Nutritional Quality of Restaurant Access through Online Food Delivery Services and Food-Related Behaviors in Hong Kong

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Abstract

The increasing popularity of online food delivery services (OFDS) has redefined the way people access food. Studies on OFDS healthiness have generally been limited to examining broad food environments by classifying types of food outlets (e.g. markets and fast food restaurants) as healthy or unhealthy, and evaluating the healthiness of popular restaurants on restaurant-specific online food delivery services (ROFDS) without considering spatial measures of access. This study aimed to synthesize these approaches by examining the relationship between (1) demographic factors (total population, working population proportion, median age, and median income) and the average accessible restaurant's nutrition risk index AAR NRI, and (2) frequency of ROFDS use and AAR NRI. We found that lower population was a predictor for higher AAR NRI, indicating a less healthy online restaurant environment, while no other demographic factors were meaningful predictors. Additionally, frequent ROFDS use was not correlated with higher AAR NRI, but was associated with frequent grocery shopping, proving that ROFDS may not detract from healthier home-cooking practices. Our findings about a general equity of restaurant distribution by nutritional risk suggests that implementing healthy restaurant initiatives targeting the only areas that were considered high risk, low-population areas, and further monitoring how ROFDS algorithms may disconnect having access to healthy restaurants from making healthy choices could be useful approaches to improving Hong Kong's public health in the face of obesity.

Introduction

Online food delivery services (OFDS) partner with food outlets to deliver products to customers through websites and mobile applications; this includes delivering groceries and dishes from restaurants (Ray et al., 2019). Given the association between individual food choices and food accessibility found in previous studies (Lytle and Sokol, 2017; Althoff et al., 2022), increasingly popular services like OFDS (Keeble et al., 2021; Zhang et al., 2023) that change the way people access food (Kong et al., 2024; Li and Wang, 2022) may also change people's food choices.

Studies investigating the healthiness of OFDS often take one of two different approaches to the topic: one focused on the general food environment, a combination of the food offered in a certain area, and another focused on restaurants offering delivery services. Papers in the former category generally create broad groups of healthy and unhealthy food sources: supermarkets as well as stores selling fruits, vegetables, and meats are generally considered healthy; fast food stores and dessert and beverage stores are generally considered unhealthy (Kong et al., 2025; Wang et al., 2022).

Both Kong et al. (2025) and Chen et al., 2025 explore the demographic patterns of healthy and unhealthy OFDS access in China through similar categorizations of different restaurant types as healthy and unhealthy. They report that offline spatial inequities that disadvantage those of low socioeconomic status (SES) persist despite the advent of OFDS (Kong et al, 2025), sometimes even worsening inequities (Chen et al., 2025). While both identified an overall increase in access to both healthy and unhealthy food outlets, Kong et al. (2025) highlights disproportionately higher exposure to unhealthy food outlets in areas with large working populations and populations of younger people in Nanjing.

However, this first approach does not fully capture the impact of OFDS on public health. By classifying only direct sources of produce and meat as healthy, these papers limit healthy eating to home cooking (Kong et al., 2025; Wang et al., 2022). Although home cooking is generally considered healthier than dine out and delivery (Saksena et al., 2018), the hard-cut labeling of all restaurants as unhealthy fails to acknowledge their potential healthiness. This may be problematic given that the recent shift towards emphasizing health and nutrition (An et al., 2025; Heidenstrøm and Hebrok, 2022) may inspire healthier menu changes or encourage the opening of healthier restaurants.

There are several papers about the offline distribution of restaurants that similarly explore demographic differences in access (Chrisinger et al., 2019; Huang et al., 2025; Wang and Li, 2022), but this practice is less common in papers about restaurant OFDS (ROFDS) (Chin et al., 2025; Gupta et al., 2025; Osaili et al., 2023; Partridge et al., 2020). Instead, they often evaluate the healthiness of popular restaurants on ROFDS platforms by aggregating the healthiness of individual dishes (Patridge et al., 2020) or survey users about their food choices through OFDS (Osaili et al., 2023).

These papers reveal concerning food patterns about ROFDS. Most papers find that although ROFDS do increase food access in general, most of these foods are unhealthy (Chin et al., 2025; Patridge et al., 2020). In fact, an Australian study on UberEats found that for areas with a high concentration of people aged 15–34 years-old, 73.5% of the most popular food outlets on the platform were of poor nutritional quality and 85.9% of popular menu items were unhealthy based on Australian Dietary Guidelines, too (Patridge et al., 2020). Such findings have caused these papers to commonly describe ROFDS as platforms that make accessing unhealthy foods incredibly easy and encourage their consumption in the process (Gupta et al., 2025; Osaili et al., 2023; Zhang et al., 2025). While such studies help provide a foundational understanding of the types of food offered on ROFDS, their comprehensiveness in determining the impact of ROFDS on public health is limited because they only consider a few demographic factors, like age (Patridge at al., 2020), if any at all.

Because ROFDS are changing the way people access food, it is important to fully explore the healthiness and distribution of restaurants people have access to via delivery. ROFDS are an important part of the food environment in Hong Kong, the focus area of this study. Hong Kong also suffers from high rates of obesity: 32.6% of people aged 15–84 are obese with an additional 22% who are overweight (CHPHK, 2023), Identifying potential health disparities in ROFDS could be an important step towards improving public health. This paper therefore aims to combine the spatial and distributive qualities of the first approach with the restaurant-specific health classifications of the second approach to understand Hong Kong's ROFDS environment. Specifically, it will aim to answer the following research questions:

1. What demographic factors are associated with access to healthy and unhealthy restaurants via ROFDS?
2. Is frequency of ROFDS use associated with area-level access to healthier restaurant options? As follow-up questions to this question, we will also examine the relationship between different food accessing behaviors, such as ROFDS use.

