; Bozkaya, B.; Pentland, A.; De la Haye, K.; and Moro, E. 2024. Effect of mobile food environments on fast food visits. *Nature Communications*, 15(1): 2291.

Giacomini, G.; Scacchi, A.; Ragusa, P.; Prinzivalli, A.; Elhadidy, H. S. M. A.; and Gianino, M. M. 2024. Which variables and determinants influence online food delivery consumption among workers and students? Results from the DELIvery Choice In OUr Society (DELICIOUS) cross-sectional study. *Frontiers in Public Health*, 11: 1326628.

Greenthal, E.; Sorscher, S.; Pomeranz, J. L.; and Cash, S. B. 2023. Availability of calorie information on online menus from chain restaurants in the USA: current prevalence and legal landscape. *Public Health Nutrition*, 26(12): 3239–3246.

Grinberg, N.; Naaman, M.; Shaw, B.; and Lotan, G. 2021. Extracting Diurnal Patterns of Real World Activity from Social Media. *Proceedings of the International AAAI Conference on Web and Social Media*, 7(1): 205–214.

Hong, C.; Choi, H. H.; Choi, E.-K. C.; and Joung, H.-W. D. 2021. Factors affecting customer intention to use online food delivery services before and during the COVID-19 pandemic. *Journal of Hospitality and Tourism Management*, 48: 509–518.

Hu, T.; Jacobs, D.; Larson, N.; Cutler, G.; Laska, M.; and Neumark-Sztainer, D. 2016. Higher Diet Quality in Adolescence and Dietary Improvements Are Related to Less Weight Gain During the Transition From Adolescence to Adulthood. *The Journal of Pediatrics*, 178.

Hu, Y.; Farnham, S.; and Talamadupula, K. 2021. Predicting User Engagement on Twitter with Real-World Events. *Proceedings of the International AAAI Conference on Web and Social Media*, 9(1): 168–177.

Iqbal, J.; Yu, D.; Zubair, M.; Rasheed, M. I.; Khizar, H. M. U.; and Imran, M. 2021. Health consciousness, food safety concern, and consumer purchase intentions toward organic food: The role of consumer involvement and ecological motives. *Sage Open*, 11(2): 21582440211015727.

Jeffery, R. W.; Baxter, J.; McGuire, M.; and Linde, J. 2006. Are fast food restaurants an environmental risk factor for obesity? *International Journal of Behavioral Nutrition and Physical Activity*, 3: 1–6.

Jesse, M.; Jannach, D.; and Gula, B. 2021. Digital nudging for online food choices. *Frontiers in psychology*, 12: 729589.

Jiang, H.; Wang, W.; Liu, M.; Nie, L.; Duan, L.-Y.; and Xu, C. 2019. Market2dish: A health-aware food recommendation system. In *Proceedings of the 27th ACM International Conference on Multimedia*, 2188–2190.

Kerr, J.; Frank, L.; Sallis, J.; Saelens, B.; Glanz, K.; and Chapman, J. 2012. Predictors of trips to food destinations. *The international journal of behavioral nutrition and physical activity*, 9: 58.

Li, C.; Mirosa, M.; and Bremer, P. 2020. Review of online food delivery platforms and their impacts on sustainability. *Sustainability*, 12(14): 5528.

Li, F.; Harmer, P. A.; Cardinal, B. J.; Bosworth, M.; Acock, A.; Johnson-Shelton, D.; and Moore, J. M. 2008. Built environment, adiposity, and physical activity in adults aged 50–75. *American journal of preventive medicine*, 35(1): 38–46.

Li, L.; and Wang, D. 2022. Do neighborhood food environments matter for eating through online-to-offline food delivery services? *Applied Geography*, 138: 102620.

Li, N.; Gao, C.; Piao, J.; Huang, X.; Yue, A.; Zhou, L.; Liao, Q.; and Li, Y. 2022. An exploratory study of information cocoon on short-form video platform. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, 4178–4182.