Methods

Dish Data Sources

We collected data on the dishes served at restaurants by scraping Dianping, the largest lifestyle and review site in China that's also largely used in Hong Kong (Huang et al., 2016), to build a dataset of 46,418 restaurants and 135,115 dishes as of October 2024. The relevant information collected from the dataset included the restaurant name, location, and a list of recommended dishes, which Dianping determined by the popularity of items as mentioned in users' reviews. Because most restaurants don't publish nutritional data, we scraped a crowd-sourced recipe site called Meishichina and collected 7,176 unique recipes from various cuisines to gauge the healthiness of the dishes from the Dianping dataset. Using the ingredients and their quantities described in the recipes, we were able to assign a nutritional risk index (NRI) value for all of the recipes using a formula adapted from Huang et al. (2025):

$$NRI = \frac{(1-NDS) + max(LIM - 1{,}0)}{2}$$

The continuous NRI ranges from 0 to 1, with higher values indicating higher nutritional risk. NDS captures beneficial nutrient density, while LIM captures limiting nutrients such as sodium and fat. Higher NRI therefore means that a dish has fewer beneficial nutrients and a heavier sodium or fat burden.

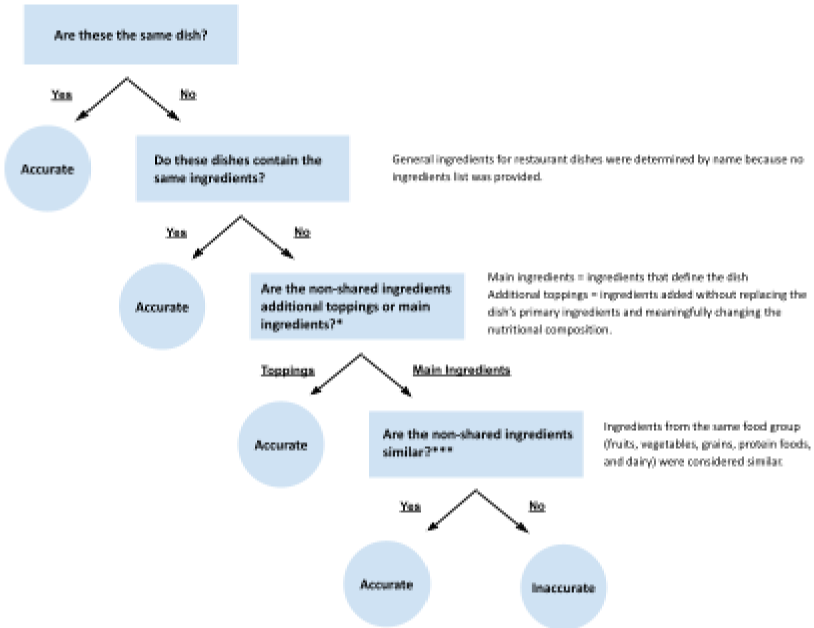
Matching Dishes with Nutritional Data

The Facebook AI Similarity Source (FAISS) is a vector search library that converts an input into a vector, searches for the most similar vector within an index, and provides a similarity score (“Pinecone”, n.d.). In our study, we used FAISS with the BAAI/bge-m3 model because of its ability to handle both simplified Chinese and English data (Chen et al., 2024) to match restaurant dishes with dishes from the Meishichina recipe list. Because matches tended to become less accurate as similarity scores decreased, we included only dishes with a similarity score of 80 or higher.

This threshold was manually determined by first splitting dishes into score intervals of 5 (i.e. 100–95, 94.99–90…) and reviewing a representative sample from each interval. Matches were coded as accurate or inaccurate using a decision tree based on dish identity, ingredients, importance of non-shared ingredients, and the similarity of non-shared ingredients. The decision tree used to evaluate accuracy is shown in Figure 1.

Figure 1

Decision Tree to Confirm BAAI Match Accuracy



*Common differences classified as "additional toppings" include different fillings (e.g. dumpling fillings), while differences classified as "main ingredients" include the addition of a serving of rice (e.g. scallion oil pork chop with scrambled egg rice versus scrambled egg and onion sauce braised pork chop).

Our manual coding found that BAAI's accuracy had fallen to around 50% at a similarity score interval of 79.99–75. To maximize the number of dishes included in the dataset while also maintaining a level of accuracy, we chose to use 80 as a similarity score threshold. Accuracy for the 84.99–80 block was 80% and the dataset included 21,194 dishes (15.7% of the original dataset). These dishes came from 11,076 restaurants (23.9% of the original dataset).

Other Data Sources

The other data for research question 1—total population, proportion of population that's part of the working population, median age, and median household income—were taken from the official 2021 Hong Kong census. The census collects data at a small-tertiary-planning-unit-group (STPUG) level, which splits Hong Kong into 211 groups.

The research team previously administered a broad survey among Hong Kong residents (n=930) from September to December in 2024. Participants were selected using quota sampling to match population distribution in Hong Kong. The food-acquisition behavior data in the survey was repurposed for this study. A sample item includes, “您平均每週線上點外賣 (如使用Keeta, Foodpanda, Deliveroo等) [On average, you order takeout online each week (such as using Keeta, Foodpanda, Deliveroo, etc.)]” (Table 1). Respondents chose between survey-specific labels that combined Hong Kong’s District Council districts model and New Towns to split Hong Kong into 28 areas when reporting their place of residence (Table 2).

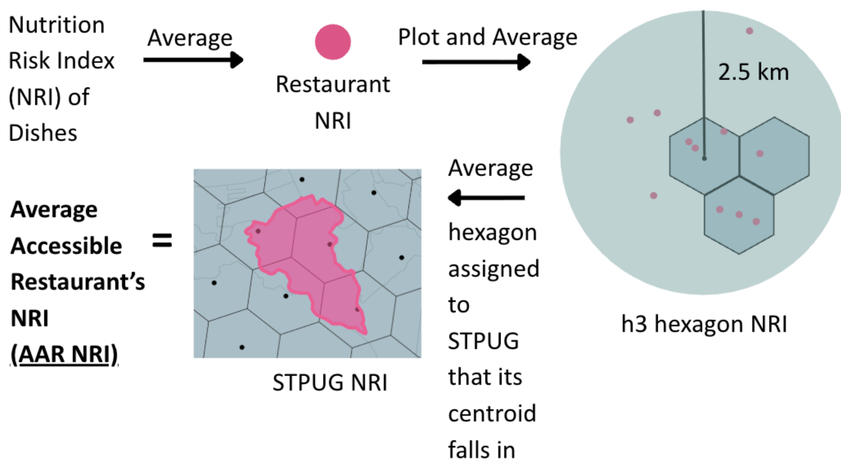
Determining ROFDS Access and Nutritional risk at the Small-Tertiary-Planning-Unit-Group Level

We divided Hong Kong into smaller hexagonal units using Uber’s h3 system (resolution = 8). Because large ROFDS in Hong Kong report their average delivery radius as between 2–3 kilometers (Foodpanda, 2025), we created a 2.5 kilometer buffer from the centroid of every hexagon and recorded how many restaurants fell within each buffer to represent how many restaurants people living in that hexagon had access to via ROFDS.

To determine the healthiness of each restaurant, we found the average NRI of their recommended dishes that fell within the threshold. The average NRI of the restaurants a hexagon had access to represented the hexagon’s NRI. Hexagons were assigned to STPUGs based on which STPUG their centroids fell into. Finally, STPUG healthiness was calculated by taking the average NRI of all the hexagons assigned to it, or the average accessible restaurant nutritional risk index (AAR NRI). AAR NRI was calculated at the STPUG level to allow for comparison to the demographic variables (Fig. 2). It was calculated identically at our survey’s 28-district level for comparison to frequency of ROFDS use.

Figure 2

Work Flow: Aggregating Dish NRI to STPUGs



Statistical Analysis

We used statistical analysis to explore the relationship between demographic features, ROFDS use, and access to healthy restaurants. Research question 1 about demographic factors associated with healthy and unhealthy online restaurant access was analyzed using a multiple linear regression, with all the demographic features as independent variables and STPUG-level AAR NRI as the dependent variable. A Pearson correlation test was used to address research question 2 about connections between ROFDS use and unhealthy restaurant access. A Pearson correlation test was also conducted for the follow up questions about other food-acquisition behavior. The number of responses per district ranged from 1 to 75 (Table 2). The low-response rate for some districts threatened to produce food-acquisition behavior data that was unrepresentative of the general area's population. Because there was a natural break in response count from 8 responses to 18 responses, we chose to run two Pearson correlation tests: one that included low-response areas, and one that excluded all districts with less than 10 responses (n = 6).

Results

Demographic Factors and AAR NRI

A multiple linear regression was used to evaluate how median age, total population, median household income, and the working population proportion may relate to AAR NRI. Assumptions for multiple linear regression were assessed prior to interpreting the model. Multicollinearly was satisfied, as the variance inflation factors (VIFs) ranged from 1.073 to 1.836 (Fig. 3). The residuals-versus-predicted plot also didn't appear to have visually significant departures from linearity. Although normality and homoscedasticity assumptions were challenged by minor residual deviation from the line towards the tails in the Q-Q plot and uneven spread in the residuals vs. predicted plot (Fig. 4), we interpreted these deviations to not substantially invalidate our findings because there were no influential cases and sample size was moderately large (N = 211). Independence, however, was not satisfied: the Durban-Watson value was calculated to be 1.353 ($p < 0.001$). Because not all assumptions were met, the following results should be interpreted with caution.