Lin, Z.; Lyu, S.; Cao, H.; Xu, F.; Wei, Y.; Samet, H.; and Li, Y. 2020. Healthwalks: Sensing fine-grained individual health condition via mobility data. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 4(4): 1–26.

Lloyd, S. 1982. Least squares quantization in PCM. *IEEE transactions on information theory*, 28(2): 129–137.

Meemken, E.-M.; Bellemare, M. F.; Reardon, T.; and Vargas, C. M. 2022. Research and policy for the food-delivery revolution. *Science*, 377(6608): 810–813.

Mejova, Y.; and Manikonda, L. 2023. Comfort Foods and Community Connectedness: Investigating Diet Change during COVID-19 Using YouTube Videos on Twitter. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 17, 602–613.

Nilforoshan, H.; Looi, W.; Pierson, E.; Villanueva, B.; Fishman, N.; Chen, Y.; Sholar, J.; Redbird, B.; Grusky, D.; and Leskovec, J. 2023. Human mobility networks reveal increased segregation in large cities. *Nature*, 624(7992): 586–592.

Orfanos, P.; Naska, A.; Trichopoulou, A.; Grioni, S.; Boer, J.; Van Bakel, M.; Ericson, U.; Rohrmann, S.; Boeing, H.; Rodríguez, L.; et al. 2009. Eating out of home: energy, macro-and micronutrient intakes in 10 European countries. The European Prospective Investigation into Cancer and Nutrition. *European Journal of Clinical Nutrition*, 63(4): S239–S262.

Osaili, T. M.; Al-Nabulsi, A. A.; Taybeh, A.; Cheikh Ismail, L.; and Saleh, S. T. 2023. Healthy food and determinants of food choice on online food delivery applications. *Plos one*, 18(10): e0293004.

Ribeiro, F. L.; and Rybski, D. 2023. Mathematical models to explain the origin of urban scaling laws. *Physics Reports*, 1012: 1–39.

Shill, J.; Mavoa, H.; Allender, S.; Lawrence, M.; Sacks, G.; Peeters, A.; Crammond, B.; and Swinburn, B. 2012. Government regulation to promote healthy food environments–a view from inside state governments. *Obesity reviews*, 13(2): 162–173.

Shroff, A.; Shah, B. J.; and Gajjar, H. 2022. Online food delivery research: A systematic literature review. *International Journal of Contemporary Hospitality Management*, 34(8): 2852–2883.

Simmons, D.; McKenzie, A.; Eaton, S.; Cox, N.; Khan, M. A.; Shaw, J.; and Zimmet, P. 2005. Choice and availability of takeaway and restaurant food is not related to the prevalence of adult obesity in rural communities in Australia. *International journal of obesity*, 29(6): 703–710.

Stein, K. 2010. A national approach to restaurant menu labeling: the Patient Protection and Affordable Health Care Act, Section 4205. *Journal of the American Dietetic Association*, 110(9): 1280–1289.

Stephens, J.; Miller, H.; and Militello, L. 2020. Food delivery apps and the negative health impacts for Americans. *Frontiers in nutrition*, 7: 14.

Stowers, K.; Schwartz, M.; and Brownell, K. 2017. Food Swamps Predict Obesity Rates Better Than Food Deserts in the United States. *International Journal of Environmental Research and Public Health*, 14: 1366.

Succar, R.; and Porfiri, M. 2024. Urban scaling of firearm violence, ownership and accessibility in the United States. *Nature Cities*, 1(3): 216–224.

Sukiennik, N.; Gao, C.; and Li, N. 2024. Uncovering the Deep Filter Bubble: Narrow Exposure in Short-Video Recommendation. In *Proceedings of the ACM on Web Conference 2024*, 4727–4735.

Thorndike, R. L. 1953. Who belongs in the family? *Psychometrika*, 18(4): 267–276.

Truong, C.; Oudre, L.; and Vayatis, N. 2020. Selective review of offline change point detection methods. *Signal Processing*, 167: 107299.