Figure 3

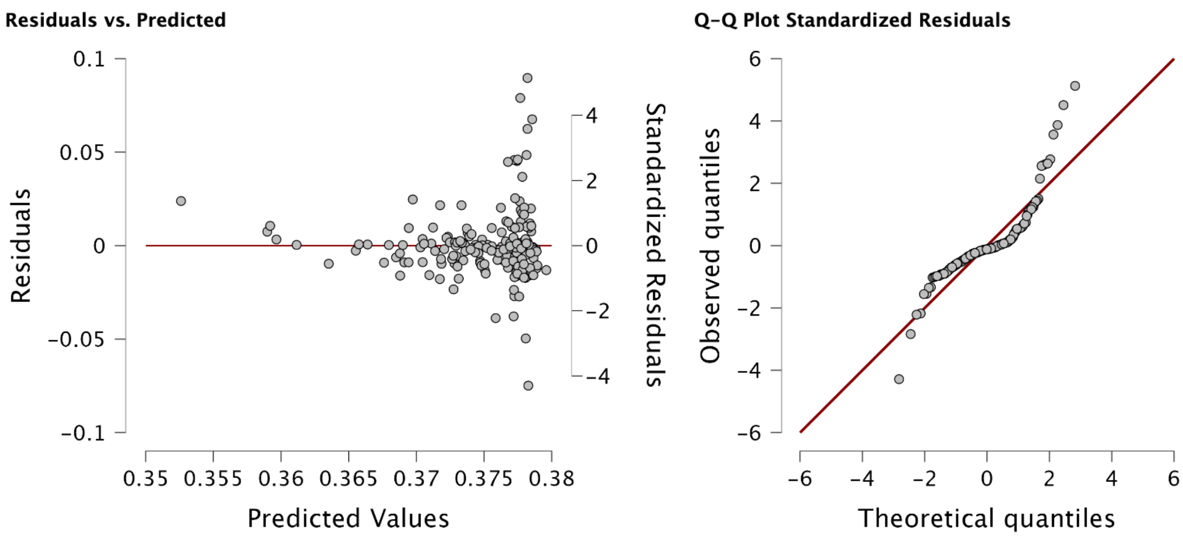
Regression Results: Demographic Factors x AAR NRI with VIFs

Coefficients ▼

Model		Unstandardized	Standard Error	Standardized	t	p	Collinearity Statistics	
							Tolerance	VIF
M_0	(Intercept)	0.375	0.001		304.887	< .001		
M_1	(Intercept)	0.385	0.017		23.217	< .001		
	total_pop	-4.672×10^{-7}	4.525×10^{-7}	−1.074	−1.032	.303	0.004	235.026
	median_age	-1.367×10^{-4}	3.510×10^{-4}	−0.028	−0.389	.697	0.871	1.148
	med_house_inc	-1.199×10^{-8}	5.262×10^{-8}	−0.017	−0.228	.820	0.833	1.201
	raw_working_pop	7.717×10^{-7}	9.245×10^{-7}	0.863	0.835	.405	0.004	231.959

Figure 4

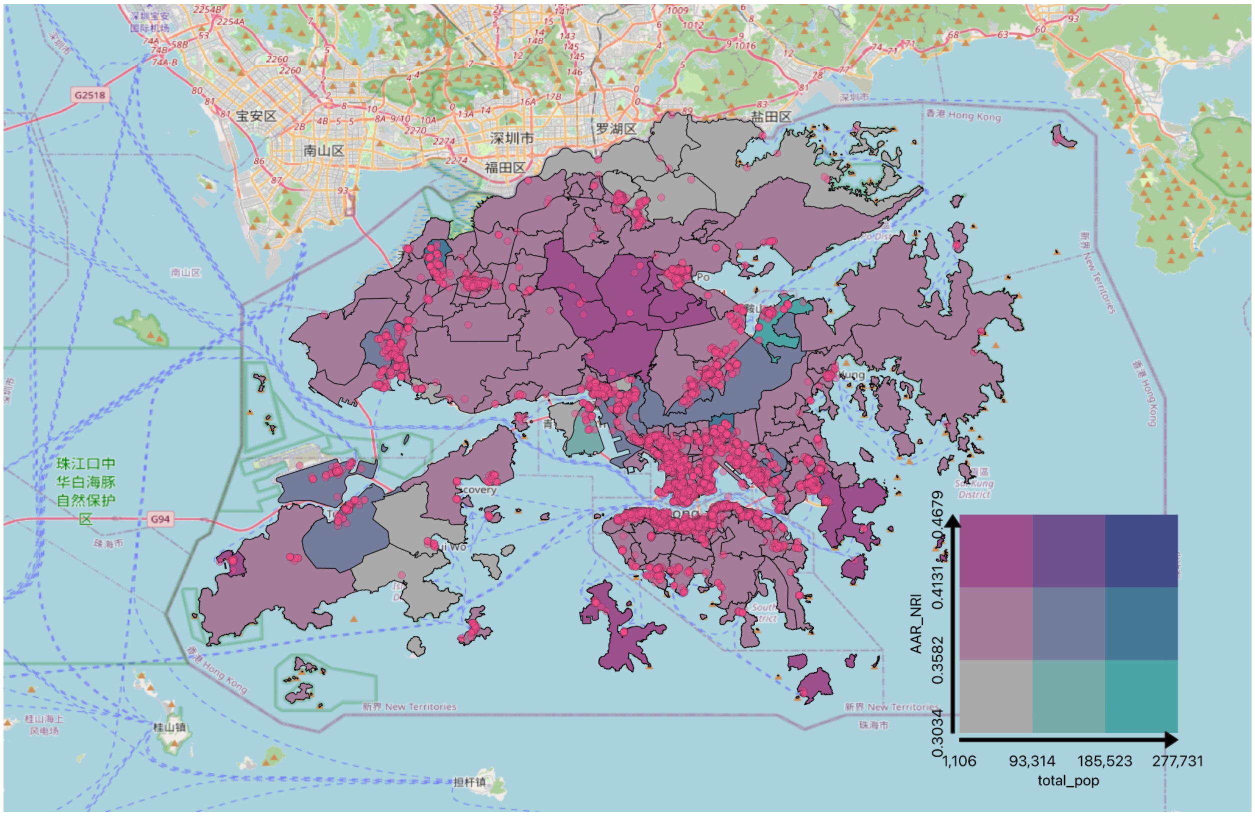
Checking Regression Assumptions for Demographic Factors x AAR NRI



The tested variables accounted for only 6.2% of the variance in AAR NRI (R-squared = .062, adjusted R-squared = .044), but the model itself was statistically significant (F(4,206) = 3.391, p = .010). The regression (Fig. 3) revealed that the only variable significantly associated with AAR NRI was total population (p = .004). It seemed to have a modest negative effect on AAR NRI (β = -.206), meaning residents of STPUGs with smaller populations tended to have access to restaurants with higher nutritional risk compared to their higher-population counterparts (Fig. 5). Other variables such as median age and median household income had relatively high p-values of .785 and .370, respectively. Although the working population proportion came close to being associated with AAR NRI, the relationship was ultimately not significant (p = .079).

Figure 5

Bivariate Map of AAR NRI x Total Population with Restaurant Points



Note: Pink points represent individual restaurant locations.

Frequency of ROFDS Use and AAR NRI

According to both versions of the Pearson's Correlation analysis (Fig. 6) between delivery frequency and AAR NRI, there was no significant correlation between these two factors. The p-value of the correlation that included the outliers was .163 and the p-value of the correlation that excluded them was .890, positing that areas where residents used ROFDS more frequently didn't tend to have restaurants with higher or lower nutritional risk (Fig. 7).

Figure 6

Research Question 2 Pearson's Correlations

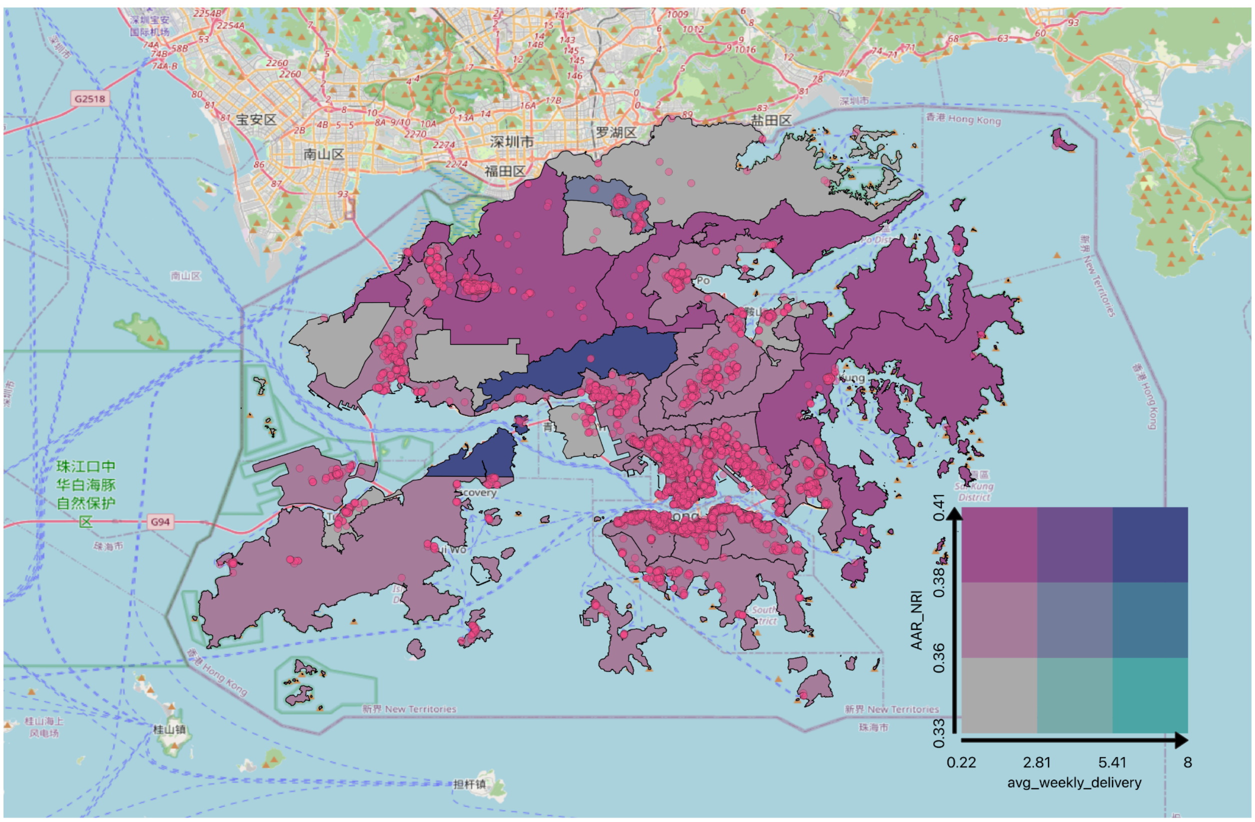
Pearson's Correlations

			Pearson's r_{with}	p_{with}	Pearson's $r_{without}$	$p_{without}$
avg_weekly_delivery	–	AAR_NRI	0.266	.163	0.031	.890
avg_weekly_delivery	–	avg_weekly_dineout	-0.331	.080	-0.630**	.001
avg_weekly_delivery	–	avg_weekly_groc_offline	0.835***	< .001	0.822***	< .001
avg_weekly_delivery	–	avg_weekly_groc_online	0.949***	< .001	0.930***	< .001
AAR_NRI	–	avg_weekly_dineout	0.331	.079	0.185	.399
AAR_NRI	–	avg_weekly_groc_offline	0.088	.648	0.068	.758
AAR_NRI	–	avg_weekly_groc_online	0.297	.117	0.214	.328
avg_weekly_dineout	–	avg_weekly_groc_offline	-0.636***	< .001	-0.668***	< .001
avg_weekly_dineout	–	avg_weekly_groc_online	-0.457*	.013	-0.573**	.004
avg_weekly_groc_offline	–	avg_weekly_groc_online	0.910***	< .001	0.814***	< .001

* p < .05, ** p < .01, *** p < .001

Figure 7

Bivariate Map of AAR NRI x Delivery (ROFDS Use)



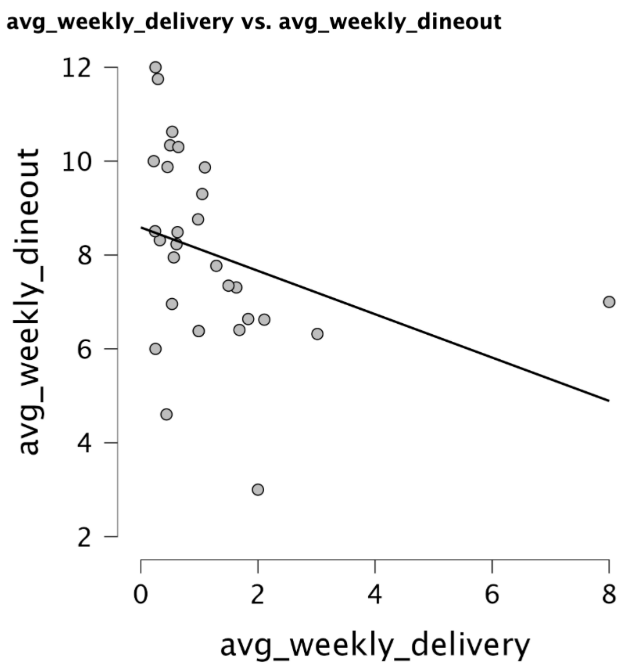
The follow-up analyses did yield significant results, though. Five correlations were found to be significant in both versions of the Pearson correlation analysis, all with a $p < 0.001$. The correlation coefficients for tests including low-response areas will be reported as r_{with} and those excluding low-response areas as $r_{without}$. Three of these relationships had strong correlations (Fig. 6): weekly ROFDS use and weekly offline grocery shopping were positively correlated (r_{with} = .835, $r_{without}$ = .822), weekly ROFDS use and weekly online grocery shopping were positively correlated (r_{with} = .949, $r_{without}$ = .930), and weekly offline and online grocery shopping were positively correlated (r_{with} = .910, $r_{without}$ = .814). All these correlations remained strong when calculated without the low-response areas. This speaks to the robustness of the correlation. Data indicates that residents in survey areas with more frequent ROFDS use tend to grocery shop more often both online and offline.