Um, J.; Son, S.-W.; Lee, S.-I.; Jeong, H.; and Kim, B. J. 2009. Scaling laws between population and facility densities. *Proceedings of the National Academy of Sciences*, 106(34): 14236–14240.

Vanderlee, L.; and Sacks, G. 2023. Recommended nutrition-related practices for online food delivery companies. *Public Health Nutrition*, 26(12): 3343–3348.

Wang, M. C.; Cubbin, C.; Ahn, D.; and Winkleby, M. A. 2008. Changes in neighbourhood food store environment, food behaviour and body mass index, 1981–1990. *Public health nutrition*, 11(9): 963–970.

Xu, F.; Li, Y.; Jin, D.; Lu, J.; and Song, C. 2021. Emergence of urban growth patterns from human mobility behavior. *Nature Computational Science*, 1(12): 791–800.

Xu, F.; Wang, Q.; Moro, E.; Chen, L.; Salazar Miranda, A.; González, M. C.; Tizzoni, M.; Song, C.; Ratti, C.; Bettencourt, L.; et al. 2025. Using human mobility data to quantify experienced urban inequalities. *Nature Human Behaviour*, 1–11.

Yeo, V. C. S.; Goh, S.-K.; and Rezaei, S. 2017. Consumer experiences, attitude and behavioral intention toward online food delivery (OFD) services. *Journal of Retailing and Consumer services*, 35: 150–162.

Zhang, Y.; Lin, Y.; Zheng, G.; Liu, Y.; Sukiennik, N.; Xu, F.; Xu, Y.; Lu, F.; Wang, Q.; Lai, Y.; Tian, L.; Li, N.; Fang, D.; Wang, F.; Zhou, T.; Li, Y.; Zheng, Y.; Wu, Z.; and Guo, H. 2025a. MetaCity: Data-driven sustainable development of complex cities. *The Innovation*, 6(2): 100775.

Zhang, Y.; Wang, D.; Liu, Y.; Du, K.; Lu, P.; He, P.; and Li, Y. 2025b. Urban food delivery services as extreme heat adaptation. *Nature Cities*, 1–10.

Zhang, Y.; Xu, F.; Chen, L.; Yuan, Y.; Evans, J.; Bettencourt, L.; and Li, Y. 2024. Counterfactual mobility network embedding reveals prevalent accessibility gaps in US cities. *Humanities and Social Sciences Communications*, 11(1): 1–12.

Zhang, Y.; Xu, F.; Li, T.; Kostakos, V.; Hui, P.; and Li, Y. 2021a. Passive health monitoring using large scale mobility data. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 5(1): 1–23.

Zhang, Y.; Xu, F.; Xia, T.; and Li, Y. 2021b. Quantifying the causal effect of individual mobility on health status in urban space. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 5(4): 1–30.

Zhao, X.; Lin, W.; Cen, S.; Zhu, H.; Duan, M.; Li, W.; and Zhu, S. 2021. The online-to-offline (O2O) food delivery industry and its recent development in China. *European Journal of Clinical Nutrition*, 75.

Paper Checklist

1. For most authors...
   (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes
   (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? Yes
   (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes
   (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? NA
   (e) Did you describe the limitations of your work? Yes
   (f) Did you discuss any potential negative societal impacts of your work? NA
   (g) Did you discuss any potential misuse of your work? NA
   (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? Yes
   (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? Yes
2. Additionally, if your study involves hypotheses testing...
   (a) Did you clearly state the assumptions underlying all theoretical results? NA
   (b) Have you provided justifications for all theoretical results? NA
   (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? NA
   (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? NA
   (e) Did you address potential biases or limitations in your theoretical framework? NA
   (f) Have you related your theoretical results to the existing literature in social science? NA
   (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? NA
3. Additionally, if you are including theoretical proofs...
   (a) Did you state the full set of assumptions of all theoretical results? NA
   (b) Did you include complete proofs of all theoretical results? NA
4. Additionally, if you ran machine learning experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? NA
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? NA
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? NA
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? NA

(e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? NA

(f) Do you discuss what is "the cost" of misclassification and fault (in)tolerance? NA

5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...