Some correlations were still significant ($p < 0.001$) but had only medium strength: weekly dining out and weekly offline grocery shopping were negatively correlated (r_{with} = .-.636, $r_{without}$ = -.668). The correlation between weekly dining out and weekly online grocery shopping was also significant (p_{with} = .013, $p_{without}$ = .004), with both showing a negative, medium-strength relationship (r_{with} = -.457, $r_{without}$ = -0.573). Opposite to the previous correlations involving ROFDS use, these correlations reveal that residents of survey areas where dining out is frequent tend not to grocery shop online or offline very often.

The correlation between weekly delivery and weekly dining out was the only correlation where significance changed based on whether low-response areas were included. Correlation was insignificant when low-response areas were included (p = .080), but significant when they were excluded (p = .001) with a moderately negative correlation (r = -.630). It seems that a low-response area could've substantially weakened the correlation, as the regression line visually seems to flatten to account for one low-response data point with a high weekly delivery rate (Fig. 8). The sensitivity of the delivery-and-dine-out correlation to low-response areas makes it less robust than the other observed correlations, but it seems to suggest that people in survey areas where ROFDS use was higher tended to dine out less.

Figure 8

Dining Out x Delivery (ROFDS Use) Regression Line Strongly Impacted by Low-Response Areas



Discussion

Interpretation of Results: Demographic Factors and AAR NRI

Our analysis revealed that total population was a predictor of STPUG-level AAR NRI: people living in small-population STPUGs lived in higher risk food environments than people living in high-population STPUGs. Our findings about other demographic factors diverged from previous research conducted in Mainland China about general OFDS. Kong et al. (2025) reported that communities with a larger working population proportion, a higher proportion of young people, and lower income tend to be exposed to an unhealthier food environment through OFDS compared to their counterparts. We operationalized these factors as working population proportion, median age, and median household income and found that none of them were predictors for AAR NRI.

Total population may have been the only significant predictor of AAR NRI because it could've acted as a proxy for urbanization. An area with more people can bring restaurants a larger customer base and support a large restaurant supply. Based on the large number of restaurants high-population STPUGs have access to (Fig. 5), it's possible that these restaurants were also more diverse than those that people in low-population STPUGs have access to. Potential diversity could've helped balance the impact of unhealthy restaurants on AAR NRI. Low-population STPUGs without access to many restaurants would not have been able to benefit from the same effect, keeping AAR NRI high.