(a) If your work uses existing assets, did you cite the creators? NA

(b) Did you mention the license of the assets? NA

(c) Did you include any new assets in the supplemental material or as a URL? NA

(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? NA

(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? NA

(f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR? NA

(g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset? NA

6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity**...

(a) Did you include the full text of instructions given to participants and screenshots? NA

(b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? NA

(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? NA

(d) Did you discuss how data is stored, shared, and deidentified? NA

Ethical Statement

All datasets collected from the O2O food delivery platform were processed under strict privacy protection protocols. User IDs were anonymized, and demographic attributes were injected with noise and coarsely categorized into no more than three levels for age and income. All geographic coordinates, including the locations of the O2O food delivery restaurants and delivery destinations, were recorded at the Geohash-6 level (approximately 1.2×0.9 kilometers) to prevent the disclosure of individual locations. All analyses were conducted on offline storage with strict data access regulations. These precautions ensure that our analysis maintains high standards of user privacy protection. In accordance with data confidentiality agreements, we are unable to share the raw data used in this study.

Appendix

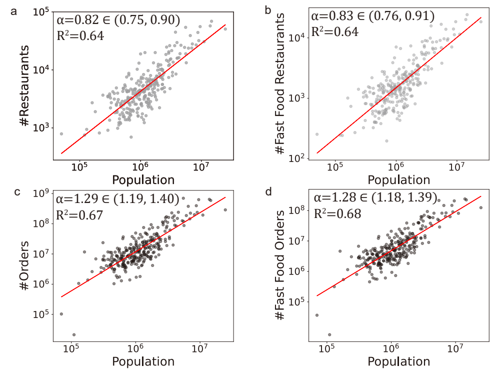

Figure 12: Scaling laws of O2O food delivery restaurants (a), fast food restaurants (b), O2O food delivery orders (c), and fast food orders (d) in Chinese cities in 2024.

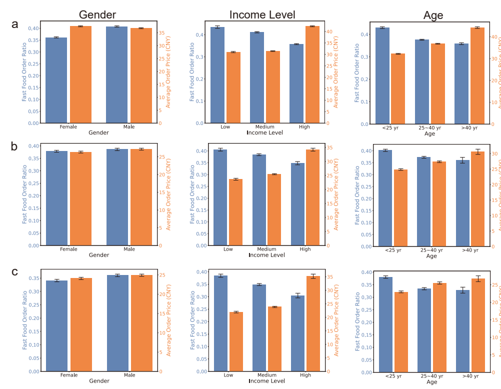

Figure 13: The average fast food order ratio and order price across different gender, income level, and age groups in Beijing (a), Chengdu (b), and Xiamen (c) in 2024. Error bars represent 95% confidence intervals.

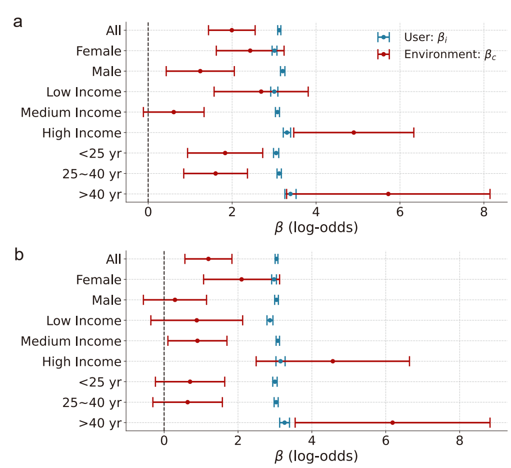

Figure 14: Effect of user's historical preference (β_i) and online food environment (β_c) on the probability of placing a fast food delivery order over a non-fast food delivery order for different gender, income, and age groups in Chengdu (a) and Xiamen (b). Error bars represent 95% confidence intervals for β's.