There are potential Hong Kong-specific explanations as to why the demographic relationships that existed in Mainland China may not exist in Hong Kong. Regarding age, some studies found that unhealthy food outlets tend to be strategically clustered near middle and high schools in Hong Kong (Zhang et al., 2025; Cheung et al., 2021). Though this could make the restaurants that STPUGs with more young people have access to disproportionately unhealthy, the presence of more schools in an STPUG doesn't have to equate to a higher youth population, especially because Hong Kong's New Town residents have less access to schools (He et al., 2025). Clustering may impact the AAR NRI of the STPUGs with more schools, but if the clusters don't correspond with the students' STPUG of residence, median age wouldn't be a predictor for AAR NRI. So while there might be no concern for young people being more exposed to a higher-risk online food environment at home than others, they could still be exposed to higher-risk environments when at school. Further research that accounts for individuals' day-to-day locations and how these locations shape exposure to high-risk food environments would need to be conducted to determine whether clustering trends cause areas with higher proportions of young people to have higher-risk food environments.

Median income also was not a significant predictor for AAR NRI in Hong Kong. This aligns with the results of Ho et al. (2023), which discovered that the offline food environments of areas across Hong Kong all had a similar proportion of healthy and unhealthy food regardless of socioeconomic status. Because ROFDS are dependent on the offline food environment, it's possible that the proportionally similar healthiness of these areas extended to the online food environment, explaining why we failed to find a relationship between median income and AAR NRI. This, however, doesn't mean income-based healthy inequalities can't exist. Even when they provided equal access to healthy foods, ROFDS use was found to amplify behavioral differences between low-income and high-income individuals, such as whether they chose to reallocate time saved from delivery use to sedentary leisure or physical activity and food choices stemming from disparities in nutrition knowledge, leading to weight gain in low-income individuals but weight loss in high-income individuals (Ding et al., 2026). Our findings can only suggest that there aren't income-based health disparities in the proportion of healthy versus unhealthy restaurants accessible via ROFDS; Hong Kong's ROFDS could still exacerbate health disparities, as described in Ding et al. (2026).

Interpretation of Results: Frequency of ROFDS Use and AAR NRI

Our examination of delivery frequency and AAR NRI revealed that STPUGs with residents who used ROFDS more frequently didn't live in a food environment with a particularly higher or lower nutritional risk. This relationship was important to examine because there would've been cause for concern if STPUGs with more frequent ROFDS use were also those with higher nutritional risk, as the chances of residents ordering unhealthy food increase in areas with a higher proportion of unhealthy restaurants on ROFDS (Zhang et al., 2025). Although our findings suggest that the distribution of high and low-risk restaurants doesn't pose health risks, it's still important to consider that access doesn't equate to use. ROFDS use may not be problematic because of restaurant distribution, but if delivery platforms are highlighting restaurants with higher nutritional risk or high-risk restaurants are simply more popular among ROFDS users, high ROFDS use could pose health problems regardless of AAR NRI. Our study tried to account for food preferences by using popularity-based lists of recommended dishes from each restaurant when calculating their NRI, but we don't know if people frequently choose to order from those restaurants. Research conducted in other countries raises some concerns, though, as it seems that people often use ROFDS to order fast food (Osaili et al., 2023). The importance of considering access to restaurants with diverse NRIs diminishes if it doesn't translate into use.

Interpretation of Results: Follow-up Questions

Regarding our follow-up questions about food attainment, frequent ROFDS use was associated with more frequent online and offline grocery shopping, while more frequent dining out was associated with less frequent online and offline grocery shopping. Frequent ROFDS use was associated with less frequent dining out, and vice versa.

There is a lack of data about what residents are buying at grocery stores, but frequent grocery shopping is typically associated with better health outcomes and is considered healthier than using ROFDS or dining out (Dubowitz et al., 2014; Xu et al., 2024). Both ROFDS and dining out are alternatives to homecooking, which requires grocery shopping, so it's unclear why the two had opposite relationships with grocery shopping. However, the positive correlation between grocery shopping and ROFDS use suggests that the two don't need to be considered competing food access options; ROFDS could simply supplement food access rather than coming at the expense of a healthier behavior.

The result that increased ROFDS use was correlated with lowered dining-out behavior should be interpreted cautiously because the significance of the relationship differed when outliers were and weren't included. This relationship makes intuitive sense, though, as people eat only so many meals in a day. Their preference for one alternative to home cooking would likely detract from the other alternative. While this preference may come from individual preferences, it could also come from differences in access. It's generally agreed that ROFDS expand access to restaurants. Visual inspection of a map of the restaurants from the Dianping datasource (Fig. 5) reveals that restaurant distribution is undeniably different depending on location, even if our study found that restaurant healthiness was not. Residents in areas with not many restaurants accessible via delivery likely have even less dine-out options, motivating their preference for delivery over dining out. Future studies could test the relationship between delivery frequency and the number of accessible restaurants online and offline to evaluate this hypothesis.

Policy Recommendations

Lower population was the only significant predictor for higher AAR NRI. This finding could serve as the basis of a framework that the Hong Kong government could implement to identify low-population areas that could benefit from closer monitoring or targeted support in the form of healthier options at restaurants already in the area or the opening of new healthy restaurants. The Hong Kong government has already launched a restaurant-focused health initiative called the Less-Salt-and-Sugar Restaurants Scheme "to encourage restaurants to provide…tailor-made less-salt-and-sugar dishes or options" (Environment and Ecology Bureau, 2026). Although there are 1000 plus restaurants participating in the scheme, they represent a relatively small proportion of Hong Kong's restaurants and may not be located in low-population areas. To promote the health of those living in less-populated STPUGs, the Hong Kong government could consider creating a new initiative focused on these areas or work to diversify the locations of restaurants that do join this scheme.

The relative equity of restaurant health distribution in terms of factors like median income, working population proportion, median age, and ROFDS usage highlights the importance of approaching any potential ROFDS-related health issues by monitoring the platforms themselves rather than the distribution of restaurants. ROFDS platforms clearly have influence over what people choose to order: when people use delivery platforms that specialize in fresh food, they're likelier to pick healthy options (An et al., 2025), and when they see mostly fast food restaurants on delivery platforms, they're more likely to pick unhealthy options (Zhang et al., 2025). The government could ensure that platforms don't promote disproportionately unhealthy restaurants, by implementing policies that incentivize platforms to increase visibility of and offer price promotions for healthy food options on ROFDS as Gupta et al. (2025) suggests. In an era of increasing awareness of health and nutrition (Heidenstrøm and Hebrok, 2022), approaches that show people the healthier options they have access to could be an effective way to handle public health concerns around obesity.

Limitations

It's important to acknowledge the limitations of this study, as they may impact the validity of our findings. First, the data was aggregated at a large STPUG-scale, rather than kept at the h3 hexagonal scale initially used to determine online access to restaurants, because there was a lack of h3-level demographic data. Considering that ROFDS typically offer a 2–3 km access radius, some factors that weren't significant at the STPUG-level could've been meaningful at the hexagonal level. Future studies would ideally use smaller scales for more accuracy by collecting demographic information via mobile phone data. Additionally, not all the assumptions were met for the Q1 regression; the results could be exaggerated as a result and low-population areas may not actually have a significantly higher-risk online restaurant environment. Therefore, our results regarding the relationship between demographic factors and AAR NRI should be interpreted as exploratory, rather than final. Despite these limitations, this study synthesizes the spatial distribution and restaurant-level nutrition approaches of previous research on OFDS, providing a solid foundation for future work with richer platform and order-level data.

Conclusion

This study bridged gaps in previous research on ROFDS by considering both spatial measures of restaurant access and restaurant-specific NRI instead in Hong Kong. The primary research questions called for an analysis of the relationship between demographic factors of STPUGs, frequency of ROFDS use, and AAR NRI. We discovered that lower total population predicted higher AAR NRI, indicating that residents had access to restaurants that tended to be higher risk. All other demographic factors—working population proportion, median age, and median income— were not significantly related to AAR NRI, contradicting previous research about Mainland China. Similarly, there was no significant correlation between frequency of ROFDS use and AAR NRI, easing potential concerns about increased accessibility-driven health risks for ROFDS users. Follow up questions revealed that people with higher ROFDS usage tended to grocery shop online and offline frequently, while people who dined out often tended to grocery shop online and offline less frequently. This paper cannot provide a full assessment of ROFDS' health impacts in Hong Kong because we did not have data about what individuals were ordering. However, it suggests that ROFDS use doesn’t detract from healthier home-cooking practices and that if ROFDS does contribute to health disparities across STPUGs, those disparities may stem from urbanization patterns reflected by total population. Considering these findings could prove helpful in designing efforts to improve public health in Hong Kong.

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Appendix

Table 1. Survey Questions on Food-acquisition Behavior

Question Topic	English Translation of Question
Restaurant online food delivery service frequency	On average, you order takeout online each week (such as using Keeta, Foodpanda, Deliveroo, etc.)
Dine-in frequency	How often do you dine in offline (using physical dining services) per week?
Offline grocery shopping	On average, the frequency you go out to buy groceries per week is
Online grocery shopping	On average, you buy groceries online weekly (such as using fresh food delivery services like Cai Xian Sheng, HKTVmall, Fresh, etc.)

Table 2. Survey Residence Options

Name	Respondents (n)
Hong Kong Island	
Central and Western District	37
East District	75
Southern District	36
Wan Chai District	22
Kowloon	
Kowloon City District	55

Kwun Tong District	71
Sham Shui Po District	44
Wong Tai Sin District	47
Yau Tsim Mong District	49
New Territories	
Kwai Tsing District (Kwai Chung)	36
Kwai Tsing District (Tsing Yi)	19
North District (New Town)	38
North District (Other Areas)*	1
Sai Kung District (Other Areas)*	6
Sai Kung District (Tseung Kwan O)	54
Sha Tin District*	1
Sha Tin District (Ma On Shan)	23
Sha Tin District (New Town)	62
Tai Po District (Other Areas)*	2
Tsuen Wan District (New Town)	41
Tsuen Wan District (Other Areas)*	1
Tuen Mun District (New Town)	56
Yuen Long District (New Town)	29
Yuen Long District (Other Areas)	16
Yuen Long District (Tin Shui Wai)	54
Other	
Islands District (North Lantau New Town)	13
Outlying Islands District (Other Areas)*	8

*Low-response areas that were excluded in the second Pearson correlation